Smart Retrofit Architecture: Enhancing sustainability of Industrial Equipment in Small-Medium Enterprises

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Abstract: Introducing the Industry 4.0 paradigm poses a new challenge to companies that must incorporate new smart technologies into their business assets to remain competitive. Digitisation and sustainability are constraints for companies' competitiveness. This article proposes the Smart Retrofit Architecture to integrate hardware and software parts into non-Industry 4.0 systems and machines from an interoperability perspective. In this way, the Smart Retrofit Architecture makes it possible to benefit from all aspects of connectivity and digitisation while respecting sustainability constraints: the recovery of old machines, the study of their parameters and the optimisation of working conditions allow social, economic and environmental sustainability. The article shows the architecture outline and an application case in the company PAMA S.p.A. in the context of the European AIDEAS project. In particular, in the case developed for PAMA, the application of the Smart Retrofit Architecture makes it possible to study the energy consumption of an old machine through the use of artificial intelligence algorithms.

Keywords: Asset Management; Resilience Engineering; Digital Transformation; Industrial System.

1. Introduction

Industry 4.0, characterised by its advanced digital technologies in manufacturing, has introduced a new era of enhanced efficiency, connectivity, and automation, thereby laying the groundwork for subsequent advancements in the Industry 5.0 paradigm. In this scenario, the significance of Smart Retrofit (SR) has grown substantially in modernising and optimising existing industrial infrastructures. SR represents a strategic approach to upgrading and revitalising outdated industrial machinery and systems by integrating advanced hardware, communication technologies, and software such as Machine Learning (ML) and Artificial Intelligence (AI) algorithms for predictions, process optimisation, and real-time monitoring. These technologies empower operators to make informed decisions and anticipate potential issues before they escalate into costly downtime. The security of retrofitted systems is paramount, particularly in the context of increased connectivity and data exchange inherent in IIoT environments. Smart Retrofit Architecture (SRA), proposed in this article, incorporates advanced communication protocols and cybersecurity measures to safeguard against unauthorised access and ensure the integrity and confidentiality of industrial data. This methodology also allows Small-Medium Enterprises (SMEs) to align with stringent regulatory standards regarding connectivity, data security, etc. In fact, the adoption of SRA holds significant strategic value, especially for SMEs, which can leverage their existing assets to preserve and enhance their value through improved performance, prolonged service life, and integration into IIoT-enabled industrial environments. Indeed, in an increasingly competitive and complex industrial landscape [1], SR provides a flexible, cost-effective pathway for SMEs to enhance their competitiveness and adapt to the rapid technological advancements characterising Industry 4.0 and beyond. This article presents the SRA to facilitate the realisation of an SR action in the context of the Horizon Europe AIDEAS project, whose scope exemplifies the application of AI-driven solutions to support and extend the entire lifecycle of industrial equipment, promoting environmental, social, and economic sustainability, resilience, and agility among European manufacturers. The modular and scalable nature of SRA is crucial for SMEs that can implement SR solutions incrementally and align their operations with smart manufacturing principles without significant upfront investment, production stoppages, or new training for operators (environmental and economic sustainability). In addition, the possibility to expand the solution step by step, the gradual integration of new technologies, the reuse of machines and the help it provides in decision-making make SRA a way to facilitate the acceptance of technological innovation for non-digital natives (social sustainability). Once the SRA is described in terms of hardware and software parts, the case study of the PAMA factory will be reported. PAMA S.p.A. is a company, located in Rovereto, manufacturing boring machines, milling machines and machining centres for various sectors and is one of the project pilots. The aim of applying the SRA in PAMA is to obtain, with low investments and small interventions, a greater understanding of the energy consumption of a machine whose operation depends on the activities carried out by other sub-groups of machinery/components/ elements. To better explain all these aspects, Section 2 will illustrate a short literature review to present the background of the SRA; Section 3 will explain the SRA; Section 4 will describe the case study realised in/with PAMA; Section 5 will conclude with future developments.

2. Background

Entering the 21st century, the manufacturing sector is undergoing a transformation marked by the emergence of I4.0, a revolution fuelled by advances in information and communication technologies. This technological shift has necessitated the adoption of SRactions and strategies aimed at upgrading existing old machinery to I4.0 standards without the need for significant capital investment in new equipment. A literature review can help understand what important changes have been made, with what technologies, for what purposes, and with what benefits. The analysis was conducted in Scopus with the key 'smart retrofit*', selecting the documents written in English. It produced 41 results, many of which have been published in the last 8 years (Figure 1).

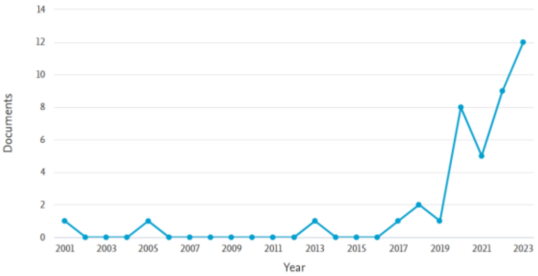

Figure 1: Documents by year - Scopus "smart retrofit*"

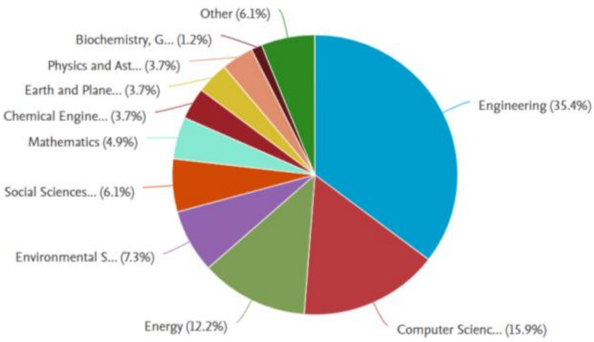

Figure 2: Documents by subject area - Scopus "smart retrofit*"

In particular, it can be seen as a "peak" in 2020 when the COVID-19 pandemic forced the development of increasingly connected and remotely accessible systems. In this perspective, SR actions make it possible to integrate connectivity aspects even on machines that were not, making them remotely accessible. The areas involving SR are various (Figure 2), but for the purposes of this research, the focus will be on those involving "Engineering" and "Computer Science". Selecting only these two areas reduces the number of documents to 34. A further selection was made by excluding those scientific documents containing irrelevant keys such as: Buildings, Zero Energy Buildings, Housing, Smart Buildings, Ancient Chinese Architectures, Architectural Heritage, Building Automation Control Strategies, Building Energy Management System (BEMS), Building Energy Management, Building Retrofits, Buildings Sector, Built Environment, Chemical Process, Commerce, Construction, Construction Process, Damping Coefficients, Damping, Decarbonising, Energy Renovation Of The Building, Building, Building Energy Management Systems, Residential Building. The number of remaining articles, therefore, fell to 22. This number was then reduced by reading the titles, abstracts and conclusions of each: a total of 14 articles were considered relevant. The results of the literature analysis identify 3 categories of articles that focus on fundamental aspects of the development of an SR action: the study of the hardware part, the study of the software part, and the study of connections and communication protocols. Each part is crucial for developing an effective SR action (Table 1). From the brief review of the literature conducted, it can be deduced that, on the hardware side, the main technologies used are those that allow data to be acquired and sent from sensors to an enterprise database/data management system; for the software part, in addition to the numerous proprietary algorithms of the specific devices that can be installed, in many cases algorithms developed in Python for machine learning, AI and deep learning are used. Finally, connection and communication are generally achieved with a Wi-Fi Internet network using HTTP/MQTT/OPC-UA communication protocols. Obviously, it may be necessary to install devices such as routers, gateways or similar on the hardware side.

Table 1. Literature review results

Ref	Hardware part	Software part	Connections & communication
[2]	A sensor node with an inertial measurement unit attached to the tap handle and a base unit displaying real-time water usage, connected to a power source, to monitor and analyse the tap handle's movements and positioning.	The software employs sensor fusion algorithms to accurately determine the IMU's orientation, position, and movement by processing the data from the sensors. The complementary filter merges the short-term precision of accelerometer readings with the gyroscope's long-term data to adjust for gyroscope drift.	Communication between the sensor node and the base unit is via Bluetooth Low Energy (BLE), while the base unit connects to the Internet via WiFi.
[3]	A Raspberry Pi 4 Model B with 8 GB RAM, a touchscreen display with a 10.1-inch IPS panel and 1920x1200 resolution, a built-in webcam with 1080p resolution, and a chain of LED lights to illuminate the user's face.	ML and deep learning algorithms, developed in Python, transform a user's facial image into landmark coordinates and characteristic values and then a facial recognition phase matches these data with the database entries.	The communication with the industrial PLC is realised via the Ethernet/IP protocol and with the central enterprise server via the FTP protocol.
[4]	ADXL335 accelerometer for capturing vibration data during the turning process and a Hall effect sensor 3144E for tracking the rotation and feed of the plate. An ESP32	The system leverages the ThingSpeak IoT analytical platform for real-time data storage, visualisation and analysis in the cloud. This enables the formation of a process performance	The data collected by the sensors are transmitted in real time to the ThingSpeak cloud platform, which supports the transmission and

	DevKit V1, equipped with an Espressif ESP-WROOM-32, serves as the core module, supported by a baseboard for connecting sensors and gathering data.	history and the comparison of correlated vibration parameters and process settings via a dashboard for visualisation and verification of correlations between the different parameters evaluated.	analysis of real-time data streams (via HTTP/MQTT)
[5]	Raspberry Pi 4 Model B, 8 GB RAM, touchscreen 1200 IPS panel, integrated webcam with 1080p and 12V LED light chains for the user's face illumination.	Implementation of facial recognition APIs using the Python programming language, suitable for Machine Learning and Deep Learning tasks.	Not specified
[6] [a]	Hardware elements include sensors for operational data collection, ranging from vibration, temperature and humidity sensors to more advanced sensors for machine status monitoring. In addition, gateway devices may be included to facilitate communication between the legacy device and the data management system or network.	Software plays a key role in processing, analysing and transforming collected data into valuable information and knowledge. It includes applications for data pre-processing, visualisation, and detailed analysis, and it can operate on cloud, edge, or fog computing platforms depending on specific data latency and processing capabilities.	Communication and connection may involve the use of different communication technologies, such as Wi-Fi, Bluetooth, LTE, or industry-specific standards such as MQTT or OPC-UA.
[7]	Raspberry Pi devices for both the Gateway and the Local Server. The Raspberry Pi was chosen for its low cost and software flexibility, meeting the requirements of low cost and ease of implementation.	A custom library in Python is developed to handle the XWare metamodel, which standardises data from heterogeneous sources into a unified format compatible with intelligent maintenance applications.	OM2M facilitates communication among devices using different M2M protocols, making XWare compatible with a wide range of existing technologies.
[8]	An electric drill modified with a self-tracking camera (Intel® RealSense™ Tracking Camera T265), an AR visor (Microsoft HoloLens 2) to provide a user interface and visualisation of the executive 3D model, and a laptop to collect and process data streams from both the instrument's sensors and the headset.	Universal Windows Platform (UWP) application was deployed on the HoloLens to visualise the executive 3D model, and data processing software was installed on the laptop to assist the operator in correcting the position, orientation, and depth of the hole. Cockroach software is also used as open-source software. NET-based toolkit for manipulating and post-processing cloud points in CAD environments, and Rhino software for processing 3D data.	The use of HTTP protocols and UDP/TCP sockets for communication between the AR HoloLens 2 visor and the laptop, as well as for accessing data stored in the cloud during the manufacturing phase.
[9]	Includes a 3D-printed enclosure made of polylactic acid material, housing an LED ring for illumination, a camera module for capturing meter images, a Raspberry Pi microcontroller for processing, and a power bank. Real-time data transmission to ThingSpeak is facilitated using an LTE-based portable WiFi hotspot.	Development and training of a CNN model, specifically the ResNet-18 model, using transfer learning from the pre-trained ImageNet dataset. The model is trained on a comprehensive dataset of digit images extracted from meter readings, employing image normalisation, resizing, and standard optimisation techniques to ensure compatibility and efficient training.	The article mentions the use of ThingSpeak for real-time data transmission, implying the utilisation of internet to communicate between the IoT-enabled water meters and the cloud server. The exact protocols are not specified.
[10][a]	The hardware aspect described in this article includes installing and integrating additional sensors into existing production machines. These hardware enhancements are crucial for enabling legacy systems to acquire new functionalities and become part of a connected, data-driven manufacturing environment.	Software for data acquisition, processing, and analysis, as well as software for machine control and monitoring. The software part would be essential for interpreting the data collected by the newly installed sensors and translating it into actionable insights, thereby enabling improved machine condition monitoring, asset transparency, and failure recognition.	Not specified
[11]	The article mentions the integration of IoT capabilities into existing machinery, even those that are outdated. This includes interfacing with existing programmable logic controllers (PLCs) through external hardware capable of connecting with the original machinery and collecting and exchanging data. This approach enables the enhancement of traditional electromechanical systems with digital capabilities.	The article discusses the development of an online dashboard for data visualisation and management, accessible to both operators and management. This dashboard is built using the Losant platform and displays real-time data from PLCs. Another significant software component is the burr recognition system, which utilises computer vision techniques to detect and evaluate excess molten material in moulds.	The article highlights the need to implement the connection with PLCs through communication protocols, which are not detailed.

[12]	The hardware setup includes integrating a Samsung S7 PLC to facilitate connections and utilising UDOOx86 boards and 4G routers to establish connectivity. This setup supports the integration of IP cameras and other IoT devices to modernise the manufacturing environment without fully replacing existing equipment.	The development of a computer vision algorithm for burrs recognition, aimed at detecting production defects in real-time, is described. Additionally, a custom Python application is mentioned for data collection and forwarding, and the use of Losant and NodeRed platforms for dashboard development and data visualisation. This allows for real-time monitoring and management of data from PLCs, enhancing the decision-making process for operators and management.	The communication setup involves connecting the UDOOx86 board to a SECO C23 IIoT gateway via Wi-Fi, with a 4G connection to the Internet, facilitating remote access to data and video streams. The PLC data communication is facilitated by an OPC DA Server on a Windows machine, with a Python script using the OpenOPC library to read and forward data to remote services.
[13]	Microsoft HoloLens overlays digital information onto the machine's real-world environment, guiding operators through the setup process. (The case study also involves the use of CAD data of tools and machine frames prepared in advance, which are essential for the AR system to accurately project the digital overlays).	Applications run on the Microsoft HoloLens display CAD models, setup instructions directly in the user's field of view, overlaying digital content onto the physical machine parts. The Static Expert Module (SEM) is an example of such software, designed to guide operators through machine setup operations up to the start of the bending program.	The integration of HoloLens with machine tools implies the use of wireless connectivity and possibly AR-specific protocols for real-time data exchange between the HoloLens and the machine control system.
[14] [a]	This article identifies several applicable hardware elements including advanced and/or smart sensors, PLCs, raspberries, Arduino, industrial PCs, etc.	This article identifies several elements that can be integrated on the software side, such as data-driven AI and ML algorithms, whose results can be visualised on user interfaces. Modelling software and digital twins are also listed.	OPC UA and MQTT, but communication methods that exploit Web APIs and cloud services are also illustrated.
[15]	The hardware parts that are upgraded or integrated into the solution to control system with feedback (advanced encoders and position sensors), the integration of CPS, and the improvement of the machine control unit.	On the software side, the article focuses on improving the software that runs the numerical control kernel and developing an intuitive and efficient human-machine interface that simplifies the decision-making process.	Several strategies can be implemented (internet, Bluetooth, etc.) which exploit protocols such as Ethernet, CAN-bus, EtherCAT, WLAN, UPC-UA, etc.

[a] The paper is a literature review

3. The Smart Retrofit Architecture

From the insights provided by the short literature review, it was possible to design an architecture that would simplify SR actions but could be generic and modular to be adapted to different situations. The literature review articles [13], [14], [15] present several steps that should be done before applying an SR action. From these articles, it was possible to identify common and necessary steps for effective SR action, which are:

1. AS-IS analysis and scope definition: to evaluate the state of the machine (presence of sensors, devices, acquisition system, etc…) and identify the final goal of the SR action.
2. Definition of the new devices needed according to the AS-IS analysis and the final goal: SRA implementation and installation.
3. Preliminary data acquisition to train an ML/AI algorithm.
4. Validation of the algorithm and of the entire SRA.

Once all these steps have been completed, a smart-retrofitted machine capable of acquiring data and returning useful information about it can be obtained. The SRA, which is modular, can be extended and linked to other business management systems. It presents a hardware part and a software part connected by the communication and connection side. The hardware part of the architecture is contained in a "box" mounted on the edge of the machine, while the software part is mostly inside the industrial PC, where the AI algorithms, user interface, connection and communication will be implemented. The SRA is designed to be easy to realise, install and ready to use. Moreover, by following the step-wise methodology proposed in this article, it is possible to apply this architecture in a simple and smooth manner. Table 2 describes the main elements of the hardware architecture. Each element was identified by combining the results of the literature review analysis (Table 1), common industrial practices and especially those provided by PAMA's experience, and by carefully studying a type of structure simple to be realised and adaptable to different situations.

Table 2. Smart Retrofit Architecture elements

Hardware side		
PLC	Compact CPU module - max of 12 I/O modules	
Digital I/O module	Digital inputs:+24VDC/3.7 mA; Input delay: 5 ms; Digital short-circuit proof outputs: +24 V DC/0.5 A.	Instead of two modules, it is possible to use a **MIX module** with a lower number of inputs/ outputs, both type analogue and digital.
Analog I/O module	Analog/potentiometer inputs (±10 V DC/16 bits or 0-100 %/16 bits); Analog outputs: ±10V DC/12 bits; output:+10 V DC/5-8.3 mA.	
Industrial PC	EC900 no LTE, Linux; RAM 4GB, FLASH 16 GB	
P. supply	Power supply 120W, 24V, 5A (DIN RAIL)	

Display	Touch-screen/monitor (according to configuration)
Connection and communication side	
RS485	RS485 No external +24 V DC supply required
Router	Router Wi-Fi
Wi-Fi	USB Wi-Fi antenna (or mini USB antenna WiFi)
Software side	
Algorithm	AI, Machine Learning, Deep Learning …
UI	Intuitive User Interface (UI)

When the architecture is applied on a specific machine, additional (with respect to Table 2) hardware devices, such as sensors, must be evaluated following an AS-IS analysis of the machine. In fact, the old machine can already have some sensors, but depending on the purpose, they can be connected directly to the PLC I/O modules or integrated with new sensors that collect other information. If the old machine does not have any sensors at all, the necessary ones can always be installed. Once the sensors are placed on the machine and connected to the PLC's I/O modules, the architecture can start working by collecting data from the sensors themselves and sending it via Wi-Fi or wired internet to the industrial PC where the trained AI algorithm or other algorithms, which can process it (Figure 3). The results will be visible via an intuitive UI from the display/ monitor and then be saved (eventually) in a cloud system/cloud database or enterprise database system. The communication protocol proposed in this paper for the communication between the box and the industrial PC is the MQTT (Message Queue Telemetry Transport) as it is a lightweight messaging protocol that is designed to be easy to implement and simple to use, making it particularly suitable for IoT, Machine-to-Machine (M2M) communication, and other situations where low bandwidth and minimal impact on the device is required. This protocol also allows near real-time communication to be developed quickly and easily.

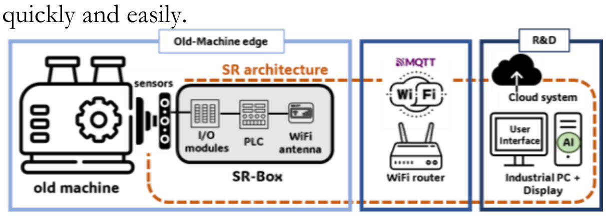

Figure 3. Smart Retrofit architecture

4. Smart Retrofit Architecture: A Case Study

This architecture is generic, adaptable in different situations and for different dated machines, expandable and modular. Being composed of simple devices, it is also cheap and easy to integrate. An example that can be given concerning the application of this architecture in an industrial context is the one being developed at the PAMA company in the context of the AIDEAS project. The company PAMA provided a machine, which has been working in the manufacturing department since 2008, on which, following an AS-IS evaluation, it was possible to proceed following the steps below.

4.1 AS-IS analysis and scope definition

PAMA's objective with the SRA application is to monitor the normal energy consumption of a subset of components essential for the machine's operation. By using predictions from the AI algorithms about the expected energy consumption under various conditions, the system can detect when the machine's energy usage deviates from the norm, indicating a non-standard condition. Once the target has been set and the initial condition analysed, it is determined that the machine is equipped with sensors to acquire information. These sensors provide data on the energy consumption of specific elements (e.g., pumps, drives, coolers) and information about the status of each element, such as 'ES' (on/off) as shown in Table 3.. Additionally, the sensors capture data on commands (whether a command has been given), SC, and the rotation speed, RS, in the case of rotating elements.

4.2 Definition and installation of the new devices

Since the sensors are already present on the machine, it was decided to complete the construction of the SR hardware side with a PLC, its I/O modules and a Wi-Fi antenna to enable data sharing with an industrial PC located close to the machine but not on its edge. There is also a router for the Wi-Fi internet network in an intermediate position between the machine and the industrial PC. Sensors on the machine acquire status, control and speed information. These sensors are then divided into groups to which a TA energy meter is assigned (configuration in the upper part of Table 3) and which return information to the PLC on the energy spent by the specific subset during the operations.

4.3 Data acquisition and AI algorithm

The data is collected by the sensors that send it via Wi-Fi and MQTT protocol to the industrial PC. The industrial PC receives them and, on the one hand, temporarily saves them locally and, on the other hand, sends them to the pre-processing algorithm, which re-processes and sends them to the AI algorithms. The acquired data can be divided into 2 categories: energy values (acquired by the TA energy meters, referred to as *'P_VAL_'*) representing the energy consumption of a subset of elements, and the state/command/rotation values of these elements (acquired by the other sensors, referred to as *'ID_'*). The command and status signals only take on the values 0 and 1, while the rotation values depend on the size of the rotating element and the process to be performed. Since the sensors only acquire and send information when they register a change or when a certain amount of time has elapsed, the data is returned in a JSON format that contains, among other information, the name of the changed variable and its value. In order to reconstruct a suitable dataset to be used in the training of the AI algorithm, a preprocessing algorithm was implemented that reads the information sent from the sensors to the industrial PC via MQTT, analyses the structure of the JSON and inserts the new value of a specific parameter into the variable table. This algorithm makes it possible to acquire the dataset as a table in which no cell is left empty: the new/changed data is inserted in the last available row, on which also the values of the other parameters (that have remained constant) are reported.

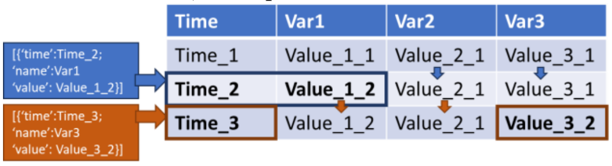

Figure 4. Pre-processing algorithm: conversion from JSON to table datasets

The "reconstruction" of the dataset is shown in Figure 4. When the AI algorithms are trained, this preprocessing algorithm will allow to send the data to the model correctly: the AI algorithm will receive only the last line from the dataset and will predict the desired value. Once the entire dataset had been reconstructed, several preprocessing analyses were conducted to determine whether there were correlations between the various parameters in order to properly select the most appropriate AI algorithms. In particular, descriptive statistics and calculation of Pearson's correlation matrix coupled with the Student's T-test were used. Since these first analyses did not reveal any strong correlations between the 'P_VAL' variables and the variables of the relevant subgroups , it was evaluated the possibility of investigating other possible correlations between the energy consumption (*'P_VAL'*) variables and all the other variables making up the dataset. In order to make the study of these variables easier, it was used the RapidMiner, which loads the data and verifies the integrity of the dataset, normalises and standardises the dataset, performs a Principal Component Analysis (PCA) and returns to us the list of variables with the highest correlation. In addition, RapidMiner simultaneously tests five different types of AI algorithms, returning which ones might be most suitable for the provided dataset. Obviously, these algorithms are tested on a limited number of conditions and therefore, although a beneficial tool and an excellent starting point, it is not the final solution. For this reason, the variables with greater correlation and stability (according to the analysis obtained by RapidMiner) were selected for the prediction of each variable of energy consumption. Then using these variables as input, 6 different AI algorithms present in RapidMiner were tested: Generalised Linear Model (GLM), Deep Learning (DL), Decision Tree (DT), Random Forest (RF), Gradient Boosted Trees (GBT), Support Vector Machine (SVM). In Table 3, the percentage of error committed by each RapidMiner algorithm is shown: RapidMiner estimates that each algorithm will predict the variable of interest, given the selected inputs, with a certain error. Of course, as was pointed out earlier, this is a starting point that must be optimised by developing specific hyperparametrization and optimised AI algorithms. It was decided that for this preliminary case, only one type of algorithm, the Decision Tree, should be developed to predict the values of the energy consumption variables as it returns acceptable error values for all the cases. The code for the implementation of the Decision Tree algorithms was realised in Python, and each includes a section for loading the data and breaking them down into independent variables X (parameters selected via RapidMiner, shown in the Table 3) and dependent variable y corresponding to the energy consumption variable (*'P_VAL'* variables). Subsequently, the data are divided into train and test data using the *train_test_split* method (*sklearn.model_selection* library) in which 80% of the data are assigned to the train-phase and 20% to the test-phase. Then, the models are realised with several *DecisionTreeRegressor* functions of the *sklearn.tree* library. These algorithms are trained on the train data and tested on the test data with the *'predict'* method and the calculation of the root mean square error and R^2 coefficient. To optimise the models, hyper-parameterisations conducted with *GridSearchCV* are also launched, testing the *criterion*, *max_depth*, *min_samples_leaf* and *max_leaf_nodes*. These hyper-parameterisations showed that the best parameters are those present by default in the *DecisionTreeRegressor* function.

4.4 Validation of the AI algorithms and SRA

The Smart Retrofit Architecture applied to the PAMA case led to the realisation of a hardware part connected to the machine, while on the software side, an AI algorithm was

Table 3. Variable subdivision – "Wired" configuration vs RapidMiner correlations

TA energy meter	Wired division of sensors		
	ID_		
	SC	ES	RS
P_VAL_1	75	76	
P_VAL_2	57,58,59,77,60,78,87,79,80,81		
P_VAL_3	67,68,69,73,74	66,70,71,72	
P_VAL_5	84,85,86		55, 56
P_VAL_6			11,14,17, 31,35,37, 39,41
P_VAL_7			21,28, 63

RapidMiner										
Value Prediction	Input suggested by RapidMiner		RapidMiner Algorithms Errors [%]						DT algorithms	
	P_VAL_	ID_	GLM	DL	DT	RF	GBT	SVM	Score R^2	RMSE
P_VAL_1	11,14,17,31,39,41,55,56,60,64,67,73,84	2,3,4,5,6,7	37.1	23.6	24.5	23.2	17.9	16.4	81.6%	1.62
P_VAL_2	17,39,41,60,67,73,31,64,55,56,84,11,14	1,3,4,5,6,7	17.2	10.7	5.8	13.9	4.7	4.7	89.3%	0.57
P_VAL_3	73,39,14,11,60,67,55,56,84,17,41,31,64	1,2,4,5,6,7	19.5	8.1	5.1	15.5	3.8	3. 7	93.8%	0.72
P_VAL_5	64,60, 67,73,55,56,84, 11,17,41,31,14	1,2,3,4,6, 7	48.9	13.2	3.3	27.7	5.1	3.4	78.8%	1.1
P_VAL_6	60,11,14,17,39,67,73,55,84,56,41,31,64	1,2,3,4,5,7	7.6	3.0	1.2	5.0	1.8	2.2	82%	1.2
P_VAL_7	17,56,73,31,60, 67, 55,11,14, 41,84,64	1,2,3,4,5,6	7.6	3.3	3.4	5.2	1.8	2.1	77.5%	0.80

developed to reproduce the machine's behaviour and predict and simulate energy consumption. The SRA application on PAMA has currently been validated in an "experimental environment"; it remains to be evaluated with online tests.

5. Discussion and conclusions

The Smart Retrofit architecture simplifies SR by indicating which and how elements can be combined to develop a generic but effective solution applicable to different machines and in different contexts. Unlike the cases developed previously and in the literature, this article wants to propose a clear and simple architecture and methodology that, if followed in its steps, allows the integration of an old machine in an industry 4.0 context without the need for new certifications. According to the proposed architecture, it is necessary to develop a hardware part containing several devices capable of enabling the software and communication/connection side of the machine. On the software side, the greatest difficulty was to identify and develop artificial intelligence algorithms capable of replicating the behaviour of the machine on which it is installed in order to obtain value-added data: in the application case reported, the aim was to best predict the power values consumed by a group of machine elements. This article also reports on an application of the architecture, the case study applied at the company PAMA, where the main purpose was to study and monitor the power consumption of certain groups of machine components. For the development of the algorithm, the dataset was studied and then the appropriate algorithm was found to predict and evaluate the energy consumption parameters ('*P_VAL*'). The data analysis showed that there is a strong correlation with the elements of other subgroups, a finding that did not surprise us as all elements are interconnected and cooperate during a specific process. For this reason, it was decided to develop an algorithm that would take information from elements of other groups as input. Although this represents a first approach and the algorithms can be further improved, the first results obtained can still be considered good and constitute a starting point for future updates. In fact, as future developments and next steps, the aim is to improve the algorithms by testing different types (e.g. those recommended by RapidMiner or others) capable of predicting these values more accurately. Among the limitations of this solution are the fact that the machines on which the architecture is implemented do not obtain the "Industry 4.0" certification but can only be made more collaborative in a connected context/company and that the application of architecture does not change the mechanics of the machine but tries to make improvement by working on the reworking and study of the information obtained from the machine itself.

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