Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Corso di Dottorato in Ingegneria dell'Informazione
Curriculum in Ingegneria Biomedica, Elettronica e delle Telecomunicazioni

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Artificial Intelligence and Internet of Things for Industry 4.0 and Society 5.0

Exploration of Theories and Practices to Implement the Future

Ph.D. Dissertation of:
Luisiana Sabbatini

Advisor:
Prof.ssa Paola Pierleoni

Coadvisor:
Ing. Michela Palmucci

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XXXIV edition - new series

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"A journey of a thousand miles begins with a single step"
Lao Tzu

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Nothing would have been possible without all of You.

Ancona, November 2021

Luisiana Sabbatini

Abstract

The societal context of today is shaped by two coexisting tendencies: technology-push and application-pull. The former is the emergence and rapid evolution and application of innovative technologies, in the realm of ICT (like IoT) and Data Analysis (like Artificial Intelligence, Machine and Deep Learning). The latter tendency is the trend of the market of today, built on requirements like low-cost, high-tech, customized, easily accessible, and so on so forth. Thanks to these coexisting and synergistic tendencies, the entire society is rapidly passing to the next level (hence Industry 4.0 and Society 5.0 paradigms). The reasoning that allowed this rapid evolution, has been the comprehension of the fact that making decisions based on real information extracted from the complex reality we live in, allows improvements in terms of costs, time, and quality. In almost every context, having good systems that allow the passage from raw actual data collected to meaningful knowledge is the key for success. From an architectural point of view, there are three main levels that allow the creation of knowledge and wisdom from the reality: acquisition, communication, and analytic. Innovation in either one or multiple levels is essential for the development of the worldwide community. This thesis presents several innovative contributions and technological explorations, belonging to either one or multiple levels, mostly focused in the realm of Industry 4.0 practices, like Condition-Based Maintenance, and Machine Vision Systems, and Society 5.0 practices, like e-Health devices and Visual-IoT systems for flood management in smart cities. IoT and AI technological paradigms have been deeply analysed from both a theoretical and practical point of view. Through their application in several research activities, each focused on specific aspects, the final aim of developing a broad and comprehensive understanding has been achieved. IoT is a revolutionary paradigm, which spans the three levels between raw data and meaningful knowledge, thus being a complex topic to deal with comprehensively. AI is an essential enabler for making IoT's impact tangible, and AI methodologies and techniques are diversified and complex too. For this reason, a bottom-up approach has been adopted, starting from a variety of real cases focused on a specific level, and each addressed rigorously applying the scientific method of research, global and adaptable knowledge about IoT and AI has been extracted. The sources of use cases have been private companies, National and International research projects, committed to Industry 4.0 and Society 5.0

paradigms, as will be presented. Specifically, the following research activities will be presented: an e-Health system based on wearable sensors, an IoT system for real-time building monitoring, a cross-protocol proxy for sensors networks, a Machine Vision algorithm for counting manually assembled pieces, a ML-based model for assessing the health status of a cartesian robot's drive belt, a ML-based model able to assess the health of an injection moulding machine based on process parameters collected by widespread sensors, an OCR-based system able to suggest maintenance intervention for painting robot's number plates, a Computer Vision solution for monitoring the water level of rivers through a camera framing the gauge, and a dynamic energy consumption rationing model for oil refining plants. By addressing more or less specific real cases centered on IoT and AI, it has been possible to understand architectural and software possibilities and peculiarities of the two paradigms. These wide variety of possibilities should be tuned in order to satisfy as better as possible context and task-specific requisites. Concluding, IoT and AI can benefit each other by the strict interconnection into the edge-AI paradigm, which together with in-network and cloud computing, have been found essential for the future successful achievement of smarter society.

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Preface

Luisiana Sabbatini, born in Recanati (MC) - Italy, gained the Bachelor in Mathematical Engineering at the Politecnico di Milano in 2014, with a thesis on Markov Chains (Branching Processes). This first experience nurtured her with strong programming and quantitative skills, like mathematics, algebra and statistics. She then continued to study at the Politecnico di Milano, graduating with the Master's Degree in Management Engineering and discussing in 2017 a thesis focused on the statistical exploration of the Design Management strategies adopted by leading furniture companies. This study experience allowed her to understand the industrial world, with all of its managerial theories and practices.

In November 2018 she started her PhD in Electronic Engineering at Università Politecnica delle Marche, where she conducted several researches on IoT applied to Industry 4.0 and Society 5.0. Her PhD belong to the so-called "Eureka" funding program, that grounds on the collaboration of the Marche Region, the Università Politecnica delle Marche, and a private company, which in this specific case is iGuzzini Illuminazione S.p.A. As the vast majority of Italian manufacturing companies, iGuzzini is pursuing Industry 4.0, hence, the strict collaboration with them provided several research questions in this direction, guiding along the entire PhD journey. Moreover, thanks to the involvement in some National and International research projects in partnership with other companies and public entities, it has been possible to expand the application horizon of the technologies applied in the industrial domain, into research activities belonging also to the wider Society 5.0 paradigm. In more details, the author addressed some objectives included in:

- POR MARCHE FESR 2014-2020, project "Miracle" (Marche Innovation and Research fAcilities for Connected and sustainable Living Environments)
- Interreg Italy-Croatia CBC Programme 2014 - 2020, project "STREAM" (Strategic development of flood management)
- PON MISE 2014-2020, project "SADABI-IT" (Smart Awareness in Digital Automation and Business Intelligence with Integrated Tools)

Finally, through the remote collaboration established with the Saint Petersburg Polytechnic University, specifically with the PhD student Nikita Kudryashov and with the Professor Vyacheslav V. Potekhin, who is the director of North-West Regional Intercollegiate Education and Research Centre (SPbPU-FESTO), the author could invest herself in another quantitative research concerning energy rationing within an energy-intensive industrial plant of oil refining.

The author delved into sub-parts of the broad and complex IoT architecture and AI techniques through several research activities, each focused on peculiar parts inside the global paradigms, thus adopting a bottom-up approach. Specifically, from practical cases centered on particular components (e.g. cross-protocol proxy, e-Health wearable device, ML classification models for equipment's health assessment, MQTT protocol, CV algorithms, etc.), it has been possible to develop a general and deep comprehension of an IoT system. Moreover, the comprehension and application of AI techniques has been essential in every work, specifically those related to the Analytic level. Weak knowledge about Electronic Engineering has been strengthened by research activities performed, while strong knowledge gained during Bachelor, Master of Science, and individual development, has been exploited for empowering all the research activities tackled.

Chapter 1

Introduction

This manuscript organizes research activities performed during the three years of PhD. The Preface paved the way for understanding how the activities have been done over time, based on my personal and professional background, and on the focus of the PhD.

1.1 Motivation and Objectives

The majority of research activities performed arose from real problems which could not be solved using more traditional techniques and technologies. I can therefore identify some general technology-related keywords characterising this manuscript: Internet of Things (IoT), Big Data Analysis (BDA), Artificial Intelligence (AI) namely Machine Learning (ML), Deep Learning (DL), and Computer Vision (CV). Focusing on the contexts of application, keywords characterising this manuscript are: Predictive Maintenance (PdM), Flood Monitoring, e-Health, building monitoring, and Machine Vision (MV). Most of the time, by abstracting the problems analysed, the core of them is centered on how to extract meaningful knowledge and wisdom from the reality, not interfering with its natural or designed prosecution. A concrete example of this can be the comprehension of health condition of an industrial equipment, without stopping it or modifying its scheduled working, or even how to monitor an elder inside his daily life routine thus reducing the number of required medical examinations and hospitalization. This kind of problems can be answered in a wide range of ways thanks to hardware and software related solutions pushed by the enormous technological advance which we have witnessed during the last decade. On the other hand, the societal evolution itself is demanding for increasingly intelligent solutions to improve overall well-being. By applying innovative technologies we are able to solve previously unsolvable problems, to reach inconceivable performances and accuracy, or create solutions for even new problems.

By applying a bottom-up approach, hence starting from practical problems and use cases where innovative technologies are essential for successfully achieving the objectives set, a broad comprehension has been reached and innovative solutions developed.

Specifically, the objectives met by this work range from devices and complete solutions able to satisfy needs of Society 5.0, to cross-protocol proxy able to ease the creation of IoT solutions for those non-experts in the field of telecommunication, and up to solutions able to optimize industrial operations thus being contributes toward the actual implementation of Industry 4.0 paradigm. The landscape of context of use of the contribution is very diversified, still their core is very similar, and it is based on the exploitation of cutting-edge technologies and techniques for improving overall state of society, and solving very complex tasks. Going deeper into specific objectives of each contribution that will be discussed, we can start by presenting the need for decreasing costs and efforts required for medical monitoring and treatment in today's ageing society. Life expectancy is in positive trend since decades, and greater age is associated with higher risks and deserves frequent monitoring for ensuring patients' health. In this context, IoT, Cloud, and AI techniques offer an affordable, customizable and efficient solution for the collection of data, analysis in real-time, and storage on the cloud for long term use and remote access (3.1).

By focusing on the problem of building monitoring, which is essential for the improvement of resilience in the face of natural disasters like earthquakes, and in the face of natural decay of architectural structures, the objective of developing an IoT solution able to meet essential requirements in a well-defined context of use (i.e. building monitoring), has been answered in Sec. 3.2.

Going further into sensors networks for multiple context of use, the necessity to mediate between well-known IoT protocols has been answered in Sec. 4.1 by proposing and testing a cross-protocol proxy, which makes easier the development of IoT solutions for non-experts also.

Moving on to the industrial context, a Machine Vision solution answering to the need of monitoring the manual production in place has been proposed and validated. The objective of monitoring manual assembly has been previously taken into consideration by a company through more traditional technologies with poor results, while innovative technologies like cameras and Machine Vision algorithms proved to be versatile and accurate (5.1).

One general objective met through different contributions is the one of optimising the maintenance of industrial equipment by monitoring it and properly analysing data collected for inferring its actual health condition, instead of waiting for equipment failures, or replacing components and sub-parts too early. The aforementioned two approaches are connected to increased direct and indirect maintenance costs, respect to the optimal maintenance which should intervene just before failures occur. Specifically, by fusing several information about process parameters of an injection moulding machine, has been possible to develop a classification model based on Machine Learning algorithms and able to predict the Healthy or not condition of the machine while it is working, thus achieving the objective of optimal maintenance just-in-time (5.2). In another case the objective was to prevent too much dirt from being created on number plates adopted inside an automatic painting system for managing consequent orders. The objective has been met through a Machine Vision solution based on Optical Character Recognition (5.3). Still in the same domain, the objective of another research activity was to understand the health condition of a cartesian robot's drive belt, without interfering with its functioning. By acquiring current consumption data and developing a proper data analytic solution the goal has been achieved (5.4).

Moving on, from a very wide perspective we can set the problem of floods, which affects millions of people all over the world. Flash floods especially could be very dangerous for people living nearby rivers. For addressing this objective, measurements about river's height are essential. A camera based solution, versatile and efficient, has been developed and tested on a real data set collected through an IP cam installed in one river site relevant for the Marche Region in Italy (5.5).

Finally, if we consider the oil refining process, it is crucially important to optimise the management of energy consumption, for avoiding waste and reducing overall costs in cost-intensive processes. Innovative technologies allow the implementation of a wide monitoring network, made of sensors and other devices able to collect an extremely wide amount of data, which can be used as predictors for modeling energy consumption rations. Through such models, optimisation can be achieved respect to the actual situation which grounds on guidelines fixed a priori, that cannot take into consideration the actual situation of the plant. The development and test of a Data Science-based solution will be presented to answer this objective (5.6).

1.2 Contribution

As previously hinted, the outcomes of research performed have been usually approaches, algorithms, systems, or applications, involving innovative hardware or software technologies, together with their empirical experimentation on the source use case. The value of each research sub-project is hence twofold, the empirically extendable value, and the general research and development procedure applied. Up to date literature regarding theories, practices and technologies has been reviewed. Innovative solutions to the analysed problems have been proposed and empirically tested on the use cases.

1.2.1 Research Methodology

The general approach followed, is the usual scientific method (Fig. 1.1).

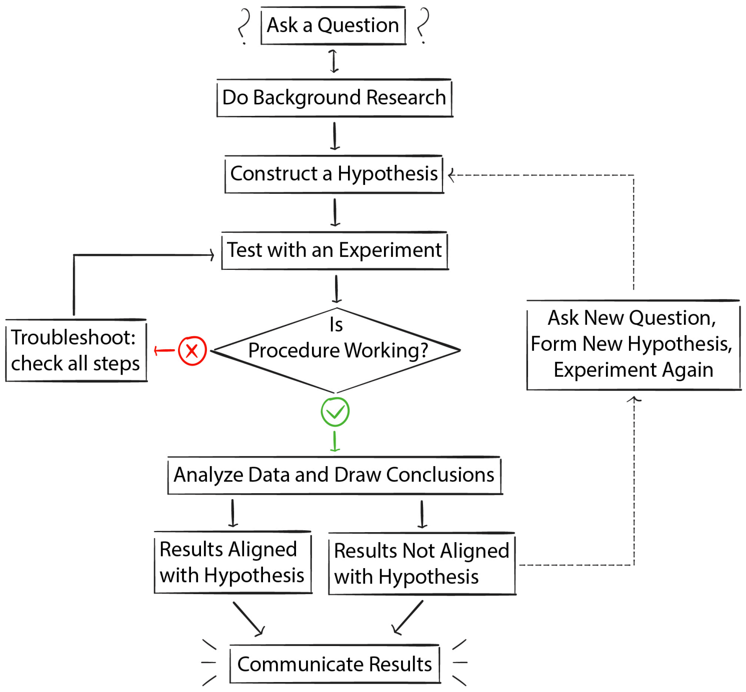


Figure 1.1: Scientific Method block diagram.

In general, first, a guiding problem has been defined through setting a question. During my research activity this phase has almost always been carried out together with a guiding entity, either the company involved in the Eureka program, or a research project objective. Then, a detailed exploration of the problem's background, and the identification of potential technologies (both hardware and software) suitable for finding a solution has been done. This phase is strictly dependent upon extensive literature research, related to the specific topic or technology identified, with the final aim of defining possible systems able to extract the desired meaningful knowledge from the reality of interest. Sometimes, it can happen that the specific context to be analysed has not been taken into account by others. In these cases I tried to develop a solution by adapting and arranging contributions belonging to comparable contexts in order to achieve the main goal. Once defined a prototype solution based on hypothesis constructed, it has been implemented and tested on the particular context under analysis. Finally, results achieved have been summarized, and usually lead to a publication.

If we want to position this study and summarize it into Research Questions (RQ) guiding the explorations, this could be the list:

RQ1. How can we customize and optimize IoT devices based on specific tasks at hand?

RQ2. How communication protocols and networks should evolve in order to meet requirements of next generation IoT and Web of Things?

RQ3. Which smart analytic, technologies and systems are suitable for dealing with complex and previously unsolvable tasks?

RQ4. How can the maintenance of industrial equipment be optimized through advanced technologies and analytic?

RQ5. Are ML and DL techniques able to support in managing extremely complex situations?

RQ6. Can innovative systems be sustainable enough for the future of industry and society?

To investigate RQ1, I carried out some researches in the domains of remote health monitoring and building monitoring, respectively addressed in details into Section 3.1 and 3.2. Concerning the second RQ, one cross-protocol proxy for sensors networks based on CoAP has been developed and tested (Sec. 4.1). Moving on to the third question, the complex task of monitoring manually assembled pieces and monitoring river flood through advanced systems have been addressed respectively in Sec. 5.1 and 5.5. For what it concerns the fourth RQ, maintenance of manufacturing equipment has been covered in Sec. 5.2, 5.4, and 5.3, by focusing respectively on injection moulding machines, on a Cartesian robot, and lastly on the metal plates used for the identification of production batches by an automatic painting robot. RQ5 has been addressed by almost all research activities in Ch. 5, and the energy rations modeling presented in Sec. 5.6 is by far the most focused research contribution. Last RQ was also tackled by the majority of research activities, and the general feeling obtained is that the so-called edge-AI could massively impact sustainability, among other requisites. Moreover, as presented in Sec. 5.3, the general approach of data re-use (multiple utilization of the same datum collected) could and should be considered in order to make technological investments worth.

1.2.2 Research Outcomes and List of Articles

The results achieved range from customized devices, entire systems, highly and easily usable cross-protocol proxy, analytic approaches, and algorithms application. From single contexts of work general comprehension and conclusions have been deducted, for creating reusable insights. The entire PhD has been useful for identifying guidelines for future research, starting from the deepened activities, which in turn have been convenient for solving problems proposed by the co-funding company or set into National and International research projects.

Summarizing tangible research outcomes, during three years these five works have been presented at International Conferences:

- Pierleoni, P., Conti, M., Belli, A., Palma, L., Incipini, L., Sabbatini, L., Valenti, S., Mercuri, M., Concetti, R., *"IoT Solution based on MQTT Protocol for Real-Time Building Monitoring"*, (2019) 2019 IEEE 23rd International Symposium on Consumer Technologies, ISCT 2019, pp. 57-62.

- Pierleoni, P., Belli, A., Palma, L., Incipini, L., Raggiunto, S., Mercuri, M., Concetti, R., Sabbatini, L., *"A Cross-Protocol Proxy for Sensor Networks Based on CoAP"*, (2019) 2019 IEEE 23rd International Symposium on Consumer Technologies, ISCT 2019, pp. 251-255.

- Pierleoni, P., Palma, L., Belli, A., Sabbatini, L., *"Using Plastic Injection Moulding Machine Process Parameters for Predictive Maintenance Purposes"*, (2020) Proceedings of International Conference on Intelligent Engineering and Management, ICIEM 2020, pp. 115-120.

- Pierleoni, P., Belli, A., Palma, L., Palmucci, M., Sabbatini, L., *"A Machine Vision System for Manual Assembly Line Monitoring"*, (2020) Proceedings of International Conference on Intelligent Engineering and Management, ICIEM 2020, pp. 33-38.

- Pierleoni, P., Belli, A., Palma, L., Sabbatini, L., *"Diagnosis and Prognosis of a Cartesian Robot's Drive Belt Looseness",* (2021) IoTaIS 2020 - Proceedings: 2020 IEEE International Conference on Internet of Things and Intelligence Systems, pp. 172-176.

In addition, these three papers have been published by International Journals:

- Pierleoni, P., Belli, A., Concetti, R., Palma, L., Pinti, F., Raggiunto, S., Sabbatini, L., Valenti, S., Monteriù, A., *"Biological age estimation using an eHealth system based on wearable sensors"*, (2021) Journal of Ambient Intelligence and Humanized Computing, 12 (4), pp. 4449-4460.

- Pierleoni, P., Belli, A., Palma, L., Sabbatini, L., *"A Versatile Machine Vision Algorithm for Real-time Counting Manually Assembled Pieces"*, (2020) Journal of Imaging, 6 (6).

- Sabbatini, L., Palma, L., Belli, A., Sini, F., Pierleoni, P., *"A Computer Vision System for Staff Gauge in River Flood Monitoring"*, (2021) Inventions, 6, 79. https://doi.org/10.3390/inventions6040079

One paper has been submitted to an International Journal and is currently under review:

- Sabbatini, L., Belli, A., Palma, L., Pierleoni, P., *"One Datum and Many Values for Sustainable Industry 4.0: a Prognostic and Health Management Use Case"*, under review in Applied Sciences.

Lastly, the collaboration with Peter the Great St.Petersburg Polytechnic University (SPbPU) is continuing and a paper containing results achieved is under preparation.

1.3 Thesis Outline

This manuscript is structured with a general background Chapter (2), which introduces technological concepts like Internet of Things, Big Data, Cloud Computing, Artificial Intelligence and Computer Vision, and societal concepts like Industry 4.0 with its best practices like Predictive Maintenance, and Society 5.0 and its optimized mechanisms like Early Warning Systems, and e-Health solutions. Inside that Chapter I'm going to lay the foundation for both the specific topics analyzed, and for the conceptual framework organised for unifying contributions into a global comprehension. Specifically, this conceptual backbone in which research activities are going to be positioned is composed of three main components, or levels. Chapter 3 is dedicated to the contributions more oriented toward the first component, the Acquisition-Level, Chapter 4 to the Communication-Level contributions, and finally, Chapter 5 deals with the Analytic-Level contributions. For the most part, it has been necessary to add some project specific literature inside the sections dedicated to each project within the three named Chapters. Lastly, in Chapter 6, answers to research questions, reasoning on findings, take home messages, and outline of future research are presented.

Chapter 2

Literature Review

In this Chapter, the grounding literature shared between research activities carried out is going to be presented. Specifically, topics strictly connected to the technological domain, like IoT, AI, and edge computing, and to the societal domain, hence the Society 5.0 and Industry 4.0 paradigms, are going to be addressed.

A more in-depth analysis of the literature will then be made within the Sections dedicated to the individual research activities inside the next chapters to complete the required overview.

2.1 Introduction

The set of concepts that need to be reviewed in order to lay the foundations of this work is relevant. Consequently, I decided to introduce a well-defined framework for presenting everything in an organised way.

Several researchers attempted to review and define a reference for the Industry 4.0 paradigm. The reference framework I appreciated the most is the one presented by Lasi et al. [4] who identified two main driving forces that jointly led to the rise of Industry 4.0 paradigm, and I would like to add, even to the rise of the broader Society 5.0 paradigm: application-pull and technology-push [5]. These driving forces are familiar to me given my background in Management Engineering, and I will present the literature reviewed following this conceptual arrangement.

Moreover, since the development of solutions for a smarter world is very complex, and research activities are usually focused on specific parts of entire technological paradigms, I will introduce at the end of this Chapter a reference structural scheme, which takes inspiration from the three-layered vertical view on IoT. Specifically, the three-layered architecture will be combined with the Data-Information-Knowledge-Wisdom (DIKW) pyramid proposed by J. Rowley [6], and research activities carried out during the PhD are going to be positioned inside this architectural and conceptual reference scheme.

As mentioned earlier, according to Lasi et al. [4], Industry 4.0 is a future project based on two development directions, application-pull and technology-push. The former induces a remarkable need for changes due to changing operative framework conditions, and it is triggered by social, economic and political changes. The latter involves the widespread adoption of the enormous amount of exceptional technologies recently developed, especially those belonging to the Information and Communication Technology (ICT) domain. What the authors proposed for interpreting Industry 4.0, I believe remains valid for the general societal evolution we are witnessing.

The set of technologies is the enabler thanks to which the application-pull tendency can be realized, hence, I'm going to present the Technology-push side first.

2.2 Technology-push

Over time innovation has always had to do with technological progress, among other things. Following the history of Innovation progress, the first generation was indeed centered on the emergence of new industries largely based on new technological opportunities (semiconductors, synthetic and composite materials, pharmaceuticals, and electronic computing), and on the technology-led regeneration and enhancement of existing sectors (agriculture, textiles and steel). This attitude has always accompanied innovation, hence, it is essential to introduce technological enablers of today.

I will present in the following sub-sections some of the so-called technological pillars that characterise the present society, following the list identified, for what it concerns Industry 4.0 paradigm, by many researchers [7, 8]. There are nine commonly accepted technological enablers: IoT, Cloud Computing, Big Data, Simulation, Augmented Reality, Additive Manufacturing, Horizontal and Vertical Systems Integration, Autonomous Robots, and Cyber-security. I will focus on some of them, and integrate this list with additional technologies identified by other researcher [9, 10, 11] and relevant for the research activities that I will present in this manuscript. Specifically, I refer to Visual Computing [12], especially Computer Vision and Machine Vision, Artificial Intelligence [13], Smart Sensors [14], and Edge Computing.

2.2.1 Internet of Things

According to Atzori et al. [15], IoT is a technological paradigm based on pervasive presence of a variety of uniquely identified "things". Through their unique addressing those objects are able to interact with each other and cooperate. IoT is decentralized and heterogeneous in its essence [16], hence the direct consequence is the possibility to exploit this paradigm into a wide variety of domains: domotics, assisted living, e-health, industrial, and enhanced learning, among others.

As the name itself suggests, the IoT can be interpreted more with a network oriented vision if we focus on "internet", or with an object oriented one if we focus on "things". From a practical point of view, this paradigm has been embodied in numerous technologies, especially in the domain of object identification: Unique/Universal/Ubiquitous IDentifier (uID), Radio-Frequency IDentification (RFID), Near Field Communications (NFC), and Wireless Sensor and Actuator Networks (WSAN). This is why a concept that emerged aside IoT is the spime, defined as an object that can be tracked through space and time throughout its lifetime and that will be sustainable, enhanceable, and uniquely identifiable. Although quite theoretical, the spime definition finds some real-world implementations in so called Smart Items: sensors equipped with wireless communication, memory, elaboration capabilities, and new potentials.

Finally, according to the "Semantic oriented" vision of IoT, the number of items involved in the Future Internet is destined to become extremely high. Therefore, issues related to how to represent, store, interconnect, search, and organize information generated by the IoT will become very challenging. Some projections say that the number of IoT devices will exceed 50 billion within a few years.

From an architectural design point of view, several researchers identified four main layers of typical IoT networks [16, 17, 8]. Sensing Layer, where the status of "things" is sensed thanks to their unique identity. Network Layer, determines and maps "things" automatically in the network thus enabling the connection, sharing and exchange of data through wired or wireless network from the Sensing to the Service Layer. Service Layer exploits middle-ware technology supporting services and applications (e.g., information search engines and communication, data storage, exchanging and management of data, and ontology database), and ensures inter-operability among the heterogeneous devices. Finally, the Interface Layer makes easier the interconnection and management of the objects and allows a clear interaction of the user with the system.

As highligthed by Aquilani et al. [11] IoT is essential in both collecting a vast amount of data (so-called Big Data), and making it available for processing and elaboration. IoT's fortune can be linked to the fact that it is the natural enabling architecture for the deployment of independent federated services and applications, characterized by a high degree of autonomous data collection, event transfer, network connectivity and inter-operability.

2.2.2 Big Data

According to Gao et al. [18] the worldwide proliferation of the number of computers, sensors, mobile devices, and smartphones has fundamentally changed the way data are generated, collected, transmitted, and stored. The worldwide connection enabled by the Internet has intensified so much the pace of data generation and collection, that a specific name has been defined to refer to this huge amount of structured, semi-structured and unstructured data, namely Big Data (BD). The IoT itself has a strong influence on this. Several researchers tried to set a clear definition of BD, which is something essential for fully extracting value from these data. Among the proposed definitions, I would like to propose here the one presented by Khan et al. in [19], which summarised BD into 7 V's: *Volume* refers to the size, *Velocity* to the speed at which they are generated, *Variety* to their heterogeneity and polymorphism (audio, video, text, etc.), *Veracity* to their truthfulness, cleanliness and precision, *Validity* to their suitability for the given objective, and *Volatility* to their lifespan (which is mandatory to be limited given Volume, Velocity, and Variety). The seventh V is *Value*, a special one not being one peculiarity but the desired outcome to be extracted from these BD. This Value is measured in function of costs associated to the data (collection, storage, processing among others) versus gain obtained from them.

Despite challenges inherently involved in BD, the rich information embedded in them has led to the proclamation that data is today the most valuable resource in the world [18]. Technological advance in sensors, storage and processing has shifted the role of data, making it an inseparable co-product of modern society. Coherently, innovative technologies arose with the aim of answering to emerging needs connected to the data-driven modern world, among others Cloud Computing.

2.2.3 Cloud Computing

Cloud Computing (CC) is the delivery of computing services — servers, storage, databases, networking, software, analytics, and applications — on-demand through the Internet, or Cloud. These characteristics let CC become and essential technology supporting the adoption of innovation. As Alcacer et al. [8] pointed out, CC has several advantages that allow cost reduction: low initial investment; direct and indirect costs associated to the removal of IT infrastructure are cut; possibility to dynamically scale resources needed based on actual requirements and consequent payment proportional to what has been used; portability to almost any type of connected device; little prior technical knowledge required respect to having in-house dedicated hardware and software; technical support from the service providers. Accordingly, CC has made the management of big data feasible. Especially the model development phase could be resource intensive, CC is a solution for outsourcing the required computational infrastructure as long as it is needed in a fast, efficient and cost-effective way.

Most CC services fall into four broad categories: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Serverless, and Software as a Service (SaaS). IaaS is where cloud service providers supply users with fundamental computing resources, with virtual infrastructures, e.g., virtual servers, networks or storage and where users into the cloud can deploy and run arbitrary software, which can include, for instance, operating systems applications. PaaS is where users develop and run applications using programming languages on the cloud infrastructures. Therefore, it can achieve scalability, high speed server and storage. Users can build, run and deploy their own applications with the use of remote IT platforms. On this layer, there is no concern on the resource's availability and maintenance. Overlapping with PaaS, Serverless computing focuses on building app functionality without spending time continually managing the servers and infrastructure required to do so. The cloud provider handles the setup, capacity planning and server management for you. Serverless architectures are highly scalable and event-driven, only using resources when a specific function or trigger occurs. SaaS is where applications reside and runs in a cloud infrastructure. Accessible from various client devices through an interface such as a web browser and programs. The focus is to eliminate the service applications on local devices of individual user, achieving an high efficiency and performance for the users. This category enables software applications such as Computer-Aided-Design (CAD) software and Enterprise Resource Planning (ERP) software, with a lower total cost of ownership.

2.2.4 Artificial Intelligence

The term Artificial Intelligence (AI) was first coined in 1956 by McCarthy, which described it as "the science and engineering of making intelligent machines". As reported by Borges et al. [2], since then, the history of AI has experienced ups and downs in terms of success and attention, mainly due to its strong dependence upon availability of a large amount of data, improvement and optimization of learning algorithms, and stronger computational power. Specifically, Lee et al. [13] identified by 'ABCDE' the key elements for AI practical adoption. These key elements include Analytic technology (A), Big data technology (B), Cloud or Cyber technology (C), Domain know-how (D) and Evidence (E).

AI is a cognitive science with rich research activities in the areas of image processing, natural language processing, robotics, machine learning and many other [13]. Today, thanks to technological and societal evolution, AI is the most important general-purpose technology of our era, particularly with regards to Machine Learning techniques, as pointed out in [2]. According to Dwivedi et al. [20] researchers have offered various definitions of Artificial Intelligence (AI) over time. Every definition usually encompasses the key concept of non-human intelligence able to perform specific tasks. Some researchers stressed the ability to mimic cognitive functions generally associated with human attributes, some other the ability to independently interpret and learn from external data to achieve specific outcomes through flexible adaptation. The relation between amount of data and performances achievable by several AI branches is indeed shown in Fig. 2.1.

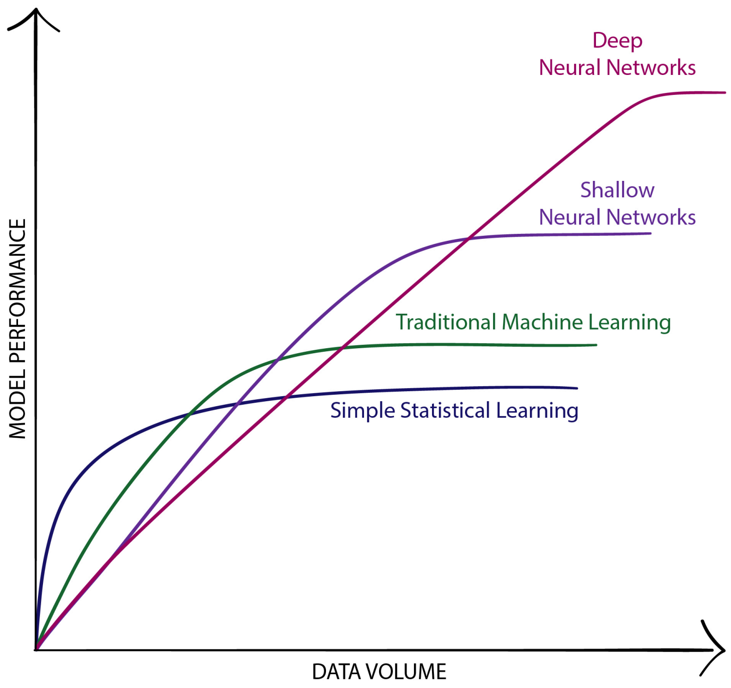


Figure 2.1: Performance versus amount of data for ML and DL models, adapted from [1].

Whatever definition we would like to focus at, when we go deeper into AI algorithms it is common the division between supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Especially supervised methodologies benefited from the data-driven world we live in. From a conceptual point of view, AI comprises the research branch of Machine Learning (ML), which in turns encloses Deep Learning (DL).

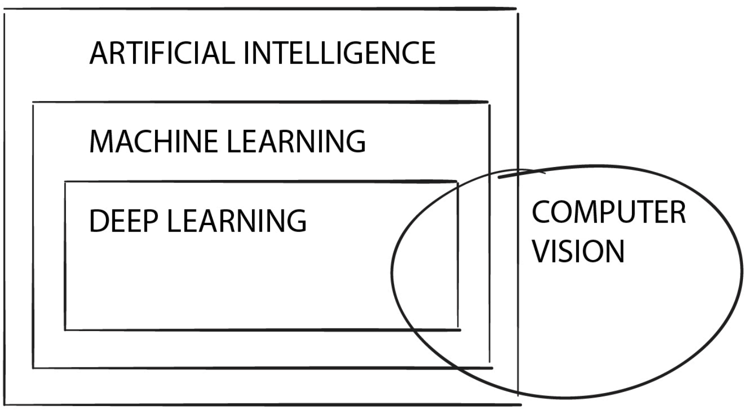


Figure 2.2: Mutual releation between AI, ML and DL, adapted from Borges et al. [2].

2.2.5 Computer Vision

Computer Vision (CV) can be intuitively described as the scientific field answering to the dream of having a computer interpret an image at the same level as humans do [21]. From a practical point of view, research on CV have successfully dealt, or is actually dealing, with the following tasks:

- Optical Character Recognition (OCR) - reading alphanumeric tags;
- Automatic inspection - rapid inspection for quality assurance and defect detection;
- Object recognition - automatic and reliable recognition of specific classes of objects;
- Face detection - finding and identifying human faces;
- Object detection - recognition and location of objects inside images;
- Semantic segmentation - classification of image pixels as belonging to a particular label;
- Motion estimation - the process of determining motion vectors between two frames;

Specifically, [21] identified some salient branches of CV algorithms: traditional image processing techniques (filtering, transforms, binary morphology), DL techniques (supervised, unsupervised, Deep Neural Networks, Convolutional Neural Networks), recognition (object classification and detection, semantic segmentation), feature detection and matching, Motion estimation, depth estimation, 3D reconstruction, and computational photography.

As Posada et al. highlighted in [12], the application of Computer Graphics and CV (broadly referred to as Visual Computing) technologies play an important role in technological landscape of today, being the enabler in many application fields.

2.2.6 Edge-AI

As could be expected since the description of IoT and CC technological paradigms, the transmission of information between IoT devices and the Cloud has been found to cause many network problems [22], e.g.latency, power usage, security, privacy, and dependence on continuous internet connection among others. Centralized processing in the Cloud is increasingly showing its inadequacy in our rapidly evolving world full of devices which could be better exploited. Real-time decisions are essential for several IoT applications, as we will see in the following section with some examples, hence, distributed intelligence between edge and Cloud currently attracts attention and seems to be the right solution to many weaknesses of CC alone. Distributed Intelligence means that devices placed wherever have the capability of analysing, modeling, and then making decisions on their own, thus being complementary to CC in handling data with varying requirements of latency [18].

When the analytical component implemented on the edge device is based on AI algorithms (either ML or DL), this device is usually referred to as an Edge-AI [23]. AI models are usually intensive in terms of memory and computation, but thanks to technological advancement in both hardware, i.e. powerful microprocessors, and AI field such as Neural Network decompression techniques (that allows to reduce memory footprint of trained models) and many other solutions, Edge-AI is recently becoming reality [24].

2.3 Application-pull

Even though quite concise, an overview on the technological landscape of today has been presented. To complete the analysis of the broad context we live in, the pulling tendency has to be addressed.

According to Lasi et al. [4], general social, economic, and political needs — short development periods, individualization, on demand, flexibility, decentralization, and resource efficiency — trigger for changes, which becomes essential given operative conditions of today. Focusing on the market features, including characteristics of the economy as a whole and of the end market, i.e. the users, we can summarize these pulling needs into the renown seven rights of logistics

[25]: "to deliver the right product, in the right quantity and the right condition, to the right place at the right time for the right customer at the right price." Putting the user at the center, needs emerge. Together with those user-centric requirements, it is the daily living itself in today's society that underlines the need for sustainability and optimization, which are then reflected in the search for innovations in this direction.

Technological evolution allows to answer to these emerging needs, and we can identify some broad paradigms arising from the two synergistic push-and-pull streams described: Industry 4.0, and Society 5.0.

2.3.1 Industry 4.0

Since the introduction of the term "Industrie 4.0" in an article published by the German government in 2011, this concept has attracted the attention of a multitude of practitioners and researchers. National governments all over the world are pushing for this paradigm to become a reality (Fabbrica Intelligente in Italy, Made in China 2025, Industrial Internet in the US, Factories of the Future in Belgium, etc.). Industry 4.0 (I4.0) grounds on the integration of innovative Information and Communication Technologies (ICT), with industrial technologies, to build an industry able to deal with market requirements of today.

From a technological point of view, nine main pillars have been identified: Industrial IoT, CC, BD, Simulation, Augmented Reality, Additive Manufacturing, Horizontal and Vertical System Integration, Autonomous Robots, and Cyber-security. Some of these technologies, specifically those particularly relevant to this manuscript, have been introduced in details in the previous Section 2.2.

From a conceptual point of view, the heart of I4.0 is the Smart Factory [26]: an highly productive engineering system based on digital technologies, information technologies and automation, with the aim of improving the management of manufacturing resources and Quality of Service through interconnection, collaboration and execution. Waste, defects and downtime are pushed towards zero [27]. The Smart Factory makes extensive use of Cyber-Physical-Systems (CPS): transformative technologies grounding on physical objects or processes closely intertwined and networked with software and computational capabilities in the virtual world. Through this interconnection different components can interact with each other and exchange information. CPS allow the creation of Digital Twins, that are virtual representations of manufacturing elements, characterised by near real-time synchronization between the cyberspace and physical space, and can be used for monitoring, control, diagnostics, prediction, and simulation [28].

Researchers all over the world analysed the I4.0 phenomenon, trying to set road-maps and guidelines. Hermann et al. [29] identified six design principles that could be followed for easing the implementation of I4.0. These principles are: inter-operability, virtualization, decentralization, real-time capability, service orientation, and modularity.

From a practical point of view, there are some best practices associated to the Industry 4.0 paradigm, as for example Predictive Maintenance (PdM) of manufacturing assets, and the broad adoption of CV solutions for manufacturing related purposes. This last broad practice has gained so much attention to deserve a specific name, Machine Vision (MV).

Predictive Maintenance

Over time, the interest and attention towards maintenance management has increased enormously because maintenance costs are among largest in any operating budget. Cutting operational costs, product cost decreases and the "right price" can be achieved. Moreover, maintenance is also responsible for product quality and lead time, therefore, it must be accounted strategically.

Maintenance strategies have evolved over time: from Reactive Maintenance (based on intervention when a complete equipment fails) to Corrective Maintenance (that takes actions on minor faults to avoid in advance the complete equipment failure), then to Preventive Maintenance (time-based or threshold-based maintenance, performs maintenance interventions scheduled statically a priori or when a condition is exceeded), and finally to the more advanced Predictive Maintenance, that grounds on I4.0 related technologies and seeks to predict machine failures just before they occur, through the precise estimation of assets' Remaining Useful Life (RUL), so to be able to avoid high costs of too early replacement or unforeseen production downtime [30]. Nonetheless, PdM is usually associated to a higher initial cost and complexity respect to other maintenance strategies. Therefore, an in-depth analysis of pros and cons in terms of cost, effort, savings connected to its implementation should be done when evaluating a PdM project.

Predictive Maintenance (PdM), also called Prognostic and Health Management (PHM) or Just-in-Time Maintenance, is a holistic approach to maintenance management, based on online (and sometimes offline too can add value to the strategy) monitoring of equipment. These real-time data from machines and components, together with production scheduling data and other company-related data, are processed and fused through advanced analytic able to extract useful and actionable knowledge from the raw data available. The ability to take into consideration as many factors as possible allow to make the decisions that would turn into the lowest possible maintenance costs for the company. It grounds on the fact that thanks to the advanced monitoring and data analyses techniques available nowadays, it is possible to predict with a high level of accuracy possible anomalies, diagnose equipment faults and make accurate prognostics as for example the estimation of RUL.

From an analytic point of view, we can discern between model-based and data-driven methodologies. Model-based methodologies assume an underlying probability distribution and require specific physical knowledge of the process. Data-driven methodologies do not require physical and technical knowledge of the process: they belong to the statistical modelling or to the AI and ML domains, hence they only need good quality data for the creation of models. This characteristic, together with the evolution done by AI and BD fields, has fostered the wide application of data-driven modeling techniques.

Machine Vision

According to Coffey [9], the global market of MV, which is the declension of CV into the Industrial domain, will grow from US$8.54 billion in 2017 to US$16.89 billion in 2026. The fortune of MV can be attributed to its salient characteristics. Being a non-contact, reliable, safe, suitable for harsh environments, and designed for working long times technology, it has been applied to a wide variety of tasks over time [31]: defect detection, assembly process check, product identification, localisation, measurement, and many others.

A MV system is usually composed of a Sensing module, consisting of the lighting system, a processing module where the analysis of sensed data is done, a camera, hence a Charge Coupled Device (CCD) or Complementary Metal Oxide Semiconductor (CMOS) sensor, lense, optical filter, frame grabber, and I/O, and usually an application module which makes the results of analysis visible and actionable [32]. The Processing module could be embedded in the camera if the MV system is a smart-camera, or could be implemented on a PC if it is a PC-based MV system.

In general, repetitive tasks where humans are error-prone like quality control, or difficult applications that traditionally required too much time or investment, are now becoming feasible through MV systems, which are usually cheap, highly customizable, accurate, and reliable. The same Condition Monitoring of manufacturing assets associated to PdM strategy, has been performed through MV by some researchers [33].

2.3.2 Society 5.0

Not only the industrial world, but the society as a whole is facing more and more challenges on a global scale, e.g. the depletion of natural resources, global warming and climate change, growing economic disparity and terrorism, which hinder the achievement of peace and prosperity for the entire planet [34]. Society 5.0 (S5.0) was presented as a core concept in the 5th Science and Technology Basic Plan, adopted by the Japanese Cabinet in January 2016. It has been presented as the fifth societal revolution, where ICT and technological advancement, merged with human-centrality and challenge-solving attitudes, allow to reach a super-smart and human-centered society, focused on well-being, collaboration, active citizens, and common health [11].

According to B20 Tokyo Summit Joint Recommendations "Society 5.0 for SDGs", the entire ecosystem of technologies and stakeholders living on the Earth, should jointly lead to effective solutions for all the societal challenges that permeate our living. This very broad landscape of challenges, technologies, stakeholders and objectives is summarized into Fig. 2.3, taken from Keidanren (the powerful Japanese Industrial Association), that promoted S5.0 as a philosophical response to the German concept of Industrie 4.0.

Figure 2.3: Figure taken from Keidanren [3].

e-Health

Among recommendations defined at B20 Tokyo Summit, we find "Health and well-being for all", with its connected guidelines: promote digitalisation, Universal Health Coverage, improve pandemic preparedness and response, support business' voluntary initiatives to promote health and productivity management, ensure healthy lives and promote well-being in the era of aging populations. The e-Health stream goes perfectly in this direction: it can be defined as the ability to seek, find, understand and evaluate health information from electronic sources and apply knowledge gained to manage or solve a health-related problems. Broadly speaking, e-Health is based on the measurement of clinical data and their management, hence, it is a topic deeply connected with almost all the innovative technologies (IoT, BD, and so on). Merging the nature of e-Health with the characteristics of IoT, it is obvious that smart devices could be exploited for monitoring and supporting patients when they are far from the hospitals, thus creating the so-called Ambient Assisted Living paradigm.

Early Warning Systems

An Early Warning System (EWS) is a set of procedures, steps and key elements interconnected with each other with the aim of monitoring, forecasting, disaster risk assessing, communication sending and disaster managing, that enable individuals, communities, governments, and businesses to take timely action to reduce in advance disaster risks connected to hazardous events [35]. Such kind of systems have been found important for many natural as well as societal hazards, e.g. financial crisis, landslides, air quality, tsunamis, earthquakes, and storms among others, thus being a possible solution for many Sustainable Development Goals (SDGs) of S5.0. Specifically, as highlighted by Zengin et al. [36], EWS are connected to SDG3 (Good Health and Well-Being), SDG9 (Industry, Innovation, and Infrastructure), SDG11 (Sustainable Cities and Communities), SDG13 (Climate Action), SDG14 (Life under Water), SDG15 (Life on Land), SDG16 (Peace, Justice, and Strong Institutions), and SDG17 (Partnerships for The Goals).

2.4 Summary

Based on the literature reviewed and on the conceptual process followed, I decided to outline an architectural and conceptual reference scheme, where I'm going to place research activities carried out during the entire PhD journey.

Specifically, the three architectural components identified are Acquisition, Communication, and Analytics. Broadly speaking, the presented conceptual framework summarises the path that brings from the complex reality we live in toward the knowledge and wisdom that can be extracted from it for better managing everything around us. The three gears architecture has been inspired by the hierarchical reference of the smart factory proposed by Chen et al. [26]: at the bottom of their factory there is the physical layer, sometimes called "Sensing Layer" by other authors ([8]), where data ***Acquisition*** (i.e. the bottom gear of the conceptual reference proposed by me) happens thanks to devices like sensors, cameras, and so on, installed in-site; then there is the network layer of the smart factory, the one through which safe and reliable ***Communication*** (i.e. the intermediate gear of the conceptual reference proposed by me) is achieved, either wireless or wired, with the aim of transmitting and sharing data collected within and among factories, to make them fruitful;

finally, on the top, the data application layer is where ***Analytics*** (i.e. the top gear of the conceptual reference proposed by me) and data mining solutions are implemented, thus allowing the extraction of meaningful knowledge, which can be used by managers and decision makers in general, for improved and optimised outcomes.

As anticipated, this architectural organization implies a conceptual evolution from raw data sensed from the complex reality, to the meaningful knowledge which allows the realization of paradigms like S5.0 and I4.0, and is therefore combined in my conceptual reference with the Data-Information-Knowledge-Wisdom (DIKW) pyramid proposed by J. Rowley [6]. Data are discrete, objective facts, observations, recorded description of things, events, activities and transactions, which are unorganized and unprocessed, hence data has no meaning or value because it is without context and interpretation. Information is data aggregated, formatted, organised, processed with a purpose and shaped into a meaningful form. Knowledge is the combination of data and information, to which is added expert opinion, understanding, skills, and experience, to result in a valuable asset which can be used to aid decision making. Wisdom, the highest level of abstraction, is defined as accumulated knowledge, that allows to apply knowledge from one domain into other domains or situations. K and W levels are those where the seventh V (Value) of BD comes true, ultimate goal and main enabler of both S5.0 and I4.0.

The reference scheme resulting from the fusion of the architectural and conceptual visions is shown in picture 2.4. It is important to highlight how much the three components, depicted as separate for simplicity and for conceptual purposes, are in general strictly connected or even overlapping each other. The same IoT paradigm embraces these three components if analysed from an architectural point of view. For this reason I decided to represent them as neighboring gears that allow the achievement of meaningful knowledge from the otherwise indecipherable complex reality. Wisdom synthetically embeds all the pulling streams described inside Sec. 2.3, while the gears stand for the wide range of technological inventions that are pushing the passage toward wisdom, since the wide variety of innovative technologies usually range from those more connected to the Acquisition of data, to those more connected to Analytics aiming at the extraction of wisdom from data.

Research activities conducted are hence going to be presented inside one of the three identified components of the architecture, even though they usually involved a broader reasoning, crossing all components.

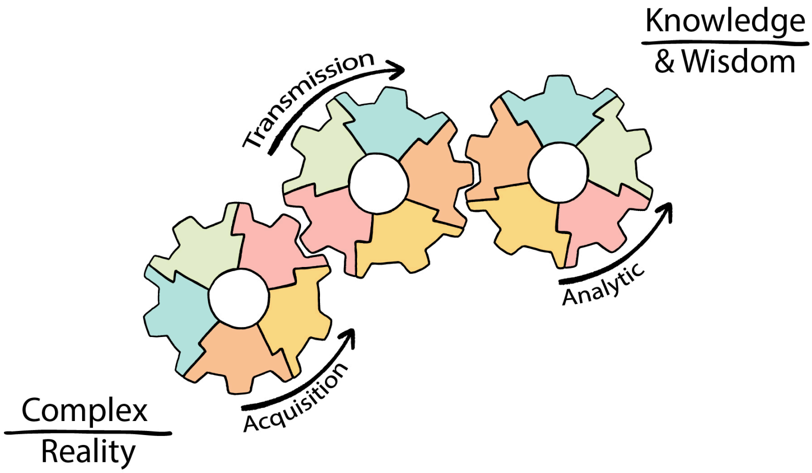


Figure 2.4: Conceptual reference, developed for positioning research activities completed.

Chapter 3

Acquisition Contributions

Inside this chapter I positioned those research activities more focused on the Acquisition, hence on sensors and devices able to collect data and information from the reality. Despite the conceptual qualification of these contributions in this component of the reference scheme, their scope usually goes well over the simple device boundary, being the three components highly inter-related, as previously said.

The first research activity is further positioned inside the S5.0 paradigm, being focused on the societal practice of e-Health and Ambient Assisted Living.

The second contribution is part of S5.0 related activities too, being a low-cost solution for monitoring buildings, thus improving their resilience toward extreme events like earthquakes, hence protecting citizens.

3.1 Biological Age Estimation Using an eHealth System Based on Wearable Sensors

Considering the rapid worldwide aging connected to the rise of life expectations, the development of advanced technologies for the objective identification of diseases and disabilities onset is essential. From this perspective, biological age (BA) should be considered as a more reliable indicator of the physiological decline of individuals, respect to the simple chronological age (CA). Over time several studies have tried to find a method to estimate the BA, but still today we lack a universally trusted and accepted golden standard. These studies take into account the psycho-physical conditions of a subject, and estimate the BA thanks to the assessment of his frailty (i.e. the state of higher vulnerability to adverse events, usually evaluated through deficits count). The frailty evaluation is a non-invasive methodology to assess BA, respect to more invasive solutions like DNAmAge (also said epigenetic clock) that measures the age of the DNA's methylation.

Innovative technologies in the domains of ICT and wearable sensing, allow the creation of devices able to reach the 24-h monitoring and remote consultation of acquired data through cloud connection. These technologies form the basis for solutions in the domain of Ambient Assisted Living (AAL), a flourishing field of research which tries to answer to the global ageing through the creation of solutions which help elderly in living autonomous inside their daily-life context as much as possible.

This is the context in which this research project emerged, with the aim of finding a non-invasive methodology for the BA evaluation in elderly people. A complete e-Healthh system based on commercial devices, wearable sensors, smartphone application, and cloud services, usable in both outpatient and home monitoring will be presented.

3.1.1 State-of-the-Art

It is not easy to directly determine the BA of a subject. For this reason largely diffused methodologies to compute BA start from the frailty estimation [37]. Frailty is a state which can be diagnosed and is characterized by an increased vulnerability, caused by age-related declining. Frailty could be present even without any other detected pathological condition [38]. Frailty topic has been addressed by a variety of researchers, ending up that it is a tangible geriatric syndrome, characterized by low reserves and poor resistance to stresses, and associated with an higher risk of bad outcomes for the subject's future health [39].

Among the frailty-based approaches, the most exploited methodology of BA estimation is the one grounding on the frailty index [40], "q" that can be determined through geriatric evaluation. This index depends on the count of deficits in the domains of cognition, mood, mobility, chronic diseases and so on, owned by the patient under analysis. Specifically, it is computed as the ratio of owned deficits versus the total number of considered deficits [41]. Rockwood and Mitnitski [42] estimated the BA of a group of Canadian, over-65 people, exploiting the Frailty Index and a total of 20 reference deficits. In another work [43] Mitniski adopted linear regression and obtained a mathematical model. He then extracted from the model the log-linear behaviour of the frailty index in relation to the CA of the subject. Applying an inverse regression to the Mitnitski's model, the personal biological age (PBA) can be derived. It is the average value for which certain deficits are present in the reference group of people ageing well. The just presented frailty index-based methodology is very precise and accurate, but requires the consideration of many deficits whenever a patient has to be evaluated (at least 30/40, for which is not available a clear and unique definition) [44, 42]. Moreover, in order to assess deficits a complete geriatric evaluation is needed, and only professional medical staff is able to well do the assessment [45].

For the aforementioned reasons, alternative methodologies have been proposed over time. Among them, Fried et al. [46] proposed a frailty evaluation based on Frailty Phenotype (FP) concept. Fried and her colleagues proposed to classify frailty based on five phenotypical criteria: weight loss, grip strength, poor endurance and energy, walk time and physical activity. These five criteria, defined as predictors of frailty, facilitate the identification of frailty. Indeed, a frail subject meets three or more criteria, a pre-frail meets one or two criteria, non-frail patients are those that do not meet any criterion. This model embeds the cyclic nature of frailty: functional losses in one or more areas might lead to decline of the whole body. Respect to past methodologies, one virtue of the one proposed by Fried et al. lies in the fact that every criterion in uniquely described and identified, and cut-off values are specified. These are the five criteria:

1. **Weight loss** - unintentional weight loss, not due to dieting or exercise, calculated with the difference between the weight in the previous year minus the current weight at the numerator, and the weight in the previous year at the denominator; if this value is higher or equal to 5 the first frailty criterion is met.

2. **Grip strength** - maximum grip strength compared to the reference Tab. 3.1 that shows the thresholds in kg (depending on gender and body mass index of the subject) below which the subject is considered frail.

3. **Poor endurance and energy** - self-report exhaustion level. In order to evaluate this criterion, two specific statements from the Center for Epidemiological Studies-Depression (CES-D) scale [47] are read: “I felt that everything I did was an effort”, “I could not get going”. Afterwords, it is asked the subject how many times during the last week has she/he ever felt like the just mentioned conditions, and the answer is scored as shown in Tab. 3.2. If the score is 2 or 3 then the subject is deemed frail respect to this criterion.

4. **Walk time** - elderly’s mobility monitoring, based on time to walk 4.57 m at the rhythm chosen on the basis of individual skills. The cut-off parameters are reported in Tab. 3.3 as function of the individual’s gender and height, above these values the subject is deemed frail.

5. **Physical activity** - based on self-assessment. Completing the short version of the Minnesota Leisure Time Activity questionnaire, a weighted score of expended kilo-calories per week was calculated considering 18 activities carried out, according to Eq. 3.1, where MET stands for Metabolic Equivalent of Task, and it is the unitary energy expenditure associated to a certain physical activity [48], *Times* represents how many

times the activity has been done, *Duration* is the activity lasting in minutes, and *Weight* is the mass of the subject expressed in kilograms. The cut-off values to discern a frail subject in function of the gender are shown in Tab. 3.4. In case the subject does not reach the values in the table the frailty criterion is met.

$$\frac{Kcal}{week} = MET \times \frac{Times}{2} \times \frac{Duration}{60} \times Weight \tag{3.1}$$

Gender	BMI	Cut-off (kg)
Man	≤ 24	29
	24.1-28	30
	≥ 28.1	32
Woman	≤ 23	17
	23.1-26	17.3
	26.1-29	18
	≥ 29.1	21

Table 3.1: Cut-off values used to asses the second frailty criterion: grip strength.

Score	How often
0	$<$ 1 day
1	1-2 days
2	3-4 days
3	Most of the time

Table 3.2: Scores associated to the answer to question related to the third frailty criterion.

Gender	Height (cm)	Cut-off (s)
Man	≤ 173	7
	> 173	6
Woman	≤ 159	7
	> 159	6

Table 3.3: Cut-off values beyond which the fourth frailty criterion is not satisfied. used to asses the second frailty criterion: grip strength.

Thanks to the detailed description of the five criteria and associated cut-off values defined, the FP methodology is easily reproducible in clinical practice and can be evaluated without the presence of professional medical staff. As Cesari et al. [38] highlighted, this methodology is better than frailty index for an immediate identification of non-disabled elders at risk of negative events.

Gender	Cut-off (kcal)
Man	383
Woman	270

Table 3.4: Values used for assessing the fifth frailty criterion: physical activity.

Theou et al. [49] assessed FP for a group of people, but did not extract a model able to estimate BA based on these values. Pierleoni et al. [50] proposed a BA estimation methodology based on Fried's FP assessment. Specifically, linear regression has been exploited for the estimation of BA starting from the assessed FP.

A non invasive method for BA estimation, based on FP assessment will be described hereafter. In more details, an e-Health system, composed of wearable sensors and a smartphone application, and able to evaluate the mobility of an elderly subject hence his phenotypical criterion, will be presented. Based on the FP assessment, the system is able to compute the BA of the subject under analysis.

3.1.2 Materials and Methods

The complete e-Health system proposed has the aim of making the FP evaluation as much objective as possible, through a user-friendly and automatic solution for the final BA estimation to the customers. It takes information form different sources and exploits cloud computing techniques, thus allowing medical staff to remotely monitor patient, to define for them personalized treatments and to diagnose diseases before they appear. In Fig.3.1 the e-Health system architecture is shown. The system allows the upload of data from three different sources:

1. Generic users, if registered, are able to autonomously register their self-evaluation of the frailty phenotype through a simple user-friendly interface;

2. Medical staff, i.e. authorized physicians, can upload evaluation of the FP performed on patients, type in additional data, medical report and the diagnostic–therapeutic path for having a complete medical history of the patient available on the cloud;

3. Distributed sensors either upload sensors' data or the automatic and non-invasive monitoring of the elderly life-style. This source can be quite diversified, including wearable and/or environmental sensors integrated in the system through Internet connection [51].

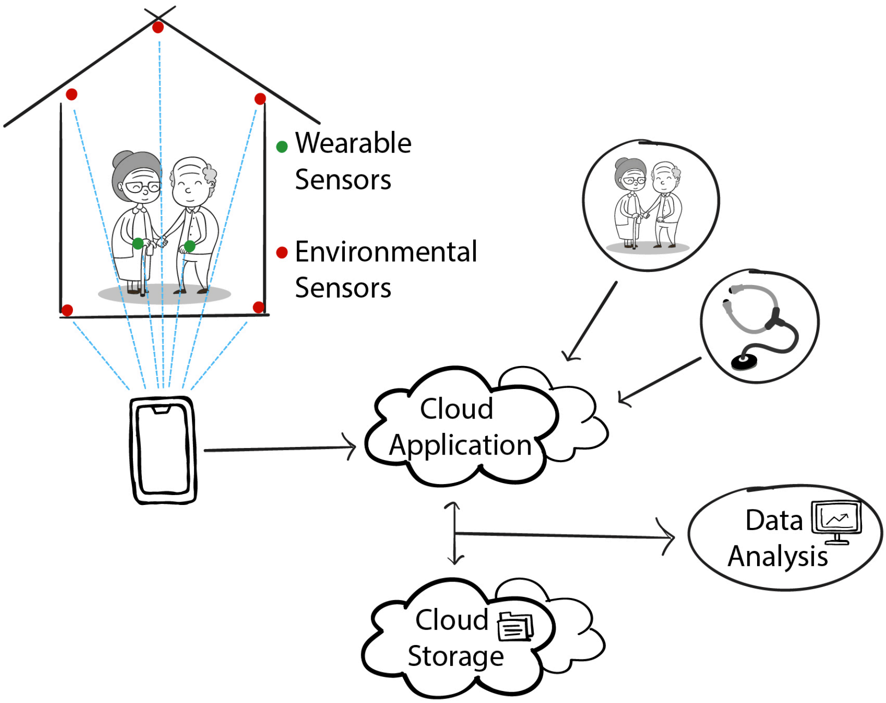


Figure 3.1: The proposed e-Health system, from data acquisition and storage to data processing.

The two key components of the e-Health system are the Cloud storage and the Cloud application. The former allows to collect the history of each subject and new evaluations whenever desired. The latter assesses the FP and deduce from it the BA of the subject. A Cloud application has been developed for its ability to scale, reliability, flexibility, and inter-operability. A full-stack JavaScript framework for Web applications whose components are MongoDB, Express, AngularJS and NodeJS has been adopted, namely MEAN. The application is able to automatically compute results concerning the five FP criteria and eventually determine the frailty state of the subject under analysis. To do this, the architecture should manage a huge amount of clinical data represented in the worldwide accepted Health Level 7 (HL7) standard format [52]. MongoDB, which is a NoSQL open source database that provides support for systems of JSON with document-oriented style, has been adopted. HL7 messages can be stored and analyzed in MongoDB after the conversion from XML to JSON format. Conversion from CSV to JSON is necessary for what it concerns elaboration of sensors' data.

In order to compare the FP assessment results obtained from the proposed system (specifically, from the wearable sensors and gait analysis algorithm) with a reference, also Fried's methodology has been adopted. The Frailty Evaluation Test (FET) addresses the five criteria introduced earlier. Specifically, the weight loss criterion has been assessed through direct question to the patient. The The weakness criterion by using an hand-dynamometer, the physical activity criterion through the Minnesosato Leisure-Time Activity questionnaire, and the mobility criterion through performing two times and averaging the values of the Timed Up and Go (TUG test). To perform this test the subject has to stand up from a seat, walk for 5 m, turn around a fixed point, and then come back to the seat and sit down [53].

Mobility problems are very common in elderly people due to age-related physiological, muscular and skeletal system changes and to the higher presence of different diseases which negatively affect the postural stability. Within the medical framework, gait and mobility are commonly assessed through simple questionnaires administered by physicians [54]. Questionnaire-based assessment is very easy to be done, still it is very subjective, assessor's experience dependent, and lacking specific gait parameters. Only specialized laboratories equipped with expensive and advanced measurement system allow a more objective evaluation. Wearable devices can help in dealing with this problem, being low-cost, light weight, small, energy efficient and portable. Over time data fusion algorithms have been successfully presented as a way for measuring and analysing gait [55]. Some researchers adopted wearable devices for monitoring gait abnormalities and for fall-detection [56]. Based on these successful examples, wearable devices' importance for acquiring and elaborating mobility data is very important in caring and supporting elderly [42], and for the evaluation of the frailty phenotype. Schwenk et al. [57] exploited for the first time wearable sensors to accurately estimate FP, but did not estimated the ageing process based on FP assessed. In this work, the FP assessment, done through the adoption of wearable devices, will be correlated with BA of the subject under analysis.

A wireless, small and non-invasive system able to help in the mobility assessment of the FP, based on preliminary works of Pierleoni et al. [58, 59], will be presented. The system exploits Schwenk's indications for the mobility analysis. The wearable device is composed by triaxial gyroscope, accelerometer and magnetometer, microprocessor, and a unit for the storage and transmission of information, as shown in Fig. 3.2.

The wearable sensor should be positioned on the instep through an elastic band, and allows to extract useful metrics of the walk, specifically stride length, stride speed, percentage of double support and hip angle.

Data coming from the sensors are gathered and processed by the microprocessor. These data can be saved in an SD card and sent to a smartphone

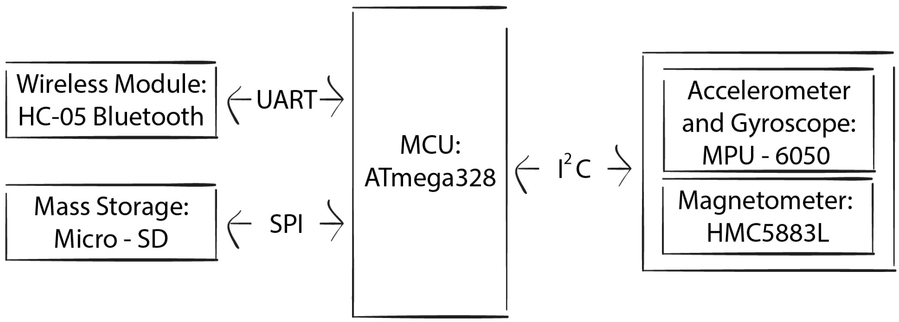


Figure 3.2: Block diagram of the wearable device developed.

through the Bluetooth interface. A sensing unit calibration algorithm and a data fusion algorithm are implemented on the microprocessor [60] and allow to estimate the acceleration and orientation of body segment on which the device is placed. Thereafter, the developed smartphone application can elaborate acceleration and orientation data collected by the device and automatically analyze the walk, estimating three relevant parameters for mobility assessment: double support, stride speed and stride length [57]. Double trapezoidal integration on the acceleration signal along walk direction allows to obtain walked length. Then, two filtering phases and two integration phases are necessary for computing speed and distance. Firstly, a Butterworth high-pass filter of the second order is applied and speed is computed as the cumulative integral of the acceleration signal adopting the trapezoidal method. Secondly, another high-pass filter and subsequent trapezoidal integration allow to extract the distance. By taking into consideration the Root Mean Square (RMS) of the acceleration vector, its peaks ca be determined. Each peak corresponds to a stride, consequently stance and swing phases can be determined by looking at local minimums. Initial contact is the point where the stance phase begins and corresponds to the minimum just before the highest peak, while the toe-off begins on the swing phase and corresponds to the minimum after the highest peak. Once identified the stance and swing phases, by comparing two subsequent initial contacts of the same foot stride length can be computed. Stride speed is then computed as the average for each stride. Lastly, the percentage of double support can be extracted by considering the portion of stance phase when the two feet are on the ground.

All the parameters just presented are uploaded into the cloud application through the developed mobile application. These data are processed in the cloud application for computing frailty respect to the mobility criterion. In Tab. 3.5 the thresholds used by the cloud platform for assessing the frailty respect to mobility criterion are resumed.

Param.	Gender	Heigth	Non-frail	Pre-frail	Frail
DS (%)			DS $\leq$ 25	25 $<$ DS $<$ 30	DS $\geq$ 30
SL (m)		$<$ 165 cm	SL $>$ 1.1	0.90 $\leq$ SL $\leq$ 1.1	SL $<$ 0.90
		$>$ 165 cm	SL $\geq$ 1.2	0.95 $\leq$ SL $\leq$ 1.2	SL $\leq$ 0.95
SS (m/s)	Man	$<$ 173 cm	SS $>$ 1.0	0.65 $\leq$ SS $\leq$ 1.0	SS $\leq$ 0.65
		$\geq$ 173 cm	SS $\geq$ 1.1	0.75 $<$ SS $<$ 1.1	SS $\leq$ 0.75
	Woman	$<$ 159 cm	SS $>$ 1.0	0.65 $\leq$ SS $\leq$ 1.0	SS $<$ 0.65
		$\geq$ 159 cm	SS $\geq$ 1.1	0.75 $<$ SS $<$ 1.1	SS $\leq$ 0.75

Table 3.5: Cut-off values adopted for Double Support (DS), Stride Length (SL) and Stride Speed (SS) in the mobility criterion assessment.

These thresholds have been experimentally deducted, as function of height and gender. Based on the values of each subject, he/she can be considered frail, pre-frail, or non-frail.

3.1.3 Results and Conclusions

In order to asses the validity of the proposed protocol, which is based on the exploitation of a wearable device, smartphone, and cloud, in substitution of medical professionals, it has been applied to a group of 15 Italian elderly: 8 males and 7 females, aged between 61 and 81 years old. This reference group considered is hence a sub-set of the group considered by Theou et al., thus making viable the comparison of results achieved. Results of the assessment performed are resumed in Tab. 3.6, that shows the outcome for each of the five Fried's criteria and the overall frailty state evaluation.

Three subjects are non-frail, two are frail, and the remaining are pre-frail. By comparing those patients negative to all criteria and the frail subjects, differences in the computed values are evident. In Tab 3.7 the results for the TUG test performed using the wearable sensors are shown. Specifically, test execution duration, double support percentage, average stride length, and average stride speed.

A normal double support is around 20% of the stride, while for pre-frail and frail subjects there is and evident increment. This suggests the fact that frail patients have a higher necessity of being in the stable phase of the stride cycle, i.e. when both feet touch the ground. The speed lowering and decrease in stride length for Frails are evident. The FP is then estimated for each subject, as the average mean weighted for his/her age. In Fig. 3.3 the results achieved with the help of gait parameters determined using the wearable sensors (in green) have been compared to results coming from the application of Theou's model (in magenta), and to results computed by the cloud application following Fried's definition (in blue). Difference in the results could be related to the

ID	Weakness	Weight Loss	Tiredness	kcal per week	Mobility	Frailty
1	—	—	—	—	—	Non-frail (0)
2	—	—	—	—	—	Non-frail (0)
3	—	—	—	—	—	Non-frail (0)
4	—	—	—	Yes	—	Pre-frail (1)
5	—	—	—	Yes	—	Pre-frail (1)
6	—	—	Yes	—	—	Pre-frail (1)
7	Yes	—	—	—	—	Pre-frail (1)
8	—	—	—	Yes	—	Pre-frail (1)
9	—	Yes	Yes	—	—	Pre-frail (2)
10	—	Yes	—	Yes	—	Pre-frail (2)
11	Yes	—	Yes	—	—	Pre-frail (2)
12	—	—	—	Yes	Yes	Pre-frail (2)
13	—	—	—	Yes	Yes	Pre-frail (2)
14	Yes	—	Yes	—	Yes	Frail (3)
15	Yes	—	—	Yes	Yes	Frail (3)

Table 3.6: FP results for each of the 15 subject in the reference group.

small amount of considered subjects, or to the fact that the developed model, embedding mobility parameters quantitatively assessed, could be more reliable than the reference model.

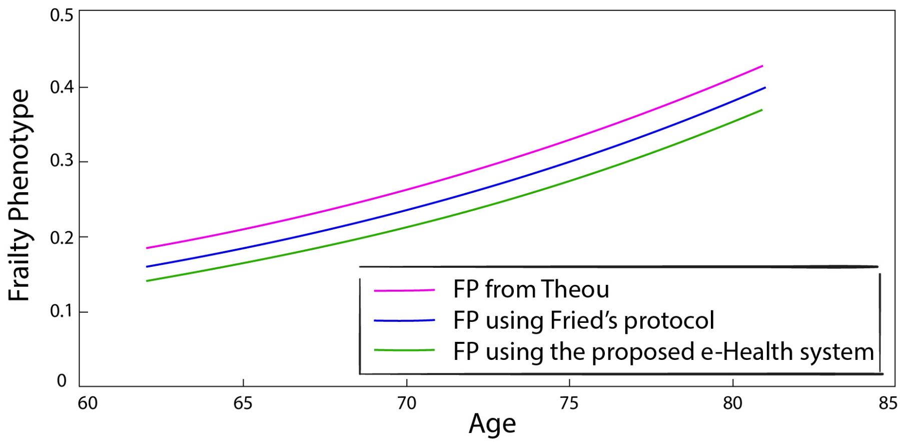


Figure 3.3: Plot of the Frailty Phenotype

Starting from the FP the BA can be deduced by applying an estimation model. In Fig. 3.4 is shown the model that estimates BA through the CA and the natural logarithm of the FP of the subjects. This model corresponds to

Patient	Frailty	DS (%)	SL (m)	Speed (m/s)
1	Non-frail (0)	20.8	1.45	1.60
2	Non-frail (0)	22.6	1.48	1.58
3	Non-frail (0)	23.1	1.12	1.41
4	Pre-frail (1)	21.8	1.36	1.40
5	Pre-frail (1)	25.0	1.10	1.33
6	Pre-frail (1)	24.0	0.92	1.32
7	Pre-frail (1)	25.7	1.22	1.28
8	Pre-frail (1)	26.2	0.94	1.17
9	Pre-frail (2)	27.1	1.07	1.39
10	Pre-frail (2)	27.0	1.00	1.30
11	Pre-frail (2)	28.6	0.82	1.05
12	Pre-frail (2)	34.0	0.84	0.86
13	Pre-frail (2)	36.1	0.85	0.81
14	Frail (3)	36.3	0.67	0.94
15	Frail (3)	37.4	0.69	0.64

Table 3.7: Results of the gait parameters evaluation algorithm.

this equation:

$$BA = 88.30 + 22.08 \times \ln FP \tag{3.2}$$

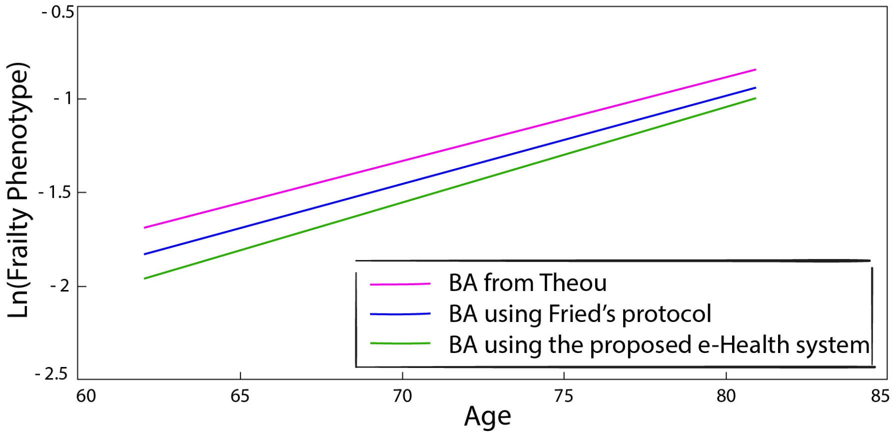


Figure 3.4: Plot of the BA estimation.

Concluding, wearable sensors have been proposed as a way for increasing reliability of the Mobility frail criterion assessment. The wearable device developed is part of the entire e-Health system implemented, which allows to compute the BA of a subject starting from the empowered FP assessment, by using innovative technologies like CC, IoT and advanced Analytic. Gait analysis algorithm, which is able to compute double support, stride length and stride speed from raw sensor data, has been integrated into the frailty assessment procedure. The cloud application takes the frailty assessment data and computes the FP, with the final aim of estimating the BA. All the evaluations performed are stored on the cloud, thus providing an easily and remotely accessible trend of patients' aging process. The entire system has been validated analysing 15 subjects, and results are comparable to those taken as reference. By collecting more data the validity and likely improved performance of the proposed system could be demonstrated.

The outcome of this work has been published by the Journal of Ambient Intelligence and Humanized Computing (Springer).

3.2 IoT Solution Based on MQTT Protocol for Real-time Building Monitoring

Another research activity focused on the first component of the proposed conceptual architecture represented in Fig. 2.4, i.e. the Acquisition, is the one that will be presented hereafter.

Specifically, an IoT architecture for continuous and real-time building monitoring, composed of a smart sensing unit able to communicate with a dedicated cloud platform and relative Graphical User Interfaces (GUIs) for the presentation to the user. The smart sensing unit, connected to the Internet, can be positioned inside the building to monitor it and send raw data to a dedicated remote server through the Message Queue Telemetry Transport (MQTT) protocol. A Web application has been developed for allowing authorized users to remotely access real-time data collected by the device, as well as historical data, and building health status computed based on acquired data. Moreover, through the Web application it is possible to send commands to the sensor node. The proposed solution is low-cost, reliable, and scalable, thus being suitable for widespread structural monitoring of buildings, which is a topic gaining importance in the last decade.

In fact, all structures, whether they are bridges, wind farms, hydraulic, gas or oil pipelines, tunnels, drilling rigs, road pavements, rails, but also ships, planes, trains or other, are subject to a variety of internal and external factors which can cause wear or malfunction. The triggering causes can be, deterioration, a process of construction not carried out in a workmanlike manner, the lack of quality controls or an extreme situation, such as an accident or environmental stress. Whatever the cause is, most of the time the effect is to threat public safety. Monitoring the vibration could help in improving reliability, quality, and limit possible damages.

3.2.1 State-of-the-Art

During the last few years there has been an increasing interest in studying and predicting the failure modes connected to progressive deterioration of civil infrastructure such as buildings, bridges, aircraft, ships, trains, and so on. Collecting data on their response to stresses and vibrations, through various instruments like sensors, is essential for being capable of predicting failure modes of these structures [61]. This methodology of data collection and analysis is at the base of Structural Health Monitoring (SHM) technology, which is an approach adopted to monitor, assess and predict the ongoing safety and integrity status of a wide variety of critical structures through the experimental observation of their in-service behavior.

By continuously monitoring structural behavior any anomaly ca be promptly detected, thus allowing more efficient maintenance and repair interventions, and hence reducing operating costs. SHM facilitates the shift from scheduled maintenance to Condition-Based Maintenance, which ensures improved security (and duration), continuous observation, maintenance automation, early detection of damages for timely intervention, and savings in terms of both costs and time.

Traditionally, the most used sensors for structural monitoring have been strain gauges, accelerometers, velocimeters and displacement transducers. Each of them can essentially capture the behavior of the structure reducing the costs associated with the installation and maintenance of the system [62]. Among accelerometers, those based on Micro Electro-Mechanical Systems (MEMS) are gaining relevance in SHM applications [63, 64]. MEMS accelerometers use capacitive coupling to detect the motion of a suspended proof mass in response to external acceleration. The way they are manufactured ensures that MEMS devices can operate in the wide range between very low frequencies up to very high frequencies, especially the latest versions. They are typically used in similar application [65] mainly due to the low cost, low power consumption, high performance and small size. Sabato et al. [64] deeply analysed and compared MEMS accelerometers, concluding that the technology is mature enough for being used in SHM-oriented monitoring.

As extensively described in Chapter 2, IoT can be broadly described as physical objects collecting and sharing information via the Internet. One of the objective of the IoT is to have smart devices able to measure, process and transmit information in real time, improving the efficiency and timeliness of the corrective actions to be taken, in multiple contexts of use. In the Web only HTTP (Hyper Text Transfer Protocol) standard messaging protocol is adopted. On the other hand, the wide variety of applications where IoT could be exploited, fostered the rise of several different IoT standards and protocols, each answering to specific needs and facilitating the job of application programmers and service providers [66]. Some are designed for applications that require data collection (for example from one or more sensors) in bound networks such as Message Queue Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP) [67]. Some others are designed for instant messaging applications and online presence detection, such as Extensible Messaging and Presence Protocol (XMPP) and Session Initiation Protocol (SIP) [68]. RESTful HTTP and CoAP client / server protocols have been instead designed to meet the web applications that require communication on the Internet. This clearly demonstrates that the IoT world is based on different messaging protocols in order to be able to manage all the possible applications of use of the IoT.

Hereafter, an IoT solution for continuous and real-time monitoring of buildings (based on the MQTT protocol and MEMS accelerometers) is going to be presented. From a practical point of view, the system is composed of a smart sensor to be placed on the structure of interest, and a web platform for the end user interactions. The sensor is "smart" because equipped with Internet connectivity, hence able to send the data measured by a low-cost tri-axial MEMS accelerometer continuously and automatically. The end user, once authenticated, can remotely access the web platform expressly developed and customized for the specific application. Here, he can visualize in real time the plot of accelerometric data, and the natural frequency of vibrations of the monitored structure. Moreover, access the historical data are accessible through the web platform, and, if necessary, commands to the sensor node can be sent from here.

The developed sensor has been installed in the Tower of the Engineering Faculty of the Università Politecnica delle Marche, used as testing structure. The structural dynamic response of the Tower to environmental solicitations can be monitored thanks to the developed IoT system. Through the empirical adoption of the proposed hardware and platform, long term and continuous monitoring viability is tested. By looking at values under normal operating conditions, it will be possible to evaluate any variation in the frequency of oscillation of the structure consequent to extraordinary events (e.g. renovation of the building, earthquakes, blasts, etc.), thus making more efficient and cost-effective maintenance and repair actions.

3.2.2 Materials and Methods

The proposed system should provide the real time visualization of data collected by the accelerometric sensor in a web based application. The application should also manage the possibility to send configuration commands to the sensor via a remote control panel, and to enable the storage of telemetry data thus allowing an off-line analysis of the data. Therefore, the system must guarantee the following functional requirements:

- R1. Acquisition and transmission of accelerometric data. Data from the acceleration sensor should be read and made immediately available on the Internet.
- R2. Telemetry data storage. The system must be able to store in a database all the data sent by the sensor node, thus allowing queries and offline analysis of historical data.
- R3. Real-time visualization. The system must provide a real-time visualization interface via a web application, accessible from every device (browser, smartphone, tablet).

- R4. Real-time analysis in the frequency domain. The system should be able to sample acceleration data for real-time analysis in the frequency domain.

- R5. Recording of simulations. In order to evaluate the performance and reliability of the sensing unit, it should be possible to perform simulations on real-time acquisitions and to store these recordings for an off-line comparison.

- R6. Sending commands to the sensing unit. From the web application it should be possible to send commands to the sensor node in order to modify some settings (full-scale sensor range, offset for each sensor axis, enable the internal low-pass filter to the sensor, increase or decrease the reading frequency, reset the sensor node, etc.).

- R7. Management of user authentication levels. The system must guarantee secure access to the web application, allowing diversified access options based on different roles (user admin, sensor node manager, real time display, real time frequency analysis, simulation manager).

The system must guarantee service continuity over time and rapid response in the event of a failure. Scalability, both horizontal and vertical, is very important too, given the necessity to store and process a possibly large amount of data and the prospective widespread diffusion of devices connected to the platform for widespread buildings monitoring.

Taking into account the functional and non-functional requirements exposed, the proposed solution can be summarized in a three-blocks architecture, as depicted in Fig. 3.5, where also a photo of the prototype smart sensor is inserted.

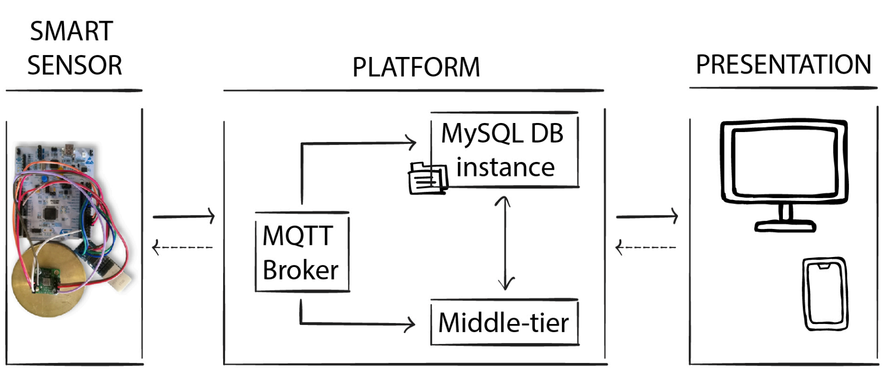


Figure 3.5: High level system architecture.

The Smart Sensor Block is in charge of data collection from the accelerometer, connection to the Platform Block and transmission of formatted data via MQTT protocol. The MQTT broker is the main component of the second block, and is meant to forward messages to the MySQL Server for storage purposes. For this reason it must support MQTT over WebSocket protocol to enable browser-based and remote applications to send and receive data to and from the third block, i.e. the Presentation Block, which hosts the web application. In more details, the Smart Sensor is composed by a low-cost embedded development platform communicating through its interfaces with an Ethernet module and a sensing unit, as summarized in Fig.3.6. For the development of the firmware, the *Mbed* online compiler was used. Providing a pre-configured lightweight C/C++ IDE, it allows to quickly write programs, compile and download them for being executed on the mbed micro-controller.

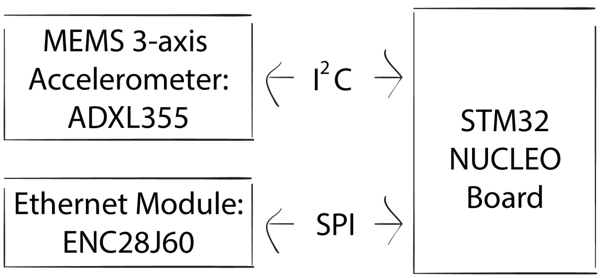


Figure 3.6: Block diagram of the proposed low-cost wireless accelerometric unit.

The prototype hardware adopted is reliable and cheap. Its most expensive component is the triaxial acceleration sensor that costs around 30 EUR because it must meet certain requirements for being suitable for structural monitoring. The overall cost of the Smart Sensor is around 40 EUR. To begin with, the embedded development platform adopted is the STM32 Nucleo board (STMicroelectronics). It is mainly used for building prototypes with any STM32 microcontroller line (various combinations of performance, power consumption and features). The board provides various hardware interfaces, e.g. USART, SPI, I2C, analog pins, and others, which can be used for the specific target applications. In this specific case it has been adopted a STM32L serie development board, equipped with MCU STM32L152RE, that fully embeds the low cost, good performance, and very low power consumption specifications. The Ethernet Shield module is based on the ENC28J60 integrated circuit working at 3.3 V, which contains everything necessary to add an Ethernet interface to embedded projects, including an 8 KB buffer. It can be controlled using the SPI interface, making it one of the most convenient solutions for this kind of projects. The module respects the IEEE 802.3 standard, is compatible with 10/100/1000 Base-T networks and supports full and half duplex modes. It contains an integrated MAC and a 10 Base-T PHY. The ENC28J60 Ethernet module also features programmable automatic re-transmit on collision, programmable padding and CRC generation and programmable automatic rejection of erroneous packets. As sensing unit the EVAL-ADXL355Z (Analog Device) has been adopted. It is a small size board that allows evaluation of the performance of the ADXL355 low noise, low power, 3-axis MEMS accelerometer. The accelerometer communicates via I2C with the STM32L NUCLEO board. To make the accelerometric measurements more reliable, the sensing unit was fixed to a brass cylinder weighing approximately 0.5 kg. The main features of ADXL355 are:

- 0 g offset vs. temperature: 0.15 mg/°C maximum;
- Low power consumption: 660 µW in measurement mode and 69.3 µW in standby mode;
- Output of ±2 g to ±8 g full scale range (FSR);
- Ultra low noise density: 25 µg/$\sqrt{}$Hz;
- 20-bit analog-to-digital converter (ADC);
- maximum sensitivity of 3.9mg/LSB @ ±2g;
- Up to 4 KHz Output Data Rate (ODR);
- Programmable high- and low-pass digital filters;
- Integrated temperature sensor;
- Operating temperature range: -40°C to 125°C.

In general, by processing in the frequency domain from the data measured by an acceleration sensor it is possible to determine which are the frequencies for which the structure is naturally excited. The ADXL355 acceleration sensor has been chosen since Valenti et al. [69] compared it with high sensitivity piezoelectric accelerometers (PCB393B31 by PCBpiezotronics), proving its good performance in estimating the natural frequencies of buildings. The sensor node is powered by an external 5 Volt power supply.

The principal operations performed by the program run on the NUCLEO board are the following:

- Connection to the MQTT broker specifying broker IP address and port;
- Request of the current time to an NTP server in order to set up the Real Time Clock (RTC) of the board (every 10 minutes);

- Reading from MEMS acceleration sensor (default sample rate of 64 sps);
- Packing in JSON (JavaScript Object Notation) format and publish on specific topic (every second);
- Management of the sensor settings (data sampling rate, offset, sensor, etc.) according to commands received from remote user.

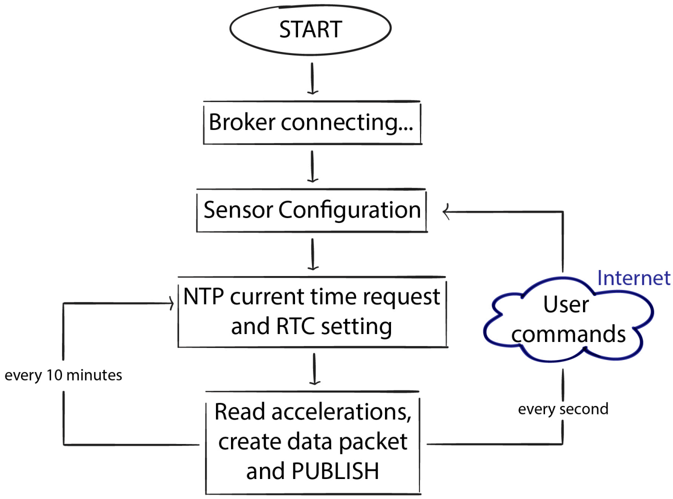


Figure 3.7: Flow chart of the sensor node operations.

The Platform block contains the MQTT broker, the MySQL Server and the middle-tier. It is developed on an Intel Xeon X5650 Server, with 12 MB cache, 2.66GHz, 16 GB RAM and Ubuntu 18.04.1 LTS as operating system.

For what it concerns the MQTT server, several studies in literature made a qualitative and quantitative performance comparison between the MQTT protocol and other protocols applied in IoT, e.g. such as CoAP [70], AMQP [71], XMPP [72], HTTP [73], showing how MQTT obtains better results in term of end to end delay and bandwidth consumption under constrained environments, thus being suitable for the task at hand. The MQTT protocol is based on a publish/subscribe paradigm and works on TCP. The pub/sub model decouples the client that sends a message (the publisher) from the client(s) that receive the messages (the subscribers). The connection between them is handled by the broker, whose job is to filter all incoming messages and correctly distribute them to specific subscribers. Mosquitto [74] is a lightweight and open source message broker that implements the MQTT protocol and supports MQTT over WebSockets, and it has been adopted in this work. For what it concerns security [75], Mosquitto allows the authentication of connected clients, their authorization through ACL configuration, and provides TLS/SSL support for encrypted network connections and authentication. In order to use TLS between the broker and clients, a set of keys and certificates has to be generated and deployed, along with configuration settings on both the broker and clients.

Given requisites and configuration of the proposed system, the right Database Management System (DBMS), able to store gathered data, should be chosen. As outlined in [76], the application needs of an IoT solution are sophisticated and current data management solutions only partially address the peculiarities of this environment. Furthermore, performance comparisons of NoSQL with SQL-based solutions [77] [78] [79] show contrasting results depending on the specific scenario taken into consideration. An a priori fixed format, as reported in Tab. 3.8, has been defined for data to be stored. Even if additional devices will be connected to the system when scaling the solution, the format will not change. Depending on the reading frequency the size of acquired data can vary. In order to allow off-line analysis on time domain, no real-time aggregation operations (e.g. window averaging, minimums, and so on) are performed on data. Therefore, the relational DBMS MySQL, v.8.0.15 [80], has been chosen.

Column Name	**Data Type**	**Storage Requirement**
primary_id	bigint	8 bytes
sensor_id	int	4 bytes
sensor_time	timestamp	4 bytes
x_value	float	4 bytes
y_value	float	4 bytes
z_value	float	4 bytes

Table 3.8: Structure of the Acquisition Table

Mosquitto does not provide a built-in mechanism to store MQTT messages in a SQL database, hence, a MQTT client has been developed, using Python and the Paho-MQTT [81] library. The client is subscribed through wildcard subscription to the topic, it stores locally one minute data and performs a bulk insert of acceleration data and their UTC times in milliseconds every minute. At the end of the day collected data are moved to a weekly entity in order to save all historical data. Furthermore, the database itself is used to manage user data and roles, like real time visualization, or sending commands to the sensor.

The task of the Middle-tier is to process the incoming data from the MQTT broker, or from the MySQL db, and to provide processed data to the Presentation Block for being visualized. This tier includes a web server, a data access framework, and a scripting language engine. Regarding the first component, the Apache Software Foundation's Apache HTTP server, with PHP add-on module as scripting language engine, has been chosen. Moving to the second component two different data access have been adopted: the Paho Javascript Client — which is an MQTT browser-based client library written in Javascript that uses WebSockets to connect to an MQTT Broker — was used for real-time data, while the Data Access Object (DAO) architectural pattern, providing an higher level of abstraction, has been used for managing data stored in the db.

System reliability has been assessed through the simulation of up to thousand publisher devices simultaneously connected to the broker, each sending MQTT messages of the same size and frequency as those sent by the actually installed node. Similarly, up to one thousand client subscribers have been simulated, each of which performs data storage operations on a shared database. During all the simulations the system obtained stable results over time, with no message loss.

The Presentation Block, which involves technologies such as HTML5, CSS3, JS, and the jQuery library, provides the application's user interface (UI) in a web browser. The navigation of the application interface is possible only after being authenticated, and each user role is associated to specific privileges to access certain types of home page. The home page shows a map with the location of all sensor for which the user has at least the real-time visualization privilege. The user can see a detail page for each allowed sensor, where it is possible to perform actions based on the permission owned.

The user privileges available are:

- Real time visualization of accelerometric values in function of time along the 3 axes, with the possibility of enabling/disabling one or more axes (Fig. 3.8).
- Visualization on the graph of historical data (stored into the database) related to a time interval that can be selected by the user.
- Sending commands to the sensing unit. This functionality sends an MQTT message over WebSocket to a topic where the device is subscribed.
- CSV export of historical data regarding a selected time interval.
- Visualization of the Power Spectrum Density of the real time signal on the 3 axes.

3.2.3 Results and Conclusions

Fig. 3.9 represents a screenshot of the web application showing the power spectral densities of the acceleration signals on the x and y axes. The power spectral density allows to the estimate the natural frequencies of the tower, which are the three peaks on the left portion of the plot.

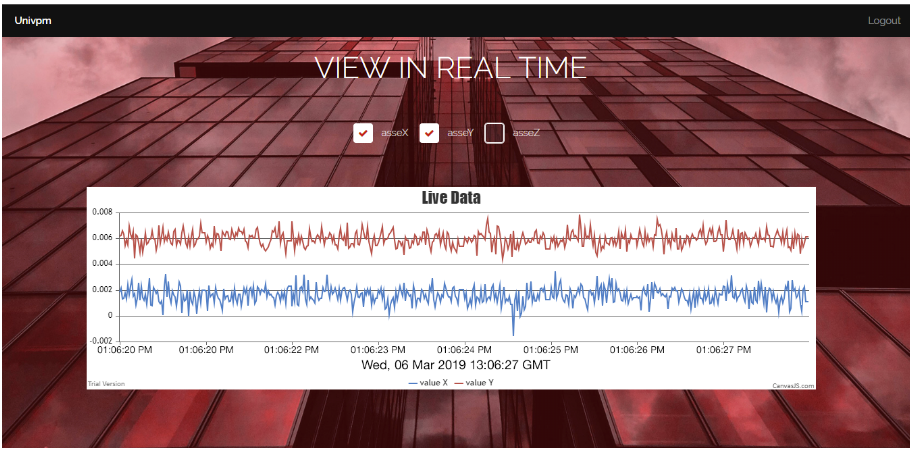


Figure 3.8: Real time plot of the acceleration data on the web application.

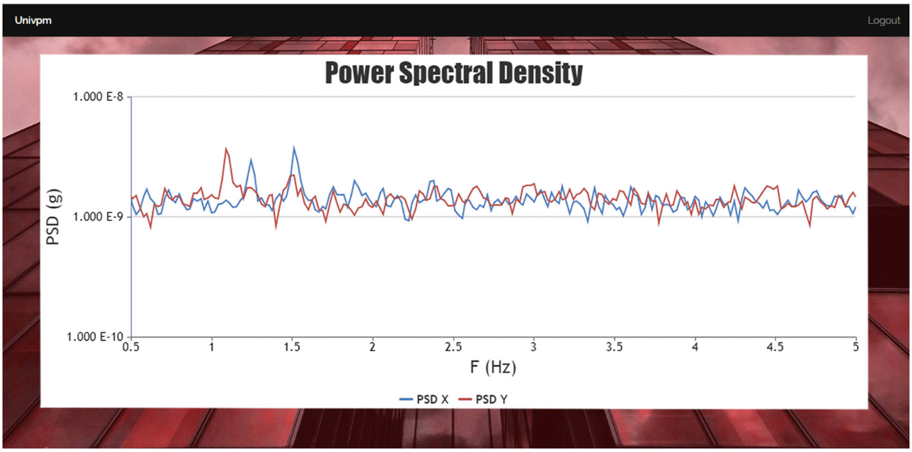


Figure 3.9: Power Spectral Densities visualized through the application

In this work an IoT solution for real-time monitoring of a data flow exchanged via MQTT protocol was presented. The proposed solution is able to monitor the health of a structure by evaluating its dynamic response, i.e. monitoring the evolution of modal parameters such as natural frequencies, which are very informative because damages to a structure can correspond to an alteration of its dynamic behavior, hence, of natural frequencies.

The proposed system consists of a low-cost tri-axial MEMS accelerometer useful for measuring the accelerations of the building on which it is placed. Measurements are then sent to a remote server via the MQTT protocol. A specifically developed web application allows each authorized user to evaluate the health of the structure in real time by examining the dynamic response of the same. The user also has the possibility to display raw accelerometric data measured along each sensor axis, to obtain historical data and to send commands to the sensor.

To date the system is serviceable and continuously working on the top floor of the Tower of the Engineering Faculty of the Università Politecnica delle Marche. Data gathered since today would allow further analysis to manage the environmental noises, and to develop machine learning algorithm suitable for the advanced management of the health status and maintenance interventions in monitored buildings. Furthermore, in the future, the use of NoSQL databases or Time Series Databases (TSDB) could be evaluated, to store an even larger amount of data, including unstructured data, from an increasing number of devices. Taking into account the architectural modularity of the proposed solution, the use of a different data layer within the Platform Block does not involve structural changes to the entire application, and for this reason it would be easily possible to scale up the developed system including more and more buildings in the study over time. Given the performance of the proposed IoT solution, future studies will also focus on its possible use in Earthquake Early Warning (EEW) systems.

This work has been presented at the 2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT).

Chapter 4

Communication Contributions

In this Chapter, the research activity more focused on Communications is going to be presented.

4.1 A Cross-protocol Proxy for Sensor Networks Based on CoAP

Constrained networks connected to the Internet have proved to be successful technologies in several domain of applications. Among the different domains, in the Ambient Assisted Living (AAL) also. Constrained network, being a particular wireless network made of devices that have limited computational power and limited storage capacity, strongly differ from the internet network. Communication protocols try to overcome the issues related to the interconnection of smart devices in constrained networks with the internet. A lot of efforts have been made in this direction, ending up with the creation of several different protocols. In the applications context, the CoAP (Constrained Application Protocol) protocol is gaining importance. Even though beneficial for optimising constrained networks performances based on the domain and aim of application, a large amount of new protocols has been created, thus making the development of proxying systems essential. Proxying systems are able to intermediate between the two kind of networks and to translate between the relative protocols.

Hereafter, the developed cross-protocol proxy able to broker among the HTTP, MQTT and CoAP protocols will be presented. The proxy implements the caching function — which will be proved to make the difference in terms of communication timeliness — also.

The proposed cross-protocol proxy has been tested under four operating conditions, in terms of Throughput and Round Trip Time. The results show excellent performances for both metrics taken into account, especially when the caching feature is enabled, thus proving the importance of caching.

4.1.1 State-of-the-Art

AAL is the set of technologies aiming at the creation of a smart, active and cooperative daily-life context around people, and deeply grounds on IoT as enabling technology [51] [82]. Through the creation of IoT devices able to monitor and support elderly, their life quality could be improved.

As introduced in the Chap. 2 IoT is the ensemble of smart objects able to communicate with each other through the internet, and enables from a practical point of view the transition toward a smart and connected world. The development of IoT sensor networks in support of patients outside of the health facilities becomes essential for the concrete creation of AAL-based environment.

A lot of efforts have been dedicated over time to address the problem of putting in communication the network of constrained devices with the internet, and the solution has been the development of sensor networks based on Constrained Application Protocol (CoAP) [83]. A promising next step for this type of network is to build scalable interaction models on top of this basic network connectivity, thus reaching the Web of Things (WoT) paradigm. In the WoT context, it is possible to foresee the exploitation of existing standards for the communication between devices and the Internet. According to several researchers [15] [84] the direct integration of smart systems into the Web is in fact based on two main requirements: devices should support the IP protocol, and services should be inter-operable at the application level. A sensor network based on CoAP protocol inherently supports the IP protocol, but allows the direct interaction with it only if using the same application layer protocol. Therefore, for making such sensor network part of the WoT the capability of direct interaction with all the different application level protocols of the IoT should be guaranteed. Widely used application layer protocols are HTTP (HyperText Transfer Protocol), MQTT (Message Queuing Telemetry Transport) and CoAP (Constrained Application Protocol). The integration of a CoAP sensor network with other protocols can take place using a cross-protocol proxy, which is a system working at the application-level that brokers the communication between a client and a server, that bridges devices based on CoAP with the other IoT application protocols. Most of the time a proxy is used with the objective of allowing the inter-operability between the Internet and a sensor network made of low cost, limited storage and low computational power devices, and of overcoming IP-related limitations. In this way these devices are made part of the WoT and their resources are accessible through HTTP protocol. An example of cross-protocol proxy for the WoT is Ponte [85], developed under the Eclipse IoT Project [86]. It is one the major attempt to address this issue by offering open APIs in order to enable the conversion between protocols (HTTP, CoAP, MQTT). Ponte ensures persistence through SQL/NoSQL database support, but lacks support for caching function, that, has will be proved, can be very important for communication timeliness. From a practical point of view, caching allows to decrease the number of requests to the server, being capable of storing and retrieving answers to specific requests already elaborated in the past. In this way the overall network performance is improved.

Hereafter, a proxy implementing caching function and able to broker between a CoAP based sensor network and the internet (which can be summarized as a receiving server based on either HTTP, CoAP or MQTT), will be presented and tested.

4.1.2 Materials and Methods

Given that the cross-protocol proxy to be developed has the aim of allowing the communication between the Internet and a sensor network based on CoAP protocol, it should implement these two functions:

- cross-protocol, that is to be able to receive requests from a client (HTTP or CoAP), to convert them into the receiving server's protocol (HTTP, CoAP or MQTT), to forward them and convert back the answer to finally send it to the source client.
- caching, that is to be able to store the answer to a request to speed up the processing of similar requests in the future, thus reducing the traffic and improving the overall response time of the network.

In order to perform the listed functions, these components are necessary (as summarized in Fig. 4.1): HTTP and CoAP servers, Cache, Protocol translator, HTTP, CoAP and MQTT clients.

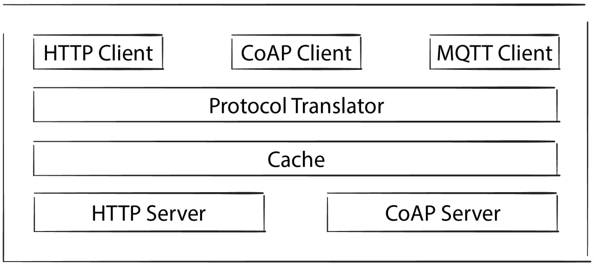


Figure 4.1: Architecture of the proposed Proxy.

The HTTP and CoAP servers (on the bottom of the architecture) have to address the incoming requests from the respective clients, and to send answers back to them at the end. The Cache level is shared among the two servers and is necessary for the implementing the caching function. The Protocol Translator is the core of the cross-protocol function between internal servers and clients. HTTP, MQTT and CoAP clients perform the communication of requests to the external servers that own the desired resource.

By analysing the cross-protocol proxy, two main contexts of action can be discerned: CoAP interaction with HTTP, and with MQTT respectively. Within the former contexts three types of proxying can be further distinguished, specifically CoAP-HTTP, CoAP-CoAP, and HTTP-CoAP, while in the latter context only the CoAP-MQTT proxying has been considered. Summarizing, these four proxying types have been implemented and tested:

- CoAP-HTTP proxying: a CoAP client willing to access an HTTP server's resource can contact the proxy, which in turn forwards the request to the server, translate the answer and gives it back to the CoAP client.

- CoAP-CoAP proxying: whenever a CoAP client wants to access a CoAP server's resource but hasn't the required privileges, it can contact the proxy that forwards the request to the server and then gives the answer back to the source client.

- HTTP-CoAP proxying: an HTTP client, that needs a CoAP server's resource, accesses the proxy which in turn maps the HTTP request in the equivalent CoAP request and sends it to the proper external CoAP server. The CoAP answer is mapped backward into an HTTP answer that can finally be sent to the source client.

- CoAP-MQTT proxying: a CoAP client willing to access a MQTT broker can exploit the proxy that is provided with a MQTT client able to mediate between the source client and the MQTT server containing the needed resource.

For the development of the CoAP-HTTP, CoAP-CoAP, and HTTP-CoAP proxying types the Eclipse Californium framework (Cf) [87] has been adopted. It is a Java library implementing the CoAP protocol compliant with the Standard IETF RFC-8075 [88]. The Eclipse Californium framework allows to convert HTTP requests into CoAP protocol-based requests, and conversely. Its principal components are:

- CoAP server - it processes the incoming CoAP requests and forwards them to the CoAP or HTTP server, based on the needed resource that is specified in the Proxy-Uri field of the CoAP message.

- HTTP server - it processes the HTTP requests and like the CoAP server forwards them to the server of interest. Moreover, it integrates an answers' caching system.

- CoAP and HTTP clients - they receive the requests sent by the servers, eventually translated when necessary, send the request to the external server that owns the resource and once collected the answer, they give it to the proxy server which in turn renders them to the source client.

It has been mandatory to add a MQTT client inside the developed solution for developing the proposed CoAP-MQTT proxying. The Paho Java Client library has been exploited for this, given that it provides APIs for the creation of clients able to communicate with MQTT servers both in synchronous way and in asynchronous way. An asynchronous MQTT client has been implemented for ensuring the processing of incoming requests also during the message exchange with the broker.

A control on the incoming request URL has been inserted, given that the proxying CoAP-MQTT feature should be accessible only through a well determined path. The URI parsing is performed to extract the broker's address to connect with, and the topic upon which the message has to be published, while the message content is obtained by the payload of the CoAP package. Thanks to the library contents the message is created, the MQTT client connects to the broker and sends to it the message to be published. Once received the answer from the broker, the MQTT client sends to the CoAP client an answer that could be either the code 2.01 (Created) if the operation has been successful or code 5.00 (Internal Server Error) otherwise.

4.1.3 Results and Conclusions

The performances of the system have been tested in an experimental setup created to validate the developed proxy. Simultaneous submission of requests from many competing clients to the proxy have been tested in the experimental setup. The system performances have been monitored both with and without the caching function, considering an increasing number of concurrent clients, and separately for each of the four types of proxying considered (HTTP - CoAP, CoAP - CoAP, CoAP - HTTP, and CoAP - MQTT).

The performance evaluation takes into consideration the Throughput parameter, which is the number of processed requests per second, and the average Round Trip Time (RTT), that is the time for answering, computed as the difference between the request submission from the client and the answer receipt to the client. The system setup adopted exploits a single machine implementing both the developed proxy and the software employed in the trials to simulate concurrent client requests. The testing machine has an Intel Core i7-2630QM @2GHz processor, 6MB L3 Cache, 6GB DD3 RAM, 500GB SSD Samsung 860 EVO hard disk and Windows 10 Home operating system.

Results that will be showed concern the four scenarios, and come from the average over multiple iteration of the simulation for each scenario. The first three types of proxying have been initially investigated with the proxy caching function disabled and with an increasing number of clients. Subsequently, the caching option has been turned on while performing the same experiments. In this way a measure of caching's influence over proxy's performance could be deduced. The fourth scenario (CoAP-MQTT proxying) deserves a detached presentation, being more complex. Two different series of tests have been done to investigate the changes in performance connected to the increasing level of message reliability: the first series operating at level 0 (at most once) of Quality of Service and the second operating at level 1 (at least once). In this analysis, only level 0 and 1 of QoS have been taken into consideration, because level 2 is not even implemented by the main Cloud platforms for IoT, such as AWS IoT, Azure IoT Hub or Google Cloud Platform.

To begin with, the performances achieved in the HTTP - CoAP Proxying scenario will be resumed. The apachebench tool has been used to continuously submit the several concurrent clients' requests for the test resource that has been created inside the CoAP server of the proxy. The number of client to be simulated was fixed for each trial, and 50000 requests have been submitted with the keep-alive option on. This means that only one TCP connection is adopted for each client for sending and receiving more HTTP requests/answers instead of opening one new connection for each single couple request/answer. In the ordinates of Fig. 4.2 is depicted the Round Trip Time, while in the secondary axis of the ordinates (on the right) the average behavior for the Throughput. It is evident that the Throughput levels off to a constant as the number of concurrent clients increases. By focusing on results achieved with the caching enabled, the performance improve by almost 50% in terms of Throughput. On the other hand, the evolution of the response time is linear respect to the number of concurrent clients both with and without caching, thus suggesting the scalability of the cache with respect to the load applied to the proxy.

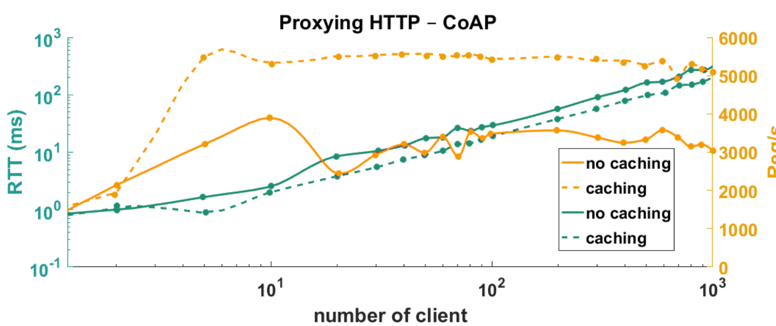


Figure 4.2: Evolution of the Throughput and of the Round Trip Time in the HTTP-CoAP Proxying scenario.

Focusing on the CoAP - CoAP Proxying scenario, specifically for the CoAP-requests, a tailored software has been developed based on the *cf-coapbench* project [89] inside the Californium Tools [90]. Originally, the tool allowed the submission of CoAP GET requests only, without the possibility to specify the Proxy-Uri field for the requests and thus making the tool unusable to successfully test the functions of the developed proxy. In this CoAP-CoAP proxying scenario the internal CoAP server and the internal CoAP client have been tested. The first trial started with the continuous submission of non-confirmable requests from several clients at once for 20 seconds. From the results obtained, summarized in Fig. 4.3, it is evident that the Throughput is much higher respect to the previous scenario and that the caching enhances a lot performances, allowing the proxy to serve more than 15000 requests per second in a configuration made of 20 concurrent clients. Performances experience a sharp drop and a more remarkable variance when the number of clients increases. This may be due in part to the limits of the machine used for testing. Caching adoption strongly decreases the response time also, while the trend is still linear respect to the number of concurrent clients involved, even though fluctuations are stronger if compared to the previously presented scenario.

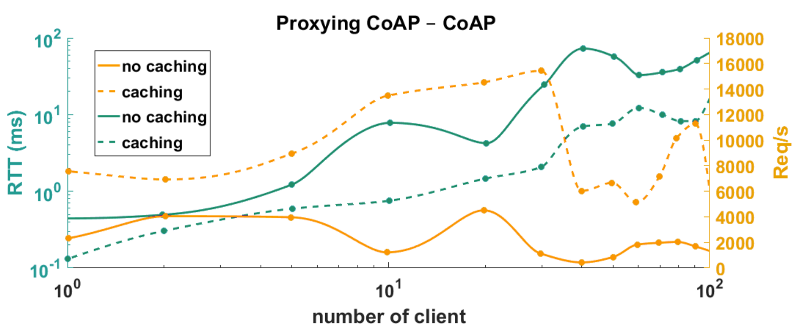


Figure 4.3: Evolution of the Throughput and of the Round Trip Time for the CoAP-CoAP Proxying scenario.

Moving on to the third scenario, which is focused on assessing the performance of the internal CoAP server and of the internal HTTP client of the proxy, an Apache HTTP server has been adopted and launched on the testing machine. The only resource available in the server is a text file containing a 7 bytes string. In Fig. 4.4 it is evident how much the caching allows to enhance the Throughput performance, allowing the proxy to reach the capacity of serving up to 14000 requests with 20 concurrent clients. Despite this, and similarly to the previously presented scenarios, if the number of clients increases the number of requests to be served up at once decreases, as the performance gap respect to the use case without the caching does. For what it concerns the RTT, the usual linear trend respect to the number of concurrent clients is respected. The response time is obviously lower when the caching is turned on then when it is off, but the gap between the two cases decreases as the number of concurrent clients increases.

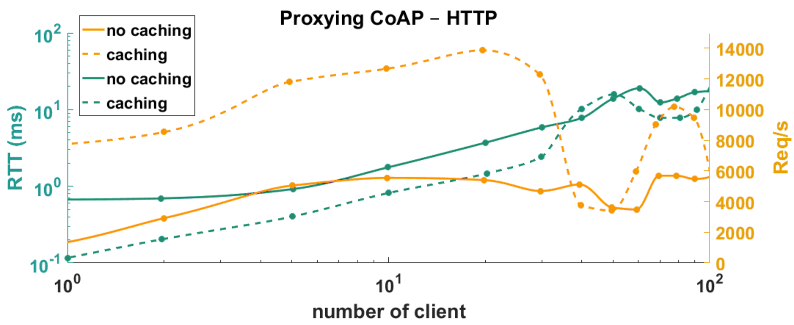


Figure 4.4: Evolution of the Throughput and of the Round Trip Time in the CoAP-HTTP Proxying scenario.

The last scenario is CoAP - MQTT Proxying, where the performances of the CoAP server and of the MQTT client of the proxy have been tested. For conducting this kind of test a MQTT broker to connect with, and to send the messages to, is needed. The open-source Mosquitto broker [91] has been used, launching an instance in local on the testing machine. As Fig. 4.5 highlights, the Throughput in this scenario is much lower then the one obtained in the previous testing scenario (CoAP-CoAP). Moreover, when using level 1 of QoS the Throughput sharply drops till a hundred requests per second. Same observations for the response time, that is very high when using a level 1 of QoS. The behavior of the RTT is still linear respect to the number of concurrent clients.

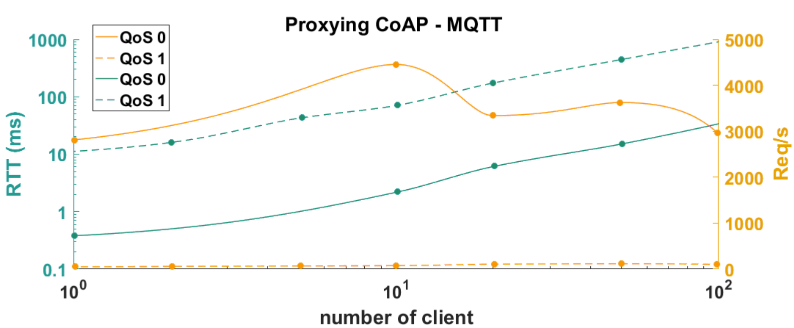


Figure 4.5: Evolution of the average Throughput and Round Trip Time in the CoAP-MQTT Proxying scenario.

In conclusion, there are two main virtues connected to the architecture that has been presented and tested. To begin with, the integration of two compatibility macro-solutions, namely HTTP-CoAP and CoAP-MQTT, definitely enlarges the contexts of application of the proposed solution inside the wide IoT universe, and so inside the AAL world also. If we focus on envisioning future scenarios where several IoT devices of different producers should coexist in places like houses, offices, and so on, the utility of a proxying unit like the one proposed in this work is immediately reasonable. Moreover, tests proved how much the caching function enhances both communication speed and the ability to manage simultaneous requests thus providing a higher level of Quality of Service.

Given the very good performance achieved, it is advisable to use the proposed proxy to develop an AAL system capable of inter-operating with the WoT and its main protocols. In the AAL context the inter-operability of a solution should be a fundamental requirement, and the adoption of the proposed cross-protocol proxy aim at reducing the technical complexity for those who want to work for the AAL without getting involved in the management of advanced communication protocols for the WoT.

This work has been presented at the 2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT).

Chapter 5

Analytics Contributions

Research activities focused on the Analytics are going to be presented in this Chapter. To begin with, I describe in the following section a MV system solving a complex task and able to deal with human interaction in the framed area. This contribution belongs to the group of I4.0-related research activities developed in strict collaboration with iGuzzini Illuminazione S.p.A., together with the second contribution, which is focused on PdM of injection moulding machines, and the third, which is a MV-based PdM solution for number plates used by the painting robot system for managing process parameters.

Moving on, the fourth contribution presented hereafter is again focused on PdM and it has been developed in strict collaboration with Campetella Robotics s.r.l., an Italian manufacturer of industrial robots. This work has been fruitful for the SADABI-IT PON MISE project, where implementation of PdM strategy in the complex and highly automatized production lines of Fater S.p.A. (project's leading partner) is among the objectives set.

Second last contribution is centered on CV from a technological point of view, and on S5.0 from a social point of view. A solution for automatically computing the water level of rivers through cameras will be presented. Through continuous monitoring of water level, a flood hazard early warning system could be implemented, by fusing data coming from the presented system with diversified data, e.g. weather forecast and map of the water-level sensors.

Lastly, a contribution showing the potentiality of ML and DL algorithms for solving complex industrial tasks, like dynamic energy rationing, in an improved way respect to methodologies adopted in the past. For privacy reasons, details about the company involved cannot be disclosed.

5.1 A Versatile MV Algorithm for Real-time Counting Manually Assembled Pieces

As introduced in Chapter 2, technological advancement together with pulling market expectations have fostered a profound advance in the way firms produce their goods and deliver their services. I4.0, deeply analysed and described in sub-section 2.3.1, is the paradigm that embeds all the technological pillars, design principles, and best practices, that allow companies to reach the high requirements needed to compete in the market.

Lean Manufacturing (LM) is a production paradigm derived from Toyota, aimed primarily at reducing times and wastes within the production system, thus lowering costs and improving response times from suppliers and to customers. LM has many reciprocal synergies with I4.0 as investigated and proved by many researchers [92, 93].

From a practical point of view with respect to the implementation of LM and I4.0, it is of extreme importance the ability of a company to precisely monitor the production, given that most of the manufacturing systems in place today are re-configurable and flexible for being able to efficiently manage the high mix of products required to offer high customization to the customers. Therefore, materials and spare components are not supplied to assembly lines in advance, but only as soon as they are required for the production (Just-In-Time), thus avoiding storage of raw materials which is a renown cost and locked investment. Obviously, Just-In-Time (JIT) production is only feasible if the manufacturing process is monitored in real-time, something that can be trivial in automatized production lines, but tricky in a context where the production still grounds on manual work of operators. In such non-standardised situations, the variability is high due to the unpredictability of operators, and it is hard to collect real time data from the production facility. This makes harder to properly and efficiently manage the material replenishment and the production line setups, obstructing the concrete implementation of I4.0 and LM, hence of JIT production. Smart and innovative technologies may provide a solution in those contexts where traditional technologies are not enough. Coherently, AI and CV branches have been gaining relevance in recent years, due to their contributions to Intelligent Manufacturing Systems [94].

5.1.1 Motivation

The objective of monitoring the production carried out by a manual assembly line cannot be met using traditional technologies, which are error prone in such a very non-standardised and unpredictable context. On the other hand innovative technologies like cameras and Machine Vision algorithms can be versatile and accurate enough.

This research activity comes from the necessity of iGuzzini Illuminazione S.p.A. to have timely and reliable data about the manual assembly process, specifically, the number of assembled pieces by each of the stations of the tens assembly lines. As previously introduced, the solution should manage human interaction and should be independent from manual trigger. The company has embraced JIT production whenever possible to keep low inventories in the production lines and in the factory in general, with the aim of reducing costs and investments locked into raw material and spare parts. This forces managers and logistics operators to have updated and reliable information of the production of assembly lines to align, in real-time, all the upstream and downstream processes of the pull production flow: material replenishment, procurement, shipping, and so on. As previously mentioned, being a high-mix low-volume company, the assembly lines are flexible and re-configurable: every single line is in charge of the production of many different product variants. The assembly sequence is composed of customer orders and frequently involves passing from one product type to another, which implies assembling some components instead of others. The availability of an incremental, reliable, and timely individual count of assembled pieces would help operators in avoiding errors due to miscounted assembled products. For a manual assembly where pieces are passed from one operator to the next one it is hard to take trace of how many pieces out of the order's target have been already produced. Moreover, solutions grounding on manual trigger would annoy operators and negatively impact on productive performance.

Two MV procedures have been proposed to address the problem under analysis. Their preliminary implementation has been presented at an international conference (IEEE International Conference on Intelligent Engineering and Management 2020). The preliminary version reached good results, but proved to be not reliable at all in dealing with the variety of unpredictable behaviors of assembly operators in placing and picking the assembled pieces. Therefore, starting from results achieved and weaknesses identified, an improved version of the two algorithms has been developed. The improvements reached in the second version are connected to an additional module, called Motion Check, added upstream respect to the processing steps aimed at counting.

5.1.2 State-of-the-Art

Many researchers focused on the exploitation of Visual Computing technologies for supporting and empowering operators of smart factories: monitoring of movements for co-bot management, easing the training of new staff, helping assembly operators of complex or small products like electronic components [95, 96, 97]. Coherently, the global market of MV is growing fast, in line with proliferation of practical applications [31]: object measurement, object location, image recognition, object existence detection, and object defect detection to name few [98]. For this reason MV has been identified as the best promising technology given the criticalities connected to the problem defined.

Going deeper into the research papers reviewed, human interaction is usually not addressed and objects to be measured, located, detected or whatever, are either stationary or moving through an highly standardised set-up like conveyor belts [99]. In contexts where products are moved by conveyor belts, counting through a MV system might be trivial [100, 101]; however, in the considered scenario, assembly can be done only manually, thus making it tricky to count pieces passed from one operator to the next one. In those rare cases in literature where objects are manually moved before being analysed, solutions usually ground on manual triggers for taking snapshots once there is no operator interference in the framed area. This possibility is not viable in this case, because adoption of conveyor belts and human participation through triggering mechanisms are not possible.

Since the beginning, the aim was to be as flexible as possible for what it concerns the proposed solution, envisioning the scalability of the system at a plant-wide level, where the product mix produced is extremely high (i.e. thousands of different products), when compared to the mix produced in one line only (i.e., order of magnitude of ten product variations per line). Products types change in terms of color, size, and shape, therefore highly customized MV solutions, are not sustainable from the scalability and re-usability points of view.

For this reason, in the proposed algorithm some basic techniques such as image pre-processing, binarization, morphological operations [102], and blob detection have been exploited. Object detection and consequent counting can be performed through a variety of techniques, from basic ones like filtering, morphological operations, and contrast enhancement, to more advanced solutions such as segmentation and classification models [100]. Most of the time, the concatenation of multiple techniques proves to be beneficial.

I propose the use of the Motion Check module — that will be described inside next subsection — followed by the blob-based counting algorithm with the aim of building a simple, computationally fast, and yet very versatile solution which is able to count manually moved pieces, mostly based on generic color and morphology. Very advanced MV solutions based on Convolutional Neural Networks (CNN) have not been tested for counting, as they are too computationally intensive [103, 104] and, given the mandatory real-time requirement for the developed solution, they likely require huge computational resources such as dedicated GPUs which hampers wide adoption of the solution. Furthermore, the usage of a CNN is probably excessive in the considered context, as the environment is very restricted, and only hands and products interfere in the framed area. This is the reason why very advanced object detectors, such as Deep Learning-based methods, were deemed excessive in comparison to the task at hand, especially considering the effort needed for training this kind of solutions. Then, the proposed blob-based counting algorithm has been compared to a Machine Learning-based one, grounding on an Aggregated Channel Features (ACF) Detector [105] which was specifically trained to detect the product types produced on the assembly line used for all the experiments. The ACF custom object detector was taken as a reference in terms of accuracy of detection and counting, but it should be specified that it performed well in the restricted context of that assembly line only, while it failed if applied to other assembly lines where the product shapes and dimensions differ from those of the training set used. The object detector needs to be re-trained every time it has to do with different products in order to be reliable. This ML-based solution is hence used as reference for what it concerns performances, but it is not in line with scalability requirement. On the other hand, the developed blob-based solution is not product type-dependent and works in a manner that allows its plant-wide application (i.e., for other assembly lines also, after minor adaptation, much easier and faster respect to adapting the ML-based detector).

5.1.3 Materials and Methods

After assessing technological feasibility of the intention to exploit a video stream for counting pieces placed on and then picked from a table, and taking into account the final aim of the company — i.e. monitoring every station of tens assembly lines that manage an extremely wide variety of products in terms of shape, size, and color — a low-cost USB camera has been selected as sensing device. As shown in Fig. 5.1, every workstation of each assembly line is followed by an intermediate bench, where assembled pieces which are ready for the next step are placed. Each of these intermediate benches should be equipped with the USB camera to continuously acquire frames, which are instantly analysed by the developed algorithm in order to count the number of pieces assembled by the upstream operator.

In particular, I selected a SVPRO USB camera, with 2.8–12 mm varifocal lens, minimum illumination 0.01 lux, a Sony IMX322 sensor, 1920 $\times$ 1080 resolution, and which reaches a rate of 30 fps and uses the H.264 compression standard. For the development of this work, I focused on one camera only, acknowledging the likeness of video sequences captured by cameras framing the intermediate bench of every assembly station, as can be understood by looking at Fig. 5.1: when acquiring in the A-B bench between operators A and B, or in the B-C bench, only the product shape changes, but the actions made by the upstream and downstream operators are basically the same. Going into the details of the system set up, I positioned the camera lens 80 cm away from the intermediate table plane, which is a white rectangle of 30 cm by 65 cm.

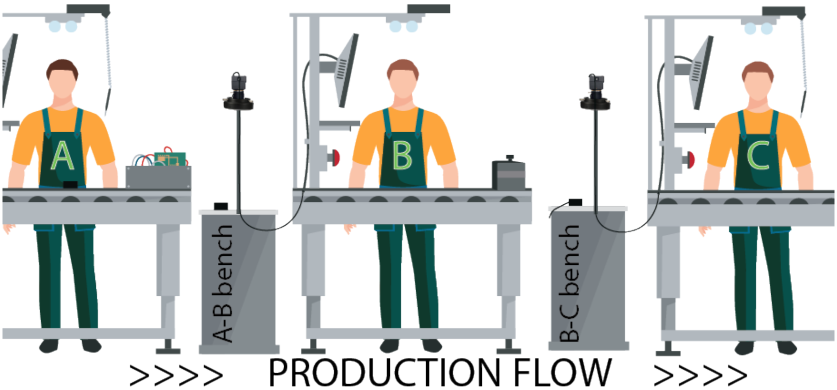


Figure 5.1: Assembly line and system setup.

The camera has been installed along the perpendicular line passing through the table center, in order to frame a little surplus; the framed portion can be reduced later to a smaller Region of Interest (ROI) using the computer interface.

During the first trial, connected to the work presented at ICIEM conference, the setup was the just described one. With respect to the setup used in the preliminary work, a light ring has been added around the camera lens in the work published in the Journal of Imaging, in order to reduce the multiple light variations inside the assembly department. Analysing data acquired for the preliminary work, evident light variations often happens, either due to the mix of artificial light (which is stable and constant) with natural light from outside (which is extremely variable during the day and depends on the weather), or to shadows connected to operators' hands. The added light source is diffused and was produced in-house by the company. Given the prototypical nature of the study, I used my laptop, a MacBook Pro with an Intel Dual Core i7 at 2.8 GHz, 8 GB RAM, 512 MB Intel HD Graphics 3000, and 512 GB SSD storage, for carrying out all the activities. To interact with the USB camera, develop the algorithms, build the real-time processing and visualizing application, build the parameter setting application, and perform offline and real-time tests, I used the *Matlab ver. R2019a Update 7-9.6.0.1307630* software, specifically equipped with the Image Acquisition Toolbox, Image Processing Toolbox, Computer Vision Toolbox, Statistics and Machine Learning Toolbox, Matlab Compiler, and the Support Package for Generic Video Interface installed.

According to the system setup depicted above, taking a typical video sequence from the camera installed over A-B bench of Fig. 5.1, under normal working conditions of the assembly operators, it is possible to discern four main phases:

1. the table is empty (*Standstill interval*);
2. the hand of upstream operator holds a piece, places it on the table and then goes away from the ROI of the camera (*Motion Interval*);
3. the placed piece is alone on the table (*Standstill interval*); and
4. the hand of downstream operator enters into the ROI and picks up the piece to take it away from the field of view (*Motion Interval*).

It may happen that a piece is placed on the table while the previous one has not been yet picked up from the following operator, which is why the solution must be smart enough to take this into account and operate efficiently during this eventuality. The MV algorithm should be able to count all the pieces placed by the upstream operator as soon as they are put on the table, while not counting when a piece is picked up by the downstream operator. The core of the algorithm is the object detection phase, which triggers the comparison between the number of detected objects with the number of already present objects, and eventually decides to count. As reviewed in the previous subsection, several image processing techniques have been tested for counting, from those more traditional and computationally light like filtering, morphological operations, and similar, to those more advanced and computationally intensive like semantic segmentation and Deep Learning based techniques. Most of the time, the concatenation of multiple techniques proves to be beneficial.

The decision of the best possible solution depends strictly on the specific characteristics of the context of use. It is, therefore, mandatory to deepen the description of the environment in which the proposed solution is going to work, before introducing the developed algorithm. Every product type and their variations, when assembled, are partly black, while the tables are white; therefore, less-advanced image processing techniques (i.e., color-based and morphology-based ones) can work fine for solving the problem at hand. Specifically, pieces assembled in the restricted context of project development are black-painted steel lighting devices, which are comparable to cylinders with a height of 10 cm. Several product variants are assembled in the test bed, but the cable length is the main difference among them. The validity of the presented algorithm is envisioned in the entire assembly department as well, after minor parameter fine-tuning which I made easy by developing the Parameter Setting Tool application. Indeed, different products mainly differ in dimension, but not in overall shape, which is characterized by a relevant light body with a circular, square, or rectangular section, a coloured light frame, and the cable. Broadly speaking, the proposed algorithm can work in any context where dark-coloured objects have to be counted when placed on a white table framed by a camera. I expected from more advanced techniques, such as custom-trained object detectors, to be able to learn how to detect the specific objects, but I also envisioned their trickier escalation into new assembly lines, due to the time required for the creation of a training data set and for the training itself of the detector. However, in a restricted context of use, a properly trained detector can be taken as reference for assessing object detection accuracy.

Regardless of the kind of technique is chosen for detecting objects, the motion phases are the main source of error for counting algorithms, as proved in the preliminary work. In fact, the way that people naturally and instinctively hold and move a piece during placing or picking up is extremely varied and unpredictable if not standardized or supervised. Accordingly, I tried to find an inter-frame analysis mechanism which could differentiate the motion phases from the stand-still phases, in order to perform reasoning targeted at counting only during stand-still phases and not during the unforeseeable and critical motion phases.

Motion Check Module

To begin with, I will describe the Motion Check procedure which was not included in the original work presented at the ICIEM conference. This module was added as preliminary step to both blob-based and ACF-based counting algorithms which will be described right after, being chronologically subsequent to the Motion Check procedure. The Motion Check makes the following counting algorithms sensitive only to the eventuality that both operators simultaneously interact with the bench, while strongly improves reliability with respect to unpredictable and strange movements or interference of operators in the framed area during object placing and picking. In detail, when one operator places a piece while the other is picking up another piece, the algorithm (incorrectly) does not count, due to the numeric balance obtained by adding and subtracting one piece at once during the same *Motion Interval*. Nevertheless, this is a human behaviour that can be standardized and avoided after brief training of the staff, but strongly improves the counting performances of the algorithms with respect to other more critical and less controllable behaviors, which caused mistaken results of the preliminary version of the solution. Indeed, every other kind of unusual product handling behaviour during placing and picking (e.g., passing over a placed piece, thus obstructing the product from the camera view for a moment, or covering a piece with the hand for a while), does not affect the performance of the counting algorithms if equipped with Motion Check module. Moreover, thanks to this preliminary Module, there is no need for analysing every video frame, which is both computationally intensive and error-prone. The idea of Motion Check comes from a variety of examples found in the literature which have used frame differencing or background subtraction to identify moving objects [106, 107]. Without going into the details of these established methodologies, it can be understood that comparing one frame (F_1) with the previous one (F_0) (specifically, by subtracting them pixel-by-pixel as in Equation 5.1), the difference image is obtained. This difference image is different from zero in every pixel engaged in capturing something that is moving or has changed.

$$p_{diff}(i,j,k) = |p_{F_0}(i,j,k) - p_{F_1}(i,j,k)|,$$
$$\forall i = 1,2,3; j = 1,...,L; k = 1,...,W., \quad (5.1)$$

where $p_{F_0}(i,j,k)$ is the value of the previous frame pixel with co-ordinates j,k in the i^{th} color channel and $p_{F_1}(i,j,k)$ is the value of the current frame pixel with co-ordinates j,k in the i^{th} color channel. Thanks to the stable lighting provided by the light ring, during the stand-still phases — where either the table is empty or one or more products are placed on it — the subtraction outcome is an image with every pixel very close to zero. In other cases, where operators are interacting with the framed area — that is, placing or picking up — there are pixels in the difference image that are much higher than zero. What is computed through the previous equation is a $3 \times L \times W$ matrix, which is not immediately analysable. Hence, in order to have a more direct and synthetic measure of the magnitude of inter-frame difference, the mean of all pixel values of p_{diff} in all color channels is computed according to the following equation:

$$m_t = \frac{1}{3 * L * W} * \sum_{i=1}^{3} \sum_{j=1}^{W} \sum_{k=1}^{L} p_{diff}(i,j,k), \quad (5.2)$$

where there are three (RGB) colour channels in the acquired frames, L stands for frame length in pixels, W stands for the frame width in pixels, and p_{diff} (i,j,k) is the punctual value (between 0 and 255) of the pixel in the i^{th} colour channel with co-ordinates j, k in the difference image computed according to Equation 5.1. Without the need for capturing and fixing a background, which allows the detection of generic foreground objects (either still or moving), it is possible to detect the frames where there is something moving with respect to the previous one, thanks to reasoning on the value of m in the current frame. Being based on the variable previous frame, this is an adaptive motion detection procedure. A detailed flowchart of the steps involved in the Motion Check procedure is depicted in Fig. 5.2.

Specifically, thanks to m_t, m_{t-1}, and BIN, which is a binary variable useful for managing the further processing as will explained in a while, the Motion Check enables the computationally intense further processing aimed at counting

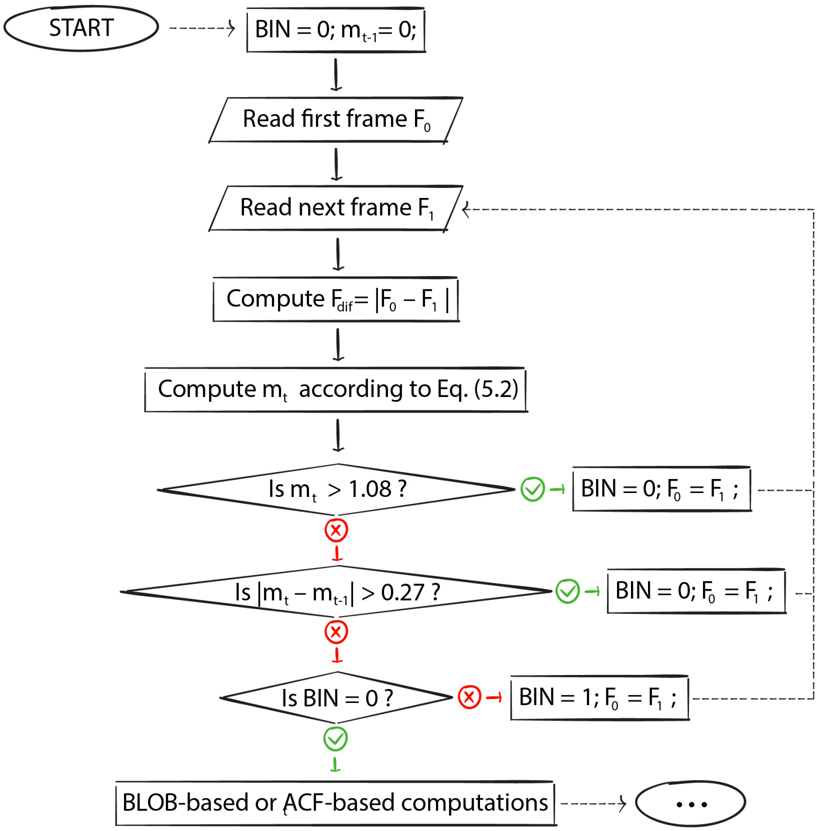


Figure 5.2: Fowchart of the Motion Check algorithm.

only in two cases:

A. In the first frame of a *stand-still interval*, just after the end of a motion phase, where BIN is equal to 0 and m_t is less than 1.08; and

B. In the image just after two frames within a *stand-still interval* which have a difference between their m values, (respectively, m_t and m_{t-1}) higher than 0.27.

Analysing the first case, should $\mathrm{m_t}$ go beyond the threshold, it means something is moving. As soon as $\mathrm{m_t}$ returns within the threshold, it means that is a *stand-still phase*, hence, the frame can be processed for understanding whether a piece has been added. The second case takes into consideration the eventuality that an operator moves very slowly, thus causing a small increment in the $\mathrm{m_t}$ value which does not exceed the threshold at 1.08. In this eventuality, the BIN variable is set to 0, allowing the further processing of the following frame captured if $\mathrm{m_t}$ will be again under 1.08. Otherwise, Motion Check never permits further image processing: if neither of the two conditions are met, it is implied that nothing has moved and no piece could have been placed or picked up. Alternatively, it indicates that it is a motion interval and there is human interaction in the framed area that can cause incorrect counting in the case of further processing of that frame; thus, further processing during these cases is prevented by the Motion Check.

Motion Check Parameters and Thresholds As can be derived from the flowchart, there are three main quantities relevant to the algorithm: BIN, $\mathrm{m_t}$, and m_{t-1}. BIN is a Boolean variable, which is useful in allowing the further processing of the first frame of a *stand-still interval* and to avoid processing the following frames of the same stand-still phase. This is strictly connected to the fact that, if we are within a *stand-still interval* of the video, nothing has moved and so no piece placing or picking up could have happened. Further processing these frames is a waste of computing power; therefore, it only occurs if BIN is equal to zero, which holds true only for the first frame of a stand-still phase (case A) or for the frame just after a slow movement (case B). The parameter $\mathrm{m_t}$ is computed for the current frame, while $\mathrm{m_{t\text{-}1}}$ is the value regarding the previous frame. This past value is necessary for the successful identification of very slow movements, which do not cause an increment of $\mathrm{m_t}$ over the 1.08 threshold. The threshold for discerning motion phases from stand-still phases was set at 1.08, and the threshold for assessing slow movements through the difference between $\mathrm{m_t}$ and $\mathrm{m_{t\text{-}1}}$ at 0.27. These two values were statistically defined. After the selection of video intervals containing stand-still phases only, I computed $\mathrm{m_t}$ at each instant of these intervals. Computing the mean and the standard deviation of these values, 0.67 and 0.13 have been respectively obtained. Then, the motion threshold has been set as the mean plus three standard deviations, and the threshold for the gap between m_t and m_{t-1} as two times the standard deviation. In Fig. 5.3, the typical behaviour of the $\mathrm{m_t}$ parameter (computed according to the Equation 5.2) in every moment of a sample video where three pieces were placed and three pieces were picked up is presented.

The current video time is the abscissa, while the value of the m_t parameter at each instant is the ordinate of the plot. The peaks and the values immediately after correspond to either the placing or picking up phases, and strongly differ from the stable trend of other intervals, connected to the stand-still phases of the video. The timeline in the upper part of the picture describes every phase. The 1.08 threshold is outlined designing a straight horizontal green line, and frames analysed by subsequent counting algorithms are pointed out with magenta dots on this line: for these frames the Motion Check decided to go ahead with further processing, as caused by one of the two conditions listed

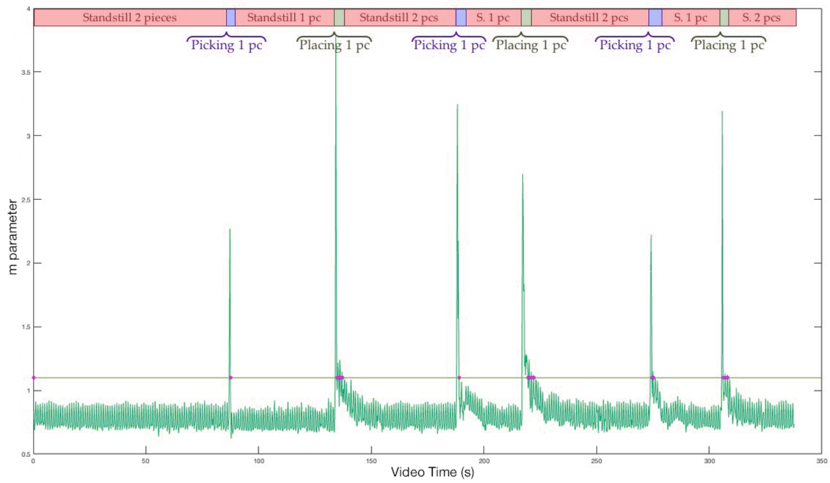


Figure 5.3: Plot of the m parameter for a sample video.

earlier.

To better understand how the values of m_t and m_{t-1} affect the processing of the video frame, six video frames — each 0.2 s after the previous one — that capture from the beginning one piece placing, are shown in Fig. 5.4. For every frame, the values of the relevant variables that are used by Motion Check to decide to go ahead or not with further computation are reported in the picture, and the final decision taken by the counting algorithm which processes the frames selected by Motion Check.

In details, the first video frame shown in panel (a) is the last of the Standstill phase, which is associated to a value of m_t within the stand-still boundary set. The following frame has a m_t value exceeding the threshold, thus suggesting the beginning of a *Motion Interval* which lasts until the fifth frame in panel (e) that, being the first stand-still frame after a motion interval, is further analysed and returns the presence of one piece. Given that there was no pieces previously, the algorithm decides to count one. The following frame in panel (f) is inside the stand-still interval and the gap between the current m value and previous m value is lower than the inter-m gap boundary, hence, no further processing is performed on this frame. The Motion Check procedure is important, both for reducing the counting errors and improving the real-time capability of the solution, as will be deepened in the Results. Yet, considering that it is unable to count by itself, it is an enabler of further processing in the frames that are the most meaningful. To actually count, it is required another processing algorithm, able to detect objects and quantify how many there are in one frame. Two different counting approaches have been implemented and evaluated: the first one is very simple and versatile, being based on basic

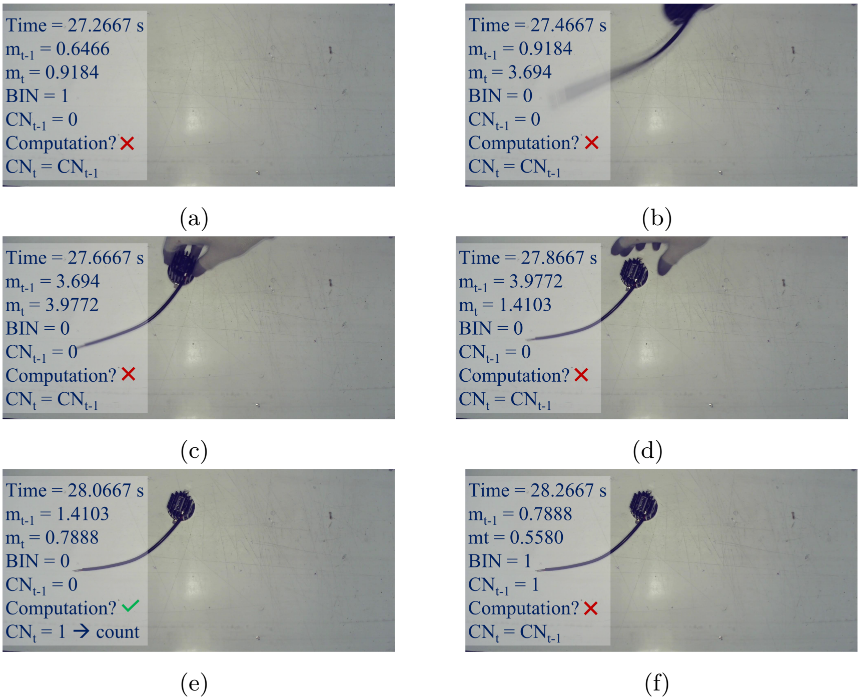


Figure 5.4: The sequence of placing one piece.

image processing techniques aimed at identifying dark objects in the framed area; while the second one is a more sophisticated ML-based object detector specifically trained.

Counting Module

Blob-based Alternative With respect to the blob-based solution proposed in the preliminary work [108], besides having added Motion Check Module I also slightly changed the processing steps in the improved version published by the Journal of Imaging. Specifically, the removal of connected components processing step as been added. Moreover, as previously highlighted image processing is done only when the Motion Check Module decides to go ahead. In the preliminary version of the solution the blob analysis steps was done for every new frame, whether it was in a stand-still or motion interval. Particularly, in the latter case, the probability to make mistakes due to the strange behaviours of operators was non-negligible and led to several hardly addressable counting errors. The blob-based image processing algorithm aims to find how many dark objects there are in a given frame. A detailed flowchart of the steps required is presented in Fig. 5.5, where the first block simplifies the entire Motion Check procedure discussed extensively earlier.

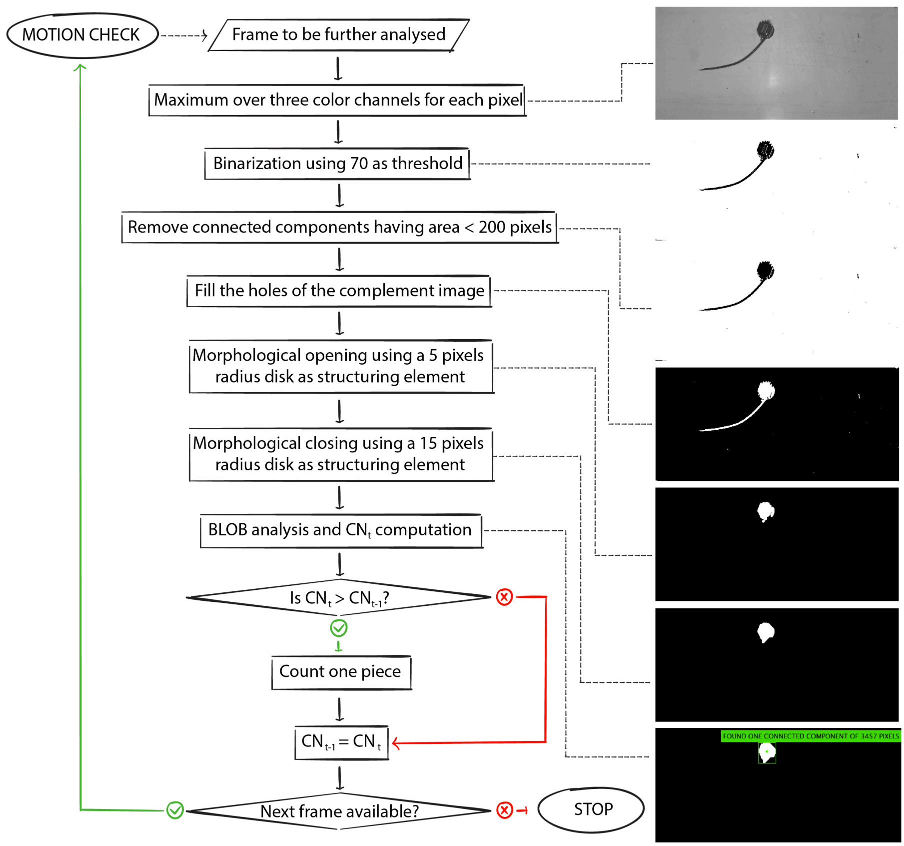


Figure 5.5: Detailed flowchart of the Blob-based algorithm, with examples.

The removal of connected components having an area of less than 200 pixels aims at better defining the core of the object after binarization. In the right portion of Fig. 5.5, the outcome of the algorithm processing steps performed on frame (e) of Fig. 5.4 — the one for which the Motion Check decided to go ahead with further processing — is shown. At the end of the processing steps, the number of white blobs and some statistics like their area, centroid, and bounding box are obtained.

The complexity of this algorithm is connected to the definition of five key elements, such as the threshold for binarization, the radii of the disks used as structuring elements for the two morphological operations, and the minimum and maximum limits for the areas to be detected, as small white blobs due to noise or dirtiness of the table should not be taken into account when counting. These variables are context specific, but very easy to be adapted in a while. Thanks to the developed Setting tool described shortly, even non-expert users can change the threshold (even though it is valid for almost any dark coloured object placed on a brighter surface), and the radius of structuring elements to adapt them to diverse working conditions. On the other hand, minimum and maximum areas will be automatically computed and set by the app based on other parameters set.

ACF-based Counting Alternative The alternative solution that can be launched as a counting algorithm once Motion Check decides to go ahead, is a ML-based custom object detector, which was specifically trained in order to be able to detect the object of interest which passes on the test-setting bench. Specifically, we used the following training options for developing the customized ACF Detector: 4 stages, 176 × 165 pixels object size, 2048 maximum number of weak learners, and a training data set with 660 positive examples and one negative sample factor. Detector training took more than 13 minutes to be performed, but its application consists basically of two steps only, as detailed in the algorithm flowchart:

(i) Apply the detector on the frame and obtain the scores and the bounding box co-ordinates;

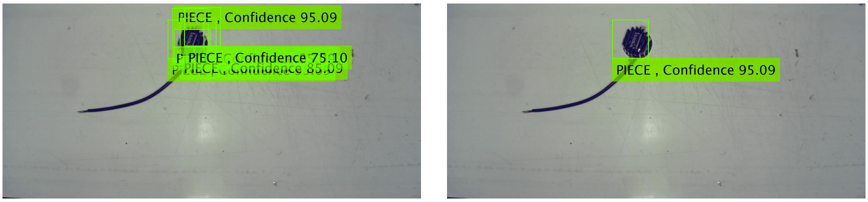
(ii) Examine, when more than one object has been detected, if any of these separate bounding boxes overlap (in which case, they correspond to the same object);

(iii) Compare the number of objects present in the current frame (CN_t), along with the recorded number of already present objects ($\mathrm{CN}_{\mathrm{t}-1}$):
- COUNT if $CN_\mathrm{t} > CN_{\mathrm{t}-1}$
- DO NOT COUNT if $CN_\mathrm{t} <= CN_{\mathrm{t}-1}$

(iv) Update $\mathrm{CN}_{\mathrm{t-1}}$ with CN_t and go back to the Motion Check procedure with the following frame.

In Fig. 5.6, the outputs of the algorithm processing steps (i) and (ii) performed on frame (e) of Fig. 5.4 are shown: the detection of multiple pieces in panel (a); and the overlapping bounding box analysis, allowing us to determine all of the detected objects which are related to the same object, is shown in panel (b).

Contrary to the blob-based algorithm, the flowchart of this alternative is much shorter; however, it hides the complex and time-consuming actions which must be done to train the detector. Specifically, the creation of an image data base for providing training data to the detector is needed, as well as the time required for training the detector. In this specific case, developing the image data base from videos collected over several days took one hour, while the training took 13 minutes. I would like to specify that only a small amount of



(a) Multiple overlapping detection after step (i).

(b) The result after step (ii).

Figure 5.6: ACF-based processing steps outcome.

training data and basic training options were used. Furthermore, on a large scale (i.e., at a plant-wide level), a detector for every product type and for every product perspective is required: in Fig. 5.6, the piece is placed on the base but, if it was placed on its back, the detector would have failed, or would have been inaccurate and not reliable in detecting it, being a very accurate model but very object specific too.

Solution Prototype

The concatenation of Motion Check with one of the two alternative counting modules serves as solution to the problem at hand. Nonetheless, it is essential to take into consideration that every implementation of the solution should reach real-time analysis of video stream. Therefore, both blob-based and detector-based solutions have been implemented into a prototypical App, developed through Matlab App Designer.

Real-time Counting Application In Fig. 5.7, the graphical layout of the prototype application, developed using AppDesigner in the *Matlab ver. R2019a Update 7-9.6.0.1307630* software is shown.

While continuously processing the video stream in real time, the Graphical User Interface (GUI) is able to instantly update the count and visualize possible errors. Specifically, slow image acquisition or irregular working conditions can be detected and self-diagnosed. Starting from the top left of the picture down to the bottom right:

- the switch for managing the video processing;
- the “placing instant record button”, which allows to manually save the actual timestamp of piece placings for debug and testing purposes;
- the incremental count visualized, which is updated in real-time;
- the manual recovery buttons, which allow to manually add, subtract, or reset the count;

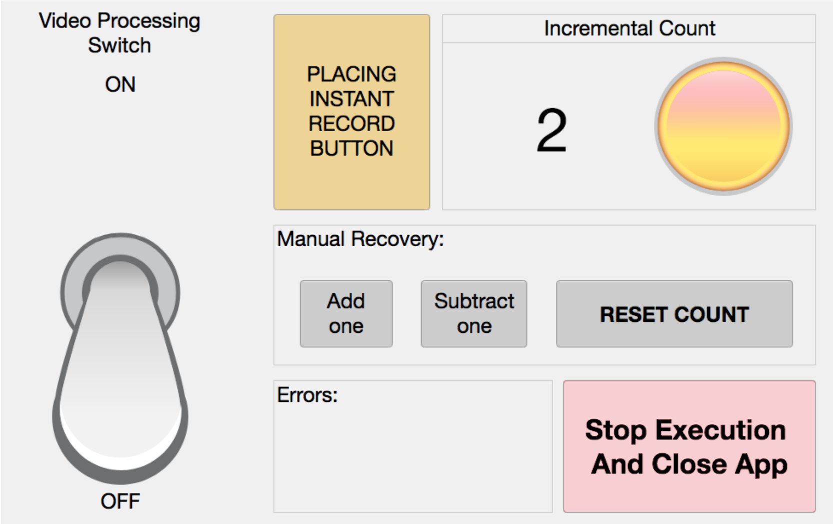


Figure 5.7: Main GUI of the prototype real-time App.

- the error panel, showing possible warnings;
- the button to stop the execution and close the app.

The "placing instant record button" is essential for testing the responsiveness of the solution, as will be presented later. The App also creates a log file that stores relevant events during working conditions. In more detail, the timestamps of every count, every frame accepted by Motion Check for further processing, every delay in image acquisition, every manual recovery, every switching of video processing, and every execution stop are registered. The log file is useful for assessing the capability of the real-time implementation of the algorithms to work for long times without losing any information due to delays in image acquisition.

Parameter Setting Tool: The importance of well-defining the value of the threshold for binarization and of the radii for morphological operations has been previously highlighted. This may be a complex task for non-experts in CV; nonetheless, to ease the adaptation of the algorithm into new assembly lines, it is essential to make this procedure fast and comprehensible. For this reason, I developed a prototype Setting Tool Application, able to guide in the proper setting of the relevant working parameters of the counting App. In Fig. 5.8, the two GUIs of the Parameter Setting App are shown.

The first GUI allows the user to connect to a USB camera and define its ROI parameters, by visualizing the framed area with each modification of X, Y, Width, or Height. Once connected to a camera and set the ROI, the second

GUI (showed in panel (b)) appears, and allows the user to see the outcome of all the blob processing steps until the morphological opening of the current situation captured by the camera. Every time that the binarization threshold (T), the radius of the structuring element for the opening (strel open), or the radius of the structuring element for the closing (strel close) are changed by the user, the final outcome of processing, according to the defined parameters, is shown in the display. This allows the user to practically understand which modification to the process parameters improves the results of processing. The user is guided in order to be sure that the minimum area and the maximum area product are both well-defined. It is important to define these upper and lower limits for the Blob analysis, in order to avoid considering image noise or table wear as objects to be counted. Once saved, at each following utilization of the real-time processing prototype App, the set parameters are automatically used.

5.1.4 Results and Conclusions

The aim of this work was to find the best solution for counting pieces assembled from an operator which manually places them on the intermediate table. These pieces are progressively picked up, one by one, by the following operator who carries on the assembly process. In order to effectively count the pieces manually placed by an assembly operator on a table, a preliminary Motion Check procedure followed by two different counting solutions, whose performances were compared, has been developed. One counting solution was designed concatenating existing image processing techniques; while the other one is a reference method, a consolidated Machine Learning object detector trained on custom object of interest. In order to objectively compare the two counting solutions, I used the requirements set by the operation managers of the company. Specifically, the solution should be able to:

(a) Count every time an assembled piece is placed on the table;

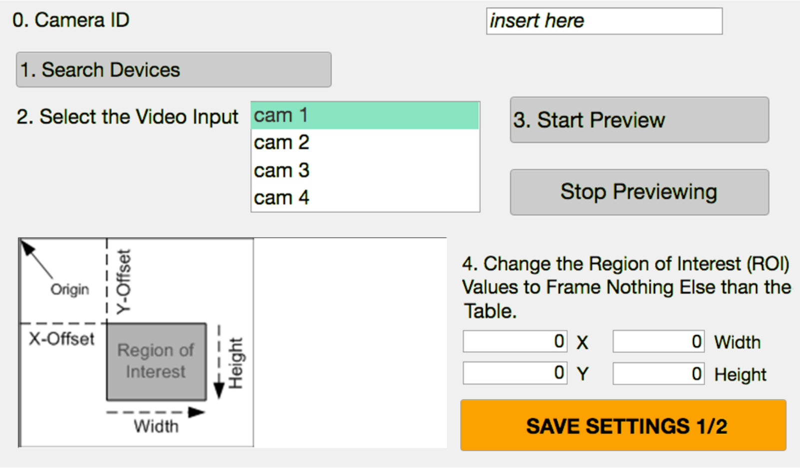
(b) Do not count whenever a piece is picked up from the table;

(c) Do not count whenever a piece is not placed on the table, given that sometimes operators interfere in the framed ROI of the camera even though they are not placing nor picking up a piece;

(d) Analyse the live video stream for long times without losing any interval;

(e) Be timely in counting; and

(f) Be easily and quickly adaptable to all of the different assembly lines in the company's shop floor.



(a) The opening GUI.

(b) The second GUI.

Figure 5.8: The two GUIs of the Setting Tool App developed.

The requirements (a), (b), and (c) are synthesized, from now on, with the name "Counting Capability", being strictly related to the counting itself. Requirement (d) was named the "Real-Time Capability", requirement (e) "Responsiveness", and (f) "Versatility". As a general result, also improvements resulting from the installation of the light ring are briefly resumed. The light ring is essential for application of the preliminary Motion Check module. In Fig. 5.9, the behavior of the m_t parameter for an old video, recorded before the light ring installation, is shown. The green horizontal line corresponds to the 1.08 threshold, and the magenta dots along this line correspond to every video frame which was further analysed.

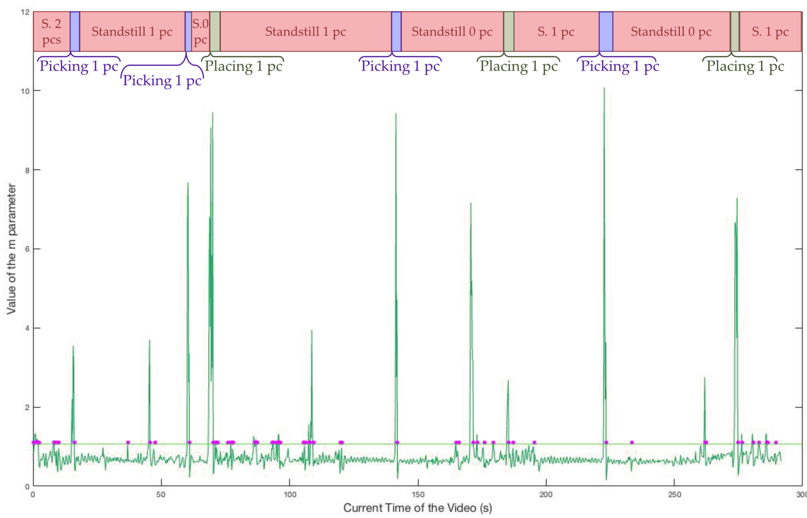


Figure 5.9: Plot of the m parameter regarding a video collected before the light ring installation.

The variance due to environmental shadows and natural lighting influences on the illumination of the framed table is evident comparing the m values with the timeline of events on the top of the figure. Indeed, the trend is not stable, even within stand-still phases, in contrast with the plot of the m parameter for a video recorded after the light ring installation (see Fig. 5.3). The excessive fluctuation of m_t results in an extremely higher number of frames further analysed (as indicated by the magenta dots) which, in turn, may affect the real-time and the correct-counting capabilities of the entire system. As a result of the light ring stabilizing the working conditions of the camera, there is no need to change the threshold once it is fixed and the behavior of m_t is not influenced by shadows or natural light changes, making the system more stable.

To test the "Counting Capability" of the two algorithms as objectively as possible, I decided to acquire videos in MP4 format and apply both algorithms offline to the same videos. In this way, we could be sure that possible imbalances of the performances achieved were only a matter of Counting Capability of the specific solution, and not caused by particular and strange behaviors of the operators under one real-time test that might differ from the behaviors analysed during the real-time test of the other algorithm. Specifically, given a video sequence, the processing algorithms could behave in four ways:

- correctly count one piece when the operator places an assembled one on the intermediate table (True Positive, TP);
- wrongly count when a piece has not been added on the table (False Positive, FP);
- correctly do not count when there have not been new pieces placed on the table (True Negative, TN); or
- wrongly do not count when an assembled piece has been placed on the table (False Negative-FN).

According to the definition of these four alternative outcomes and the performance evaluation criteria proposed in [109], three metrics that summarize the capability of each of the two solutions in managing the counting task can be defined:

- Sensitivity, computed as the number of TP divided by the sum of the number of TP and FN, measures the solution's capability of correctly identifying placed pieces and counting;
- Specificity, computed as the number of TN divided by the sum of TN and FP, measures the solution's capability of correctly identifying the picked up pieces without counting; and
- Accuracy, computed as the sum of TP and TN divided by the sum of TP, FP, TN, and FN, measures the overall solution's capability of correctly behaving.

In this case, I expect a comparable total frequency of occurrence of Negatives and Positives, given that all the piece pick ups have been considered as Negative samples. Particularly, the recorded videos contained 88 piece pick ups and 90 piece placings, which were unconstrained and completely instinctual. I specify that they were unconstrained as, in the preliminary work, I partially constrained the manner of picking up and placing objects to improve the previous solution's performance.

To show the improvement resulting from the introduction of the Motion Check module, I compared the two alternative solutions provided with the

Motion Check procedure (improved versions of the solution) to their original version presented in the previous version of this work. Thus, the validity of the counting system with Motion Check, compared to the versions without, has been proved. Additionally, by comparison with the improved versions, the comparable performance of the simple and versatile Blob algorithm has been proved. In Table 5.1, the TP, TN, FP, and FN results regarding the offline test performed on videos collected after the installation of the light ring are presented. Specifically, the results achieved by the two alternative algorithms, both in their original version where all of the frames were indiscriminately analysed (flowchart and details can be found in the groundwork [108]) and in their new versions provided with inter-frame Motion Check, are presented.

	Original Blob		**Or. ACF**		**Improved Blob**		**Imp. ACF**	
	Pos.	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**
True	90	75	80	85	88	86	87	85
False	13	0	3	10	2	2	3	3

Table 5.1: Summarized results for the blob-based and the ACF-based original algorithms, as well as for the improved blob-based and improved ACF-based algorithms.

In Table 5.2, the values of the Sensitivity, Specificity, and Accuracy metrics for the two algorithms in both the original implementation and in the improved ones, to show efficacy of Motion Check module and of Counting modules, are resumed.

	Or. Blob	**Or. ACF**	**Imp. Blob**	**Imp. ACF**
Sensitivity	100%	89%	96.7%	97.8%
Specificity	85.2%	96.6%	96.6%	97.7%
Accuracy	92.7%	92.7%	96.6%	97.8%

Table 5.2: The three performance metrics computed on the results reached by the two algorithms, both in their old version and in the new one with Motion Check and some modifications.

The aforementioned test could only provide information about the counting capability of the two alternatives once the video files were collected; however, the system should ensure its potential to analyse a continuous video stream without information loss over long times—at least for sixteen hours, given that the company is organized in two working shifts. To test this, the Real-time Counting App run on the Macbook for an entire day, supervised for a portion of time. As described before, the prototype App, while continuously processing frames, produces a log file containing timestamps for every count, frame further analysed, and even delays in frame capturing or other warnings. If the interval between two consecutive frame grabbed is higher than 0.3 s, which means the algorithm is processing less than 3 frames per second, then the log file will list the timestamps of the *"Frame Capturing Delay"* warning. By letting the application work for an entire work day and analysing the related log file, I could count the number of times in which the application was too slow in acquiring frames. I found only 1 occurrence of this kind of error in the log file within sixteen hours of continuous real-time processing using the blob-based algorithm for further processing, and 10 occurrences using the detector-based algorithm for further processing; proving that, being computationally intensive, the latter alternative solution was implemented less successfully for real-time purposes. Blob-based counting proves to be better that ACF-based counting in terms of real-time capability.

As far as Versatility is concerned, an ad-hoc experiment using pieces which are different from the usual types assembled in the considered test assembly station has been done. The only similarity between usual pieces and the ones used in this experiment was the chromatic characterization (they were partly black), while they differed in dimension and shape. The Improved Blob algorithm, with parameters regarding this new context of use which were easily and quickly defined using the Setting Tool App (minimum and maximum blob area parameters), demonstrated performances perfectly comparable with those reached during the Counting Capability Test with the usual product types presented. On the other hand, the Improved ACF, which was trained on the original product type, made several mistakes, due to its unsuitability for the different objects placed on the table during this test. The adaptation of the detector to this new context is not as easy and fast as that for the adaptation of the blob-based solution, due to the mandatory necessity of training which, in turn, necessitates the development of a training set of images. Therefore, the ACF proved to be unsuitable for easy plant-wide implementation.

With regards to Responsiveness, additional live experiments using the Real-time Counting App have been conducted. This App allows the manual recording of the timestamps connected to the piece placing and autonomously saves the timestamps of the algorithm's counting decisions. In this way, by simply comparing the two vectors of timestamps, the mean difference between the moment of placing and the moment of counting can be computed. In Fig. 5.10, the results of this test done on 200 pieces placed are summarized.

It can be seen that 94% of pieces were correctly counted within 1 second after placing, which means almost simultaneously, while 3% of pieces suffered from a subtle delay of around 1 s. This may be due to the fact that the operator was very slow in taking their hand out of the framed area. The remaining 2% of pieces were not counted, these errors being due to the only eventuality that has not yet been addressed by the proposed algorithms: when both operators

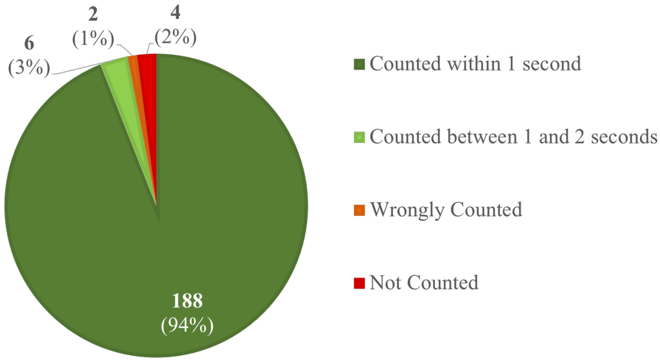


Figure 5.10: Results of the Counting Application *Responsiveness* test.

simultaneously intervene in the ROI, one picking up and the other placing a piece, thus generating a balance if analysing the number of objects present in the previously analysed frame and the number in the currently analysed frame.

The final version of the solution is a complete system, which is able to process a video stream and count pieces placed as soon as they are left on the table. Relying on color-based processing and blob analysis, it is computationally fast and adaptable to every case in which a dark-coloured product is placed on a pale-coloured table. For the sake of completeness, it is easily adaptable to the opposite scenario, in which brighter products are placed on a dark table. Tables 5.1 and 5.2 show a Sensitivity performance degradation concerning the Blob algorithm in its Original configuration, as compared to the Blob algorithm in the Improved configuration with preliminary Motion Check. This reduction is due to the only eventuality that the Motion Check cannot address, which is when the two operators simultaneously interfere in the framed area by placing and picking up at once. Indeed, the data collection was carried out without any sort of training for the assembly operators, who were left completely free to behave as they are used to. In order to implement this solution, the company must train their staff to avoid simultaneous interactions on the table. Original algorithms without Motion Check are error prone during the intervals in which one operator is either placing or picking up a piece. This reflects on the False Positive number of the Original Blob and, so, in both Specificity and Accuracy metrics. It can be inferred that, when using videos collected after the staff training, all the performance metrics of the Improved Blob should be equal or higher that the Original Blob's metrics. Moving on to the best-performing solution, the ACF detector provided with the preliminary Motion Check procedure, it had metrics only 1% higher than the proposed versatile and simple blob-based solution, which is why, for plant-wide implementation, I recommend the use of the blob-based algorithm. The solution is not yet absolutely reliable, as it commits some errors; however, its improvement from the first version is concretely noticeable, looking at Table 5.2. We aim to find other improvements for the processing algorithms, which allow it to reach very close to 100% in the Counting Capability metrics. Possible improvements for the Motion Check module and for the counting module of the solution, in both the detector-based and blob-based alternatives are possible.

A Machine Vision algorithm which is able to analyze a video stream in real-time and automatically count the pieces assembled by an operator and placed on a table in a framed area, has been proposed and described. The developed algorithm integrates an inter-frame analysis mechanism which handles the human interactions in the framed area that can cause incorrect piece counting. In fact, after the development of a first solution in a preliminary paper, the interaction of the operators with the framed area has been identified as the biggest weakness of the preliminary solution developed. In order to overcome these limitations, the Motion Check module has been introduced as a preliminary step before conducting image processing, finalized at counting. This Motion Check is a novel adaptive examiner of motion which is not dependent on the specification of a fixed background, and understands whether there have been relevant movements between the current frame and the previous one. Using Motion Check and exploiting blob detection to identify the objects, the proposed solution was able to reliably count the pieces assembled by an operator. In fact, the proposed solution demonstrated very good performances, in terms of Sensitivity, Specificity, and Accuracy, when tested in a real situation in an Italian manufacturing firm's shop floor. Moreover, the Real-time Capability, Responsiveness, and Versatility of the solution were evaluated through specific tests.

By analysing the frames corresponding to counting moments, I found that the improved algorithm counts when there are no hands in the framed area. Therefore, by collecting frames corresponding to counting moments, a perfect and considerable data set for training a Machine Learning-based detector, or even a Deep Learning based one, is available. There would be the possibility to merge the basic blob-based solution as a preliminary automatic way for developing a more robust detector-based solution for every station and for every assembly line. With this insight, I aim at simplifying in general the development of advanced MV detectors for custom object recognition purposes, even for non-experts, with a quite simple and fast way.

Another point I would like to address is that, with the presented configuration of the solution, between 3 and 10 fps are analysed; nonetheless, it will be possible to further improve the frame rate, speeding up computation by implementing the algorithms directly on a dedicated hardware platform provided with FPGA and GPU. This goes together with a need for system optimization, in order to ensure the correct and real-time analysis of multiple converging video streams. Coherently, source coding and communication protocols have to be optimized and tested for the design of a system architecture which exploits either edge computing or cloud computing for carrying out the simultaneous and continuous processing of several and parallel video streams, which is the final objective of the company.

5.2 Using Plastic Injection Moulding Machine Process Parameters for Predictive Maintenance Purposes

As introduced in Chapter 2, maintenance cost inside a company can be the largest part of operational expenses, second only to energy. Usually, replacing a component or equipment just before a breakdown occurs is the best way to minimize the maintenance cost. This is the main reason why a lot of companies are struggling in collecting data from equipment, and in finding ways to exploit these data for predictive purposes.

5.2.1 Motivation

This general objective of optimising the maintenance of industrial equipment by monitoring it and properly analysing data collected for inferring its actual health condition, instead of waiting for equipment failures, or replacing components and sub-parts too early, is widely desired. The aforementioned two approaches are connected to increased direct and indirect maintenance costs, respect to the optimal maintenance which should intervene just before failures occur. Specifically, by fusing several information about process parameters of an injection moulding machine, has been possible to develop a classification model based on Machine Learning algorithms and able to predict the Healthy or not condition of the machine while it is working, thus achieving the objective of optimal maintenance just-in-time.

In this work multiple sensors' data extracted from an injection moulding machine have been exploited for developing a Predictive Maintenance model tailored on the specific machine utilization profile. These data refers to several process parameters measured while the machine is working. After the extraction of data related to multiple cycles, and splitting them into a training set and testing set, ML algorithms have been adopted to model with the aim of discerning between correct functioning and border line functioning of the injection moulding machine under analysis. Machine fault analysis carried out with maintenance managers and operators, helped in defining critical parameters, that have been exploited for labeling data. Classification models trained have been compared using commonly adopted performance metrics. The best performing model has been tested on the testing set.

The briefly introduced work has been presented at the International Conference on Intelligent Engineering and Management in 2020, and published in the proceedings [110].

5.2.2 State-of-the-Art

Over time, the interest and the attention toward the maintenance function is hugely increased because maintenance costs, among operational expenses, are second only to energy [111]. Actually, faults and failures causing sudden stoppages of machinery are linked to high costs for companies in terms of money and reputation toward its customers: the cause identification and the damage repair can both be time consuming, thus impacting on the customer satisfaction and on the company's profit [112]. Moreover, machining systems' performance degradation associated with wear in the subsystems undermines production process accuracy hence, the quality of produced goods [113], negatively affecting system reliability that is essential for companies competing in contemporary market [114]. According to [115], the cost of replacing worn-out components may be as high as 70% of the total maintenance budget, nevertheless the majority of companies do not monitor the actual condition of equipment to improve their maintenance management strategy and the associated cost [116]. Still, the value associated with operations' monitoring that allows an optimized management of production and maintenance is known, and for this reason manufacturing systems have evolved over time from being merely cost-driven at the early 1900s, toward being transparency-driven and analytic-based since a decade, and this obviously apply for maintenance management too [117], as described in details inside Section 2.3.1.

Transparency is one of the design principles of Industry 4.0 identified by Hermann et al. [118], and in manufacturing systems it can be achieved implementing massive data collection together with advanced predictive analytic on data, to transform meaningless numbers and information into practical insights and useful knowledge, with the final aim of making everything available for decision makers that would take empowered and more conscious decisions. Among other company departments that can benefit from such a transparent and intelligent architecture, maintenance can obtain a very huge gain due to the high and largely avoidable associated costs. Specifically, 30% of the maintenance expenses are caused by misplaced maintenance schedules, leading to unnecessary production costs according to [119]. On top of that it should be noted that most of the failures do not occur instantaneously but can rather be predicted through a proper predictive system [120]. Even though the value of PdM is well understood by both academicians and practitioners, it is still hard to put in place a concrete and reliable PdM System, and in addition every equipment, based on its own architecture and on the specific usage that it is subject to, should be analysed independently in a tailored and personalised way for obtaining efficient solutions.

This study focused on four injection moulding machines adopted by iGuzzini Illuminazione S.p.A., each dedicated to the production of slightly different pieces. The moulding machines produce components that are assembled into a wide variety of lighting devices, hence characterised by different shapes and colours, which require to set specific process parameters based on the component in production. After a qualitative research on past faults and malfunctioning it was possible to develop a methodology and a model for predicting equipment wear and avoiding the complete break of machines' components. The problem of lacking fault data is very common in PdM researches [121]. Given that most of the companies want to absolutely avoid unplanned production stops, they adopt the Preventive Maintenance approach (in such a way that no fault occurs because components or equipment are replaced well in advance). In this case it couldn't be possible to collect functioning parameters under faulty conditions. For this reason, I tried to qualitatively estimate which variables could be indicative of forthcoming malfunctioning, based on the analysis of possible and more frequent damages together with maintenance experts and company managers engaged in maintenance interventions.

Going deeper into the specific context in which this research activity is positioned, injection moulding of plastics is a process that starts with melting plastic pellets. These are subsequently injected with pressure into a mould cavity, which fills and after a cooling phase solidifies to produce the final product with the tailored three-dimensional shape. This process is widely adopted in the industrial context thanks to its high productivity, the possibility to automate the process, the flexibility in the shape definition and the low production cost associated [122]. The main components of an injection molding machine are the injection unit and the mold locking unit, as summarized into Fig. 5.11).

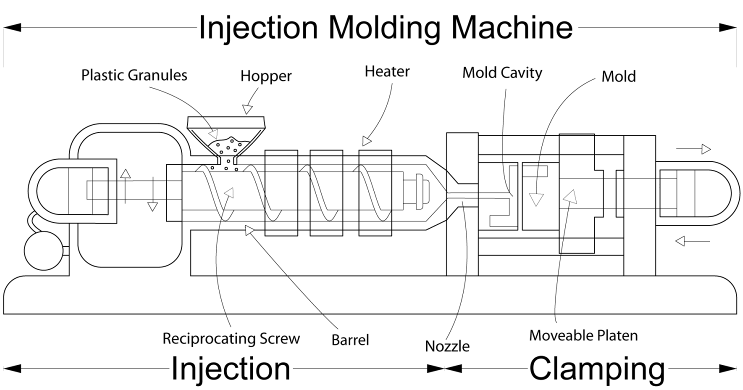


Figure 5.11: Main components of an injection molding machine (Source: Wikipedia).

5.2.3 Materials and Methods

In the considered context, four fully electric Engel moulding machines are available. Two of them have 55 tons of closing force (M55a and M55b), the other two have 100 tons (M100a and M100b). The four machines are employed for the production of three different products each, reason why data extracted from the platform have been organised into twelve data sets, each related to a specific moulding machine while producing a specific product type. In this way, once the twelve models are trained, we have solutions applicable for future similar productions (same product type made from the same machine). In fact, according to [123], particular attention should be paid to the process inherent variability (different working load for example) because the production of different components might require different process parameters to be set, but this should not be interpreted by the monitoring system as a strange or alarming behaviour. The moulding machines are Industry 4.0 ready, specifically, they are equipped with a variety of sensors and connected to the OPC server through EUROMAP protocol. This system architecture allows the easy exportation of data collected into Excel files. From a practical point of view, the following twenty-seven variables are measured at each cycle:

- V1) Specific injection pressure peak value (bar), measured from the pressure sensor placed in the nozzle, describes the push of plastic material injection given by the screw;
- V2) Post injection pressure peak value (bar), is linked to the force that the cylinder exercises on the closing unit after mold closing;
- V3) Specific back pressure peak value (bar), is a measure of the pulling force exercised by the fluid;
- V4) Plasticizing volume (ml), is the quantity of material that enters in the cylinder during the dosing phase;
- V5) Shot volume (ml), measures the effective quantity of fluid that crosses the nozzle and enters the mould;
- V6) Cushion (mm), measures the residual plastic material at the end of the injection;
- V7) Screw position switch-over point (mm), indicates where the screw is positioned between the injection and holding phases;
- V8) Screw position at end of hold pressure (mm), is the last measured position of the screw;

V9) Plasticizing stroke (mm), is the displacement of the screw for charging the material before the injection;

V10) Temperature zone 1 (C°), measured by the thermocouple installed near to the nozzle;

V11) Temperature zone 2 (C°), relative to the ceramic resistance that envelops the cylinder, if any;

V12) Temperature zone 3 (C°), relative to the ceramic resistance that envelops the cylinder (different position respect to the precedent);

V13) Temperature zone 4 (C°), relative to the ceramic resistance that envelops the cylinder (different position respect to the precedent);

V14) Temperature zone 7 (C°), related to the cooling circuit near to the access point of the plastic material;

V15) Temperature zone 8 (C°), related to the warm room, if the mould has cavities;

V16) Temperature zone 9 (C°), same as the previous one;

V17) Temperature zone 10 (C°), same as the previous one;

V18) Temperature zone 11 (C°), same as the previous one;

V19) Torque mean value current cycle (Nm), related to the electric motor that rotates the screw backwards for the melted plastic material recharge;

V20) Torque peak value current cycle (Nm), is the punctual maximum reached by variable V19);

V21) Closing force (kN), is the punctual value measured while closing the mould;

V22) Clamping force peak value (kN), is the punctual maximum of the clamping force while the mold is closed;

V23) Cycle time (s), the seconds necessary for completing the cycle;

V24) Cooling time (s), is the time interval during which the material solidifies;

V25) Plasticizing time (s), the time needed for the entire dosing phase;

V26) Injection time (s), the time to push the plastic fluid into the mould;

V27) Shot counter, the number of cycles performed by the moulding machine, that is reset every day when the machine stops working.

For each variable I specified both a short description, the unit of measurement associated, and a reference code in order to be able to easily refer to each of them in the remaining of the paper.

Every moulding machine produces three types of products, and for each product type there are slightly different working parameters set by the operators. For this reason, when trying to monitor for predictive purposes the machines, we have to develop models able to deal with a total of twelve different working conditions. The methodology followed for the development of each of the twelve models is fixed: after a common labeling phase, data have been given as input to several different ML Classification models, and the best performing one has been taken as reference for testing its validity in each of the twelve scenarios.

The problem of lacking fault related data has been addressed thanks to a qualitative analysis of failures most affecting the injection moulding machines. Indeed, during the 8 months to which data adopted refer no concrete malfunctioning of any kind happened. Talking with maintenance experts, the historical staff, and the maintenance managers, it has been possible to schematize and comprehend the most common problems of these machines. In Table 5.3 the conclusion of reasoning is summarized. Every line represents a cause, every column represents a problem that can be connected to the identified causes, and in every cell connected to the association of a cause with an effect the variables that are most likely affecting or linked to the specific scenario are specified.

		Effects	
		Material Loss	Inadequate Filling
Causes	Worn Out Screw Thread		V1-3-5-19
	Toecap Breakage		V1-6-19-23
	Clamp Wear	V1-2-6-23	

Table 5.3: Qualitative Analysis of Machine Failures

Specifically, logical induction has been applied for understanding that if the screw thread gets damaged it may happen that the material filling is inadequate. This can be mirrored in the injection pressure (V1) higher than the usual, in the back pressure (V3) value, in the shot volume (V5) or in the torque mean value (V19), because the physical wear of the screw thread affects all of these parameters given that the plastic material flows through the thread and is then pushed into the mould. On the other hand the toecap breakage affects the material filling, and is linked to specific behaviors of the injection pressure (V1), of the cushion length (V6), of the torque mean value (V19) and of the cycle time (V23). Lastly, if the clamp is worn, material might be lost, thus affecting the values of injection pressure (V1), of the post injection pressure

(V2), of the cushion length (V6) and of the cycle time (V23).

Based on this reasoning just presented, two health condition have been set, namely *Optimal* and *Border Line*, based on the value of most important working parameters with respect to the aforementioned malfunctioning table. In more details, these are the criteria that make a sample *Border Line*:

- V1 3% higher than the mean;
- V6 65% lower than the mean;
- V19 6% higher than the mean;
- V23 5% lower than the mean.

From an empirical point of view, production cycles presenting the variations of these four relevant functioning parameters are associated to an increased number of junked pieces, proving the overall viability of the presented reasoning.

At the end of this phase, every sample acquired has either the *Optimal* or the *Border Line* label associated, thus being a suitable input data set for training ML-based classification models. Summarising, twelve data sets composed of 23 variables and a categorical variable corresponding to the associated label are available for modeling. In Table 5.4 the labeled data sets, for each of the twelve scenarios, are summarized.

Scenario	**Total Number of observations**	**'Optimal' observations**	**'Border Line' observations**
M55a-Pr01	3330	1946 (58.4%)	1384 (41.6%)
M55a-Pr02	3851	3229 (83.8%)	622 (16.2%)
M55a-Pr03	4367	3947 (90.4%)	420 (9.6%)
M55b-Pr04	3547	2924 (82.4%)	623 (17.6%)
M55b-Pr05	2354	2255 (95.8%)	99 (4.2%)
M55b-Pr06	3180	2909 (91.5%)	271 (8.5%)
M100a-Pr07	3906	2434 (62.3%)	1472 (37.7%)
M100a-Pr08	4178	2571 (61.5%)	1607 (38.5%)
M100a-Pr09	4190	3284 (78.4%)	906 (21.6%)
M100b-Pr10	3882	2675 (68.9%)	1207 (31.1%)
M100b-Pr11	3075	1872 (60.9%)	1203 (39.1%)
M100b-Pr12	3396	2207 (65%)	1189 (35%)

Table 5.4: The Twelve Training Data Sets

For each of the twelve data sets, each connected to a specific scenario (one type of moulding machine producing one type of product), seven different Classification models have been implemented and compared: Fine Tree, Medium Tree, Coarse Tree, Fine K-Nearest Neighbor, Medium K-Nearest Neighbor, Coarse K-Nearest Neighbor and Logistic Regression. As a training specification 10-folds cross-validation has been used with the aim of improving model performance and reducing the risk of over-fitting.

Results regarding models' performances are synthesized in Tables 5.5 to 5.16. Thereafter, every best model has been tested on completely new data, collected under the same scenario but not used during the training phase, to check the reliability of the chosen models. In order to be able to compare models' performances in an objective way some performance metrics have been computed, namely the Accuracy (A), Sensitivity (Se) and Specificity (Sp). Ahead of defining each of the three metrics, it should be specified that a classification model can classify each observation given in input (which is the set of 23 independent variables). The model reaches a True Positive (TP) if the sample was associated to the *Optimal* label and the model actually predicts *Optimal* class, False Positive (FP) if it is predicted as *Optimal* but it is *Border Line* for real, True Negative (TN) if it is predicted as *Border Line* and it is actually *Border Line*, or False Negative (FN) if it is predicted as *Border Line* but it is *Optimal* in truth. Once computed the results achieved by each trained model for each training sample, Accuracy can be computed as the sum of TP and TN divided by the sum of TP, FP, TN and FN, according to the following equation:

$$Ac = \frac{TP + TN}{TP + FP + TN + FN} \tag{5.3}$$

Sensitivity is computed as the number of TP divided by the sum of the number of TP and FN, according to the following equation:

$$Se = \frac{TP}{TP + FN} \tag{5.4}$$

Lastly, Specificity can be computed as the number of TN divided by the sum of TN and FP, according to the following equation:

$$Sp = \frac{TN}{TN + FP} \tag{5.5}$$

Accuracy is a performance metric summarising the overall model capability of classifying right an input, Sensitivity is a measure of how well the model can identify TP, hence *Optimal* cycles, while Specificity is a measure of how well the model can identify TN, hence *Border Line* cycles.

5.2.4 Results and Conclusions

For each of the twelve scenarios analysed one table summarizes performances reached by each of the seven trained models. Specifically, results related to

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	97.60%	97.64%	97.54%
Medium-Tree	98.11%	98.82%	97.11%
Coarse-Tree	96.97%	99.28%	93.71%
Fine-KNN	94.35%	95.07%	93.35%
Medium-KNN	92.94%	91.78%	94.58%
Coarse-KNN	89.58%	87.15%	92.99%
Logistic Regression	92.22%	92.55%	91.76%

Table 5.5: M55a-Pr01 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	97.90%	98.64%	94.05%
Medium-Tree	98.03%	98.70%	94.53%
Coarse-Tree	97.84%	98.30%	95.50%
Fine-KNN	96.18%	97.31%	90.35%
Medium-KNN	95.85%	96.44%	92.77%
Coarse-KNN	95.22%	97.18%	85.05%
Logistic Regression	95.59%	97.21%	87.14%

Table 5.6: M55a-Pr02 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	99.45%	99.70%	97.14%
Medium-Tree	99.45%	99.70%	97.14%
Coarse-Tree	99.50%	99.82%	96.43%
Fine-KNN	98.28%	99.19%	89.76%
Medium-KNN	98.26%	99.42%	87.38%
Coarse-KNN	97.21%	99.97%	71.19%
Logistic Regression	98.58%	99.39%	90.95%

Table 5.7: M55a-Pr03 Models Performance

M55a-Pr01 in Table 5.5, to M55a-Pr02 in Table 5.6, to M55a-Pr03 in Table 5.7, to M55b-Pr04 in Table 5.8, to M55b-Pr05 in Table 5.9, to M55b-Pr06 in Table 5.10, to M100a-Pr07 in Table 5.11, to M100a-Pr08 in Table 5.12, to M100a-Pr09 in Table 5.13, to M100b-Pr10 in Table 5.14, to M100b-Pr11 in Table 5.15, and to M100b-Pr12 in Table 5.16.

By looking at all the performance metrics of all models, for each of the twelve scenarios at least one of the seven models tested reaches the 90% in all the three metrics, except for the M55b-Pr05 and M55b-Pr06 scenarios. Looking at Table 5.4 it is evident how these two models have been trained with a smaller number of 'Border Line' samples (99 and 271 respectively), and this may be the cause of these worse models' performance values.

Algorithm	Ac	Se	Sp
Fine-Tree	96.96%	98.26%	90.85%
Medium-Tree	96.39%	98.80%	85.07%
Coarse-Tree	95.60%	98.67%	81.22%
Fine-KNN	95.24%	97.13%	86.36%
Medium-KNN	94.02%	95.96%	84.91%
Coarse-KNN	92.73%	95.49%	79.78%
Logistic Regression	95.74%	97.57%	87.16%

Table 5.8: M55b-Pr04 Models Performance

Algorithm	Ac	Se	Sp
Fine-Tree	98.00%	99.11%	72.73%
Medium-Tree	98.13%	99.25%	72.73%
Coarse-Tree	97.32%	99.25%	53.54%
Fine-KNN	97.07%	98.76%	58.59%
Medium-KNN	96.56%	99.96%	19.19%
Coarse-KNN	95.79%	100.00%	0.00%
Logistic Regression	97.49%	99.42%	53.54%

Table 5.9: M55b-Pr05 Models Performance

Algorithm	Ac	Se	Sp
Fine-Tree	96.70%	98.07%	81.92%
Medium-Tree	96.67%	97.97%	82.66%
Coarse-Tree	96.32%	97.49%	83.76%
Fine-KNN	97.45%	98.59%	85.24%
Medium-KNN	96.42%	97.56%	84.13%
Coarse-KNN	94.53%	99.28%	43.54%
Logistic Regression	97.14%	98.45%	83.03%

Table 5.10: M55b-Pr06 Models Performance

Algorithm	Ac	Se	Sp
Fine-Tree	97.34%	97.78%	96.60%
Medium-Tree	97.62%	97.62%	97.62%
Coarse-Tree	96.93%	98.40%	94.50%
Fine-KNN	97.90%	98.27%	97.96%
Medium-KNN	97.26%	96.84%	97.96%
Coarse-KNN	93.50%	91.29%	97.15%
Logistic Regression	95.80%	96.01%	95.45%

Table 5.11: M100a-Pr07 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	93.11%	94.52%	90.85%
Medium-Tree	92.48%	96.15%	86.62%
Coarse-Tree	90.81%	94.20%	85.38%
Fine-KNN	91.91%	93.39%	89.55%
Medium-KNN	90.81%	92.69%	87.80%
Coarse-KNN	84.47%	90.51%	74.80%
Logistic Regression	81.95%	89.34%	70.13%

Table 5.12: M100a-Pr08 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	97.37%	98.23%	94.26%
Medium-Tree	91.62%	94.58%	80.91%
Coarse-Tree	87.88%	92.51%	71.08%
Fine-KNN	97.59%	98.54%	94.15%
Medium-KNN	96.35%	98.14%	89.85%
Coarse-KNN	92.12%	97.38%	73.07%
Logistic Regression	89.88%	94.95%	71.52%

Table 5.13: M100a-Pr09 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	97.58%	98.13%	96.35%
Medium-Tree	97.91%	98.77%	96.02%
Coarse-Tree	97.35%	97.79%	96.35%
Fine-KNN	98.17%	98.65%	97.10%
Medium-KNN	97.68%	98.13%	96.69%
Coarse-KNN	96.58%	96.47%	96.85%
Logistic Regression	97.22%	97.98%	95.53%

Table 5.14: M100b-Pr10 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	98.93%	99.09%	98.67%
Medium-Tree	98.93%	99.09%	98.67%
Coarse-Tree	98.83%	98.66%	99.09%
Fine-KNN	99.45%	99.47%	99.42%
Medium-KNN	98.47%	98.77%	98.00%
Coarse-KNN	97.89%	97.97%	97.76%
Logistic Regression	99.19%	99.52%	98.67%

Table 5.15: M100b-Pr11 Models Performance

Algorithm	**Ac**	**Se**	**Sp**
Fine-Tree	95.38%	96.74%	92.85%
Medium-Tree	95.02%	94.15%	96.64%
Coarse-Tree	91.73%	93.11%	89.15%
Fine-KNN	97.41%	98.10%	96.13%
Medium-KNN	95.94%	95.92%	95.96%
Coarse-KNN	93.35%	93.61%	92.85%
Logistic Regression	94.11%	95.97%	90.66%

Table 5.16: M100b-Pr12 Models Performance

Based on the results achieved, I decided to use the Fine Tree for each of thw twelve scenarios as best model to be tested. In Table 5.17 the performances reached in the testing phase by the Fine-Decision Trees with 100 split points are resumed. For the sake of simplicity only performances reached by the models related to respectively the M55a-Pr01, M55b-Pr04, M100a-Pr07 and M100b-Pr10 scenarios are shown, given that for the other eight scenarios numbers are almost the same.

Scenario	**TP**	**FP**	**TN**	**FN**	**Ac**	**Se**	**Sp**
M55a-Pr01	1102	70	205	65	91%	94%	75%
M55b-Pr04	1231	80	194	39	92%	97%	71%
M100a-Pr07	991	60	160	27	93%	97%	73%
M100b-Pr10	1051	74	188	47	91%	96%	72%

Table 5.17: Performance Achieved during Testing of the Fine-Tree Models

By comparing testing performances with the training performances, Specificity values are lower, something that can be caused by model over-fitting. In order to overcome this a better organization of the training process and training data in order to improve the testing performances of all the models for each of the twelve scenarios is envisioned as a possible next step.

The idea for exploiting the developed models in real-time is to classify each production cycle of the four machines, based on the specific product type produced during that cycle, into either 'optimal' functioning or 'border line' functioning. When the frequency of border line cycles increases, it is advisable that maintenance managers intervene in the specific machine that is showing repetitively abnormal working cycles.

Concluding, twelve models able to discern between optimal functioning and border line functioning of four injection moulding machines, depending on the specific product type, through the analysis of 23 process parameters used as independent predictors, have been developed and presented. After the training phase, every model has been tested with completely new data, showing how the Accuracy and Sensitivity related to the testing data set are comparable to the results obtained during the cross-validation phase, while the Specificity is quite lower. From a practical point of view, extracting the 23 process parameters related to a production cycle, and giving them as input to the model linked to the scenario from which data have been extracted (specific moulding machine and specific product type), the predicted class (either optimal or border line) can be obtained, and used by maintenance managers and decision makers for better managing maintenance interventions. Specifically, by doing the analysis for each cycle we can trace the behavior of the machine and plan maintenance intervention based on the frequency and recidivism of border line cycles. Through the developed models, decision makers are able to promptly manage maintenance scheduling thus avoiding undue costs.

The main limitation of this work, is connected to the lack of fault-related data, which are expected to push a strong improvement in model achievable performances. One objective is hence the one of collecting more data, even simulating faults, so to be able to have data that truly correspond to the bad working condition, hence giving a great insight about. Moreover, by enlarging available data both in quality (fault related) and quantity (number of samples), better performing models can be adopted.

5.3 One Datum and Many Values for Sustainable Industry 4.0: a Prognostic and Health Management Use Case

Industrial context of today, driven by the Industry 4.0 paradigm, is overwhelmed by data. Decreasing cost of innovative technologies, and recent market dynamics have pushed and pulled respectively for those architectures and practices in which data are the masters. While advancing, we have to take care of waste, even though intangibility of data makes them hardly connected to waste. In this research activity a reflection on the data intensive context of today, focused on the industrial sector, will be defined. A smart approach for fully exploiting data collecting infrastructures is proposed, and its declination in a Prognostic and Health Management (PHM) use case is presented. The general conceptual take-away, together with the results of the painting system's plates PHM solution proposed, are discussed. The already-in-use data sharing tendency, that allows to achieve transparency and integration, is presented as complementary with data multiple use/reuse tendency, in order to develop a really sustainable shift toward the future.

5.3.1 Motivation

The Industry 4.0 paradigm has attracted a lot of attention from both practitioners and academicians. Several efforts have been made in order to define and establish best practices from disparate points of view. Focusing on the industrial data domain, given that the innovative and technologically advanced configuration of the smart factory — introduced in Chapter 2 — enables massive data collection, data fusion has been identified as a promising field for extracting value from raw industrial data.

On the other hand, investments in Industry 4.0 technologies are generally expensive, reason why it is essential to define and envision all obtainable values from each investment during the evaluation phase. Specifically, I refer to envisioning possible second level and modular applications, starting from the same data, for making the investments worth.

To corroborate this concept, an implementation example inside an Italian manufacturing firm will be presented. The objective of this work it to show how already collected data can be adopted for multiple usages inside the connected and technological industrial context of today. Moreover, in the specific use case presented for proving the validity of the intuition, the objective has been to used images collected by a camera for the additional task of monitoring the health condition of number plates with respect to dirtiness associated with the painting system they belong to.

In other words, an investment has been exploited for performing additional tasks respect to those mentioned in the original innovation project, thus enlarging the value obtained. In this experimental work the cameras, usually adopted for implementing Optical Character Recognition (OCR) to take trace of batch number associated to the production orders, will be exploited for carrying on the maintenance of painting system's number plates in a predictive way. Specifically, the number plates, essential for properly managing the equipment set-up coherently with the kind of product to be painted, enter the painting system together with the products loaded on each of them, reason why part of the sprayed paint can stick to the number plates. This, can in turn cause the partial occlusion of carvings, making the number recognition harder and prone to errors. The reliability of the number plate recognition should be very high, because an incorrect recognition could bring to damages of robot's arms. The purpose of the proposed solution is to perform Prognostic and Health Management (PHM), alerting the operator when the reading accuracy for each number starts to decrease.

The main objectives of this work are:

1. to propose a Machine Vision (MV) based prognostic system, able to support maintenance decision makers;

2. to highlight and show the fruitful general approach of using one datum for creating many values inside Industry 4.0 environments, starting from the experimental use case presented;

3. to analyse the actual situation and define possible future directions given the gaps found in theory and practices.

5.3.2 State-of-the-Art

The industrial context of today is studded by advanced, connected, and automated manufacturing equipment, able to self-adapt working parameters coherently with the diversified customers' orders among other things [124, 125]. Flexibility, accuracy, precision, and effectiveness are mandatory for properly managing the low-volume and high-variety product portfolio which characterises the vast majority of manufacturing firms [126, 127, 128]. Industry 4.0, simplistically summarized into the wide adoption of innovative technologies within the manufacturing environment, has driven the change toward the essential smart factories of the future: digital, collaborative, connected, automated, and optimized [129, 26]. Along with the industrial revolution, sensors themselves are becoming more and more advanced in order to meet the requirements of the contemporary manufacturing context, enabling applications as self-identification, up to self-configuration of industrial machinery, also referred to as self-X [30, 130, 131]. These innovative sensors have driven the change toward innovative practices, like PHM, which tries to predict upcoming failures and faults of manufacturing equipment, starting from the collection of data in real time, and analysing them with advanced analytic [112, 132].

Among best practices in Industry 4.0 PHM can be found. It can be summarized into the estimation of the current health status of a component or equipment, and the subsequent prediction of Remaining Useful Life (RUL) with the aim of optimizing maintenance interventions [133]. The PHM concept is often connected to the Predictive Maintenance (PdM) philosophy, which can be viewed as the application of sensors and analytic to predict equipment's failures and prevent them doing maintenance before the failure occurs [134]. There are several works in present Literature that deal with PdM using images or videos as data to be analyzed. Nonetheless, none of them uses Optical Character Recognition nor is focused on doing maintenance of number plates. A PHM use case, where images of number plates are used for assessing their dirtiness, and the consequent need for maintenance of these number plates that are used by an automated painting system to manage product customization, will be presented.

In order to present the smart factory from a practical point of view, some researchers focused on architectures, and implementation road-maps, presenting some solutions in the realm of data fusion techniques as fruitful value extraction method [135, 136, 137, 138]. Indeed, one very common pattern is to collect data, eventually heterogeneous and polymorphic (i.e. in different formats), from disparate sources, and to use all of them for achieving improved accuracy and more specific inferences respect to those achieved by the use of a single data source alone [139, 140, 141, 142, 28]. Their proposals aim at merging various disseminated information, collected or elaborated through technologically advanced instrumentation, in order to develop a broader and deeper understanding of things, useful for coherently manage decision making in a more conscious way [115, 143, 144]. Certainly their proposal is promising and already attempted, but it proved to require in-depth and complex studies on a case-by-case basis.

Additionally, several research streams on data management and data exploitation in Industry 4.0, are focused on presenting the value of data and information sharing inside the industrial environment [145, 146, 147, 148, 149]. The Cyber-Physical Production Systems (CPPS), which means developing each physical manufacturing asset in the virtual world also, through the adoption of sensors collecting data in real-time and updating their digital twin, is an essential example of information sharing and transparency [94, 150, 151, 152]. Indeed, the virtual part of CPPS usually lives inside the Cloud, which makes everything accessible from almost everywhere, putting in place the kind of sharing required in Industry 4.0 for a reduced cost [153, 154, 155, 156]. In some works, information sharing is presented as the key to extend conclusions drawn for one system, to similar systems [157]. The kind of sharing discussed in these works, is the one incorporated in the integration and virtualization design principles [29, 158, 159]. In more dept, horizontal integration is inter-companies, while vertical integration is intra-company [8], and both strongly relies upon information availability to several interested users and entities.

Whether fed into data fusion models or simply shared within and outside the company boundaries, data is king in today's industrial context. One conclusion backed by almost all researchers dealing with the topic of industrial data, is that the technological advancement and the efforts toward Industry 4.0 have driven the development of data collecting architectures able to gather a huge, often redundant, amount of data from a wide variety of sources[160]. The reliability of the data architecture itself together with data manipulation and knowledge extraction methodologies are hence of critical importance [161, 162]. It is crucial to highlight the difference between data and information, the former being sometimes useless, and unreliable [163], the latter being something that has to be extracted from the data in order to develop real and practical knowledge [164]. In fact, between data and knowledge there is an entire data life-cycle to be covered [8]. For this reason, too many data, collected and not fully utilized, can increase confusion, damper knowledge extraction process [165], and increase costs [166]. Moreover, an additional problem arising in data-driven contexts is the difficult provision of the right data to the right "person", otherwise the usefulness of the entire system becomes borderline [167]. In [168] in-site processing is proposed as a means of solving the problem of excessive data transmission and storage. Despite this attempt, only very few researches are focused on highlighting how much it is necessary to develop a critical and prioritized data collection architecture while ensuring sustainability of the whole system. Especially the sustainability of production models innovation, and so of the smart factory, should be definitely prioritized, as highlighted in [169, 170, 171].

In order to extract as much value as possible from the investments in Industry 4.0, avoiding to be overwhelmed by data acquisition quirk, it is necessary to exploit technologies already installed, and data gathered, for as many purposes as possible. In this way the obtainable results and values can be enlarged at almost no additional cost and without complicating architectures and practices in use. In more depth, what is going to be conceptually proposes is the implementation of the Semantic and Operational Interoperability, and Decentralization design principles [27], into the investments planning and data utilization phases, for nurturing and fully exploiting the innovative architecture of the smart factory. Two approaches for data utilization can and should coexist inside the manufacturing environment, for almost every kind of datum collected: edge processing for decentralized decision making and precise information extraction, and cloud integration, eventually using data fusion techniques, for implementing the CPPS and for sharing information across companies' boundaries. This proposal has not been detailed and deepened enough in existing literature. In [172] field-level networking is proposed in order to cope with horizontal and vertical integration. Moreover, the authors envision field level data gathering and processing for various purposes (from a layer and protocols point of view), but without organizing this concept and without going into details. According to [4], we lack models of development of Industry 4.0, moreover, according to [169], the majority of academic literature is technical and focused on engineering aspects, while very few works deal with managerial strategies and approaches. Coherently, a conceptual and strategic approach for a better evaluation and prioritization of Industry 4.0 investments, able to ensure sustainability and full value extraction from installed technologies, will be defined. The proposal is broader and more structured respect to the suggestion made in [173], which is the inclusion of primary and secondary stakeholders into data collection phase, or to the concept of data re-use loosely mentioned in [174] and [167].

As mentioned earlier, the use case that will be presented exploits Optical Character Recognition (OCR) technology. OCR is a Computer Vision technique which allows to impart the human reading capability to machines. In [175] several OCR-based nonindustrial applications have been implemented in one system only, but they remain somewhat disconnected one from another. Focusing on the industrial environment, OCR is widely adopted for automatically reading numbers associated to production planning systems [176, 177], especially in those contexts where other identification technologies like RFID might not be reliable or durable enough. In [178], an attempt of integrating multiple value extraction into one system has been proposed. In more details, the authors propose a modular toolkit that allows various applications grounding on MV methods, thus extracting many values from the same system, hence, from the same datum. Focusing on MV in general, a detailed description and list of industrial applications is presented in [32]. In some of the presented use cases the image captured is used for multiple purposes, which is one example of what I am broadly conceptualizing here.

5.3.3 Materials and Methods

The use case that will be presented, as practical example and origin of the concept, has been developed inside a renown Italian Manufacturing firm, iGuzzini Illuminazione S.p.A. Thanks to relevant investments in Industry 4.0, the firm has acquired an innovative autonomous painting system, made of several painting robots able to self-adjust working parameters coherently with each production batch. Automatic painting systems, being precise, effective still fragile, require an extremely reliable identification system, which allows them to set working parameters coherently with the dimensions and requirements of the batch under process. Products are automatically transported along the entire route by a suspended conveyor belt, where the racks and their relative tags are attached. The numeric tags are metal plates with carved digits, as shown in Fig. 5.12. They travel both inside and outside the painting rooms, together with the hanging products, reason why part of the sprayed paint can stick to the carvings making the next reading of the plate harder.

Figure 5.12: Example of number plate.

In fact, in order to manage robot's settings, a RGB camera, with 2064x1544 resolution and Gigabit Ethernet connection, frames the back-lit carved metal plates entering the painting room with the aim of reading the associated number, and acquire related batch information from the information system of the company. Erroneous readings of the plates can cause incorrect robot's settings and turn into expensive damages to robot's arms, together with production stop and related consequences. In Fig. 5.13 it is shown the picture of a clean plate (reading accuracy achieved is 93%), compared to another reasonably dirty (reading accuracy achieved is 67%), which may require maintenance after the current passage in the painting rooms given the actual health status, already not optimal even if legible. The frames shown are snapped by the installed camera and back-lit system, and are typical input frame for both the original OCR system, deputed to painting robot's parameter setting, and for the plates'

(a) Example of clean tag. (b) Example of reasonably dirty tag.

Figure 5.13: Typical frames of a clean and a dirty tag.

maintenance system.

The already-in-use data acquisition system has been exploited, and a PHM solution able to help maintainers in up-keeping the painting number plates has been developed. From an architectural point of view, a modular application was added, able to work in real-time and to extract additional value from the investment made by the company. The data acquisition architecture is not modified by the additional system, which works in parallel by taking as input data the frames already captured for the automatic reading of the plates' number. These frames are temporarily stored into a database, which is easily accessible in real-time, allowing us to exploit the data collected in parallel for the additional PHM-related purposes. The prognostic system proposed takes trace of the percentage of number plates reading accuracy, with the aim of eventually sending alert to maintainers.

The process steps followed for developing the PHM system are:

Step 1. collect sample images to be used for developing a custom OCR;

Step 2. clean and pre-process the images;

Step 3. train the customized OCR;

Step 4. collect a testing data set;

Step 5. label each test frame as either "Clean" or "Dirty";

Step 6. apply the prognostic algorithm to the testing set, simulating the real behavior (one frame after another, as in the real-time situation, some frames are connected to the same plate, framed after one additional painting cycle).

Specifically, the training set of single digits used for customising the OCR algorithm is composed of 188 samples of the '0', 186 samples of the '1', 186 samples of the '2', 189 samples of the '3', 189 samples of the '4', 185 samples of the '5', 175 samples of the '6', 187 samples of the '7', 192 samples of the

'8', and 171 samples of the '9', thus being a fairly balanced set of data. These samples have been collected using the system implemented. Each frame has been pre-processed through binarization, morphological closing, and noise reduction thanks to blob analysis, and contains one digit only. By training a custom OCR, an optimized model for the specific font and characteristics of the system under analysis is created.

Once trained the custom OCR [179], each testing sample has been labeled. Among the 950 test images, 795 are "Clean" and 155 are "Dirty". The prognostic algorithm, whose flowchart is shown in Fig. 5.14, starts with reading a frame collected by the already in use system, by drawing in real-time from the database where the frames are temporarily stored. This frame is firstly binarized using a fixed threshold, easy to be set given that the distance in intensity value between dark pixels and light ones is very large, and that the working conditions are very standardised. Once binarized, the developed custom OCR is applied and the accuracy of the number reading extracted and stored in the historical series of accuracy created for each number plate. If the current accuracy is lower than 60%, or if it has dropped more than 20% respect to the last reading of the plate under consideration, the system sends an alert to the maintenance manager in order to warn him that a specific plate needs maintenance if he is willing to avoid possible misreading of it at the next cycle inside the painting system. The second criterion for generating an alert, is a rapid drop in percentage, which suggests the fact that the past painting cycle faced by the plate has caused heavy painting residuals on carving. Therefore, the particular plate require maintenance even though reading accuracy is higher than the threshold value identified as critical. Given that an historical series of accuracy associated to each specific number plate is defined, it is easy to find when one has suffered a strong decrease during the last painting cycle, hence suggesting maintenance intervention. It is non trivial to have some plates associated to a constant accuracy for several cycles, and some other suffering from rapid decrease. This, because every plate carries a specific order, which is associated to specific painting parameters and materials. By changing these factors, the overall dirtiness level that can stick on carvings changes too. The just described algorithm used on the testing set, suggested 798 times to avoid maintenance (no alert has been generated), and suggested maintenance in 152 cases. All the 795 "Clean" plates have been read with accuracy higher than 85%. Three "Dirty" plates have been read with an accuracy higher than the 60% threshold, reason why the system did not suggest maintenance for them. Labeling has been carried out manually, and the degree of dirtiness affecting the plates labeled as "Dirty" is variable. The three mis-classified plates are not among the most dirty ones, justifying in some ways the error made by the algorithm.

For the sake of experiment, maintenance on the 152 plates for which the algorithm generated an alert has been avoided. In 67 cases the frame of these plates after another cycle inside the painting rooms caused misreading of the number, suggesting the importance and efficacy of the PHM solution created.

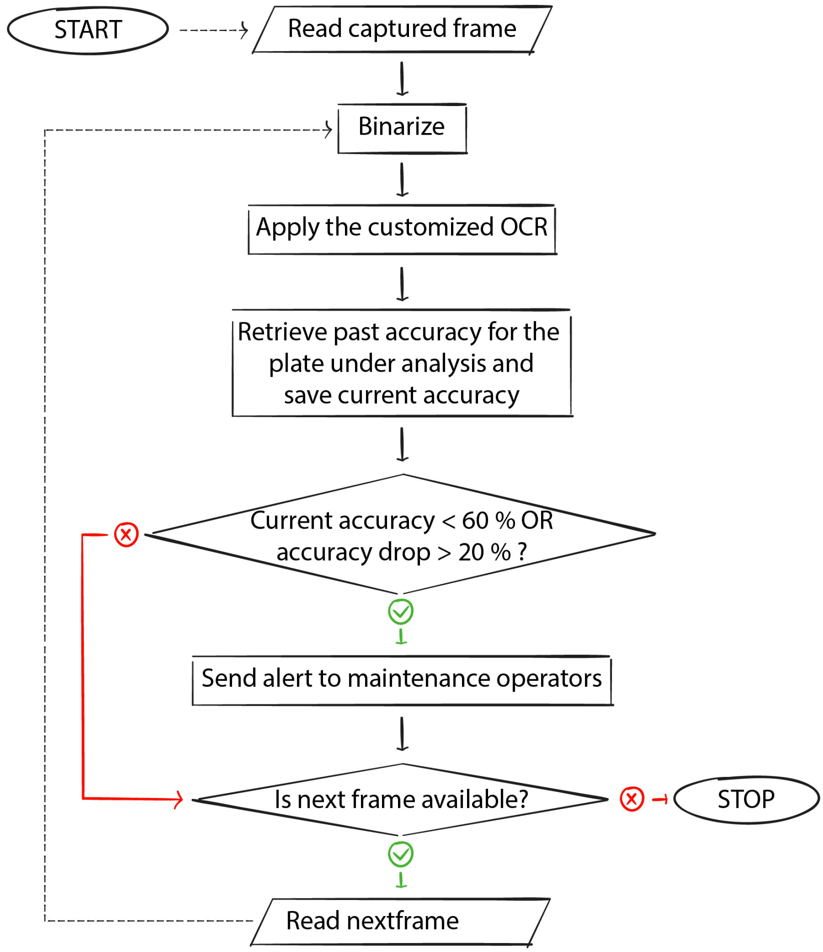


Figure 5.14: Flowchart of the processing algorithm.

5.3.4 Results and Conclusions

In the presented use case, the actual Industry 4.0 architecture has been empowered by the addition of a modular analytic system for an almost zero investment. The added application works in parallel respect to the existing system, and uses currently collected data to extract further value from them. From a conceptual and managerial point of view, it improves the Return on Investment.

The efficacy of the prognostic solution has been practically proved, by avoiding to maintain the dirty plates for experimental purposes, and observing that more than a half of these not maintained plates would cause misreading at the next passage into the painting system. This suggests us the goodness of the developed prognostic solution.

Based on the presented use case, it has been developed a conceptual takeaway, briefly summarized into Fig. 5.15, which can be extended into other use cases and almost all Industry 4.0 projects. Specifically, I propose to enlarge obtainable results and applications, from every investment made. Most of the companies dealing with Industry 4.0 have innovative architecture in place, but can't fully exploit them for developing practical knowledge and useful decision making support. Almost every investment could be regarded as something broader based on the concept of "data re-use" or "data multiple-utilization", which is present in the literature as highlighted inside the State-of-the-art Section , but is only loosely mentioned in two past papers. Respect to past works, I better characterised the concept, and showed its core and value through a specific use case. With the belief that "data re-use" or "data multiple-utilization" should be seriously considered in mind, I suggest to involve several stakeholders from diverse departments while evaluating Industry 4.0 investments, in order to envision multiple value extraction ways, thus avoiding excessive and eventually redundant data collection architectures which do not bring to practical useful knowledge extraction. Intangibility of data leads to the mistaken thought that they are associated with low or no costs, but this is not the reality. Data collection, storage, processing, and manipulation come at a non negligible cost, from a monetary, ethical, and environmental point of view [180, 181]. Sustainability is mandatory for every investment in innovative technologies.

Focusing on MV systems, their value could be frequently extended by adding modular analytic solutions, using as input data the same video stream in parallel. MV is indeed a branch of AI that reached a lot of success. It is versatile and can be customised to meet requirements and objectives of multiple actors starting from the same data collecting architecture.

Another promising example of data multiple-utilization inside the typical predictive maintenance context, is the exploitation of current consumption data. These kind of data is usually adopted for assessing equipment's health status, usually after the aggregation with other relevant sensors' data, such as vibrations, acoustic emissions, and temperatures. Nonetheless, that datum alone is already very important for energy management purposes also. For this reason, its easy multi-purpose utilization for current consumption data can be imagined.

These are only two examples of how the concept described and motivated in this paper should guide the to-be Industrial Data Management. By taking

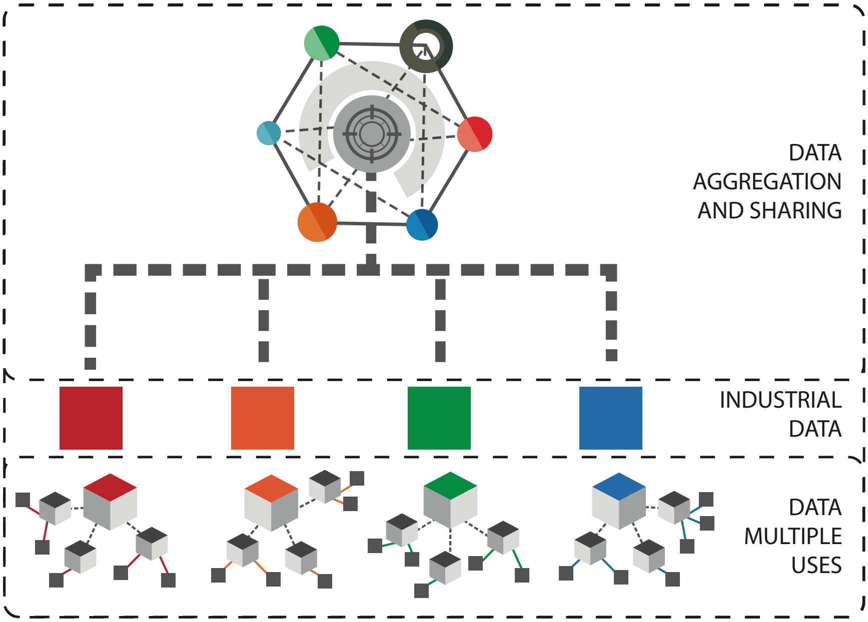


Figure 5.15: Summary of the two main possible data exploitation methodologies inside the industrial context.

it into consideration, sustainability increases, and additional knowledge and value is extracted with little effort.

All the researchers agree on the pivotal role of data in the context we live in. Nonetheless, data redundancy, data waste, and data incomplete exploitation should be avoided for an efficient transition to valuable Industry 4.0. In this paper, an experimental use case of PHM inside an Industry 4.0 environment is presented, together with the definition of a conceptual take-away regarding "data re-use" or "multi-purpose data" as a value extraction approach in synergy with already-in-use data management techniques, such as data fusion and edge computing, among others. The validity of the presented PHM solution has been tested and proved showing results of the experiments performed. The stand-alone concept developed extending and generalizing the reasoning behind the implemented system can be fruitful to all the managers and engineers involved in Industry 4.0 projects. Almost every industrial context could be coherently re-shaped in light of the presented conceptual approach, thus improving overall sustainability and effectiveness of investments (more extracted knowledge from the same data collecting architectures).

This work is under revision in an International Journal.

5.4 Diagnosis and Prognosis of a Cartesian Robot's Drive Belt Looseness

Maintenance cost is among the highest operational expenses for manufacturing firms, as said inside Chapter 2. Proper scheduling of maintenance intervention results in optimized equipment life utilization, higher product quality, and reduced costs.

5.4.1 Motivation

For Cartesian Robot's accuracy and precision it is important that the belt, which transmits motion from electric motors to robot's arms, is well calibrated. Nonetheless, manual assessment of calibration requires to stop the robot, which in turns causes the stop of the production with related consequences. The objective of this research activity was to understand the health condition of a Cartesian Robot's drive belt, without interfering with its functioning. By acquiring current consumption data and developing a proper data analytic solution the goal has been achieved.

Coherently, a ML based Classification Model, able to use cycle current consumption data collected from a Cartesian Robot while working, is going to be presented. This model aims at understanding if the drive belt is calibrated or not, without interfering with robot's functioning. This research activity belongs to the Analytic component of the conceptual reference scheme, being a model able to use data collected for inferring health status of the robot's drive belt.

5.4.2 State-of-the-Art

The ever increasing need for production costs reduction, reflects in companies embracing paradigms like Industry 4.0 and Predictive Maintenance (PdM) strategy [111, 132]. Maintenance contribution to operational costs is anything but negligible, forcing companies to be attentive toward proper management of maintenance scheduling [115]. Identifying the cause of a problem and completely repairing the machine may take several days of production stop [112].

Among manufacturing equipment, the industrial robots are made of several components such as induction motors and drive belts, and are usually involved in non-stop production. Any kind of unexpected breakage or failure of the whole tool or even of one component will result in reduced quality, unplanned stop of production and consequent cost for the company, in terms of reputation and machine fixing. Specifically, fixing a complete breakage is more complex and more expensive than replacing worn sub-components of an equipment before they fail [119] [113]. Therefore, several researchers focused on PdM and strictly related research topics, proposing a wide variety of approaches and methodologies that can be implemented for forecasting the equipment failures and faults [182, 183].

Widely adopted data for PdM purposes are electric currents and vibrations [184]. Multiple branches of data analysis techniques aimed at predicting Remaining Useful Life or failures of industrial machines are present in literature. One branch of researches focuses on the use of Motor Current Signature Analysis (MCSA) for predicting machine failures of induction motors and bearings [185] [186] [187]. Other researchers proposed alternative methodologies like Empirical Mode Decomposition (EMD) on vibration signals with the aim of predicting the state of health of an equipment [188] [189].

Industrial Robots are largely adopted inside modern manufacturing for their efficiency and precision. On the other hand, to perform the assigned tasks with precision and accuracy they are composed of a huge amount of components, that make complex the health status assessment and upcoming failures forecasting [190, 191]. Among industrial robots, Cartesian Robots (CR) are used by manufacturing companies for a wide variety of procedures, given their low cost and high productivity. They reach cycle times of around 5 seconds, which makes them highly productive still highly precise, in the order of 0.1 mm under normal working conditions. The drive belt is extremely important for ensuring the precision while working, and to assess its calibration it is necessary to stop the equipment for a while, which in turn requires the complete stop of the production line. Other researchers focused on this important component of CR, trying to define methodologies for diagnosing its health [192]. Bonci et al. proposed a PdM solution based on MCSA and Wavelet Transform to diagnose rotor faults of a Cartesian Robot in [193].

In this research, motor current consumption data has been exploited for inferring the health status of the robot's drive belt.

5.4.3 Materials and Methods

Specifically, data regarding several complete cycles of the arm, under a specific belt tension fixed prior to data gathering, has been collected. The drive belt can either be too loose or too tight. the latter condition is not so common in practice, since working conditions and wear cause the relaxation of the belt. For this reason the primary focus of this work is on the former case identification. Among several possible data which could be collected from the machine, current consumption has been chosen being an easily collectable kind of data, whose gathering does not interfere with robot's operations. Therefore, current data seems to be suitable for developing a Diagnostic and Prognostic Model, capable of understanding when a drive belt begins to get loose, and consequently suggest the maintenance manager to plan a system stop in order to calibrate again the belt, or replace it in case of excessive wear.

Thanks to this solution useless production line stops, targeted at assessing the drive belt calibration, are avoided, while optimal working conditions of the CR are guaranteed.

Going deeper into the experimental set-up of this work, it has been carried out together with an Italian firm that produces CR and is deeply interested in proposing to its customers smart products, which have PdM strategy on-board. Going into detail of the CR, whose representation is shown in Fig. 5.16, their normal working condition makes the arms — each managed by a dedicated motor and drive belt — complete cycles by moving from one hand to the other in few seconds.

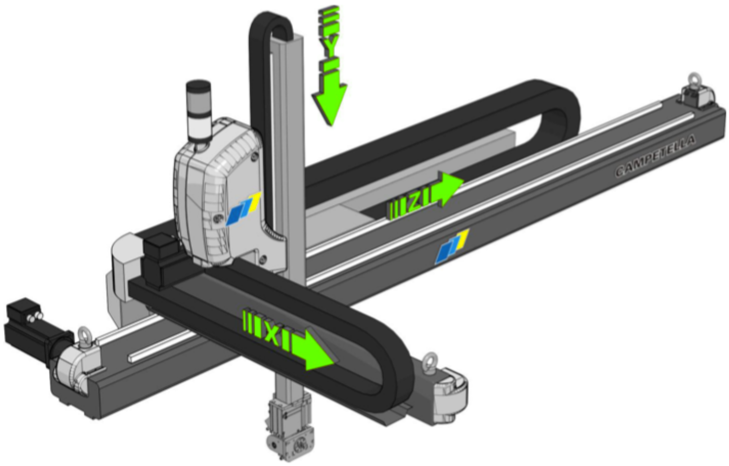


Figure 5.16: Cartesian Robot Computer Aided Design (CAD).

For this reason, when looking at the electric current signal acquired during one round-trip, it is non-stationary, and abrupt changes in frequency and amplitude happen (Fig. 5.17).

The CR provided to us for experimental purposes by Campetella Robotics Centre s.r.l. has three induction motors and three drive belts, one for each arm. For the sake of simplicity when developing models the focus was put on one spatial direction only, the z. This arm is perfectly comparable with the x-axis' one, while the y-axis arm might be quite different from these two, being vertically oriented. In the future possible differences of this arm will be taken into account, for the moment the main aim is to understand the feasibility of the conjecture developed for one axis, and in future works the extension of the reasoning shown in this work for what it concerns other arms will be carried

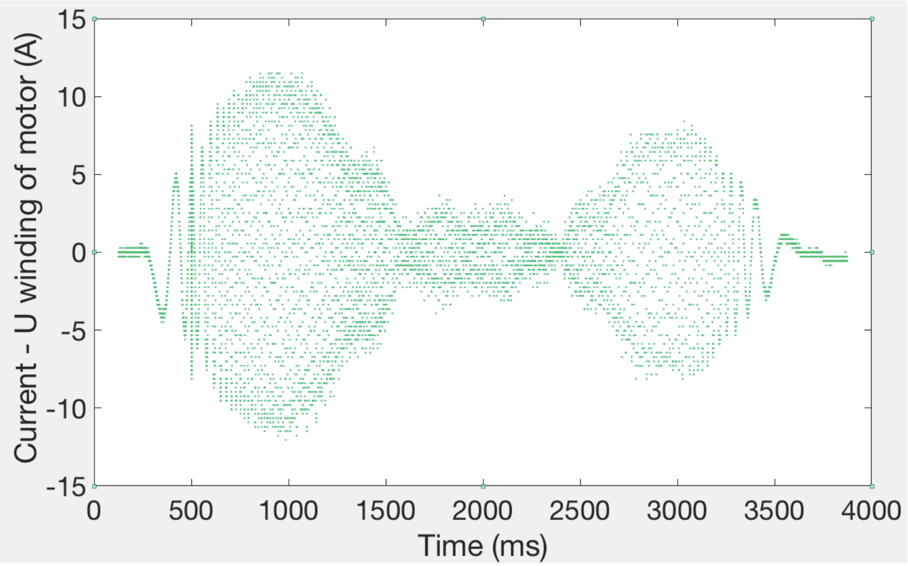


Figure 5.17: Plot of Time (ms) versus Electric Current (A).

out.

Being able to manipulate the robot, specific drive belt tensions have been set during the experiments. Specifically, current data regarding the z arm's motor when the drive belt is correctly calibrated, and when it is too loose, have been collected. Based on suggestion provided by the manufacturer of the belt, the normal frequency of a well calibrated belt for the CR under consideration is between 65 Hz and 55 Hz. When the tension of the belt goes under a frequency of 55 Hz it means that maintenance should be considered. Working at frequency lower than 35 Hz might impact on robot's accuracy and health, and maintenance is mandatory at this point.

The software provided by the motor's manufacturer allowed to collect electric current data of round-trips of the z-axis arm, with variable belt tension previously set manually. In more depth, data at a sampling rate of 8 kHz regarding all of the following drive belt tensions has been collected:

- 21 working cycles with belt at 120 Hz
- 10 working cycles with belt at 65 Hz
- 32 working cycles with belt at 64 Hz
- 20 working cycles with belt at 55 Hz
- 12 working cycles with belt at 54 Hz
- 11 working cycles with belt at 44 Hz

- 11 working cycles with belt at 34 Hz
- 11 working cycles with belt at 24 Hz
- 21 working cycles with belt at 20 Hz

Then, signal processing has been carried out offline, in order to develop a model that could be eventually used online for monitoring the robot while working. The final aim is to train a model that gets as input the current signal, computes relevant features of it, as will be deepened later, and outputs the category predicted for the analysed signal. Specifically, one signal can belong to the Healthy Condition $(65-55Hz)$ group, or to the Border-Line Condition $(54-40Hz)$ group, or to the Loose Condition (lower or equal to 39 Hz) group.

To summarize, 62 samples belonging to Healthy Condition, 23 samples regarding Border-Line Condition, and 43 regarding Loose Condition, are available. A slight imbalance between classes can be noted, and will be addressed when dealing with performance metrics of the classification model [109].

By looking at original signals belonging to different groups, it is hard to understand which group does each sample data belong to, given the peculiar current signal behaviour during one cycle of the arm, as can be noted in Fig. 5.17. It is essential to process the signal in order to extract relevant features that better highlight the different belt tension effects. These features with the associated group label will then be used to train a ML classification model.

The signal collected, being related to transient states of the robot's arm that continuously changes its velocity, is non-stationary. Therefore, tools like Fast Fourier Transform (FFT) are not applicable in this context. As highlighted by Bonci et al. [193], the Wavelet is applicable, but I would like to propose an alternative method that exploit ML algorithms. Traditional time domain features [114], such as mean, standard deviation, skewness, kurtosis, peak to peak, root mean square (RMS), first quartile, third quartile, median, root sum of squares, and peak to rms, have been extracted from signals. In addition, also time-frequency domain features, namely the Welch's power spectral density (PSD) estimate, has been computed and the main 15 peaks and their location have been extracted from it. By looking at the overlapping plot of Welch's PSD estimate regarding different groups, it is evident that the belt calibration seems to affect, at least to a small extent, the Welch's PSD behaviour (Fig. 5.18).

Specifically, in Fig. 5.18 each color belongs to different belt calibration frequencies: the red are related to the Loose Condition group, the yellow lines are related to the Border-Line Condition group, while the the shades of green lines are related to the Healthy Condition group. The different behavior is evident between the Loose and the Healthy groups.

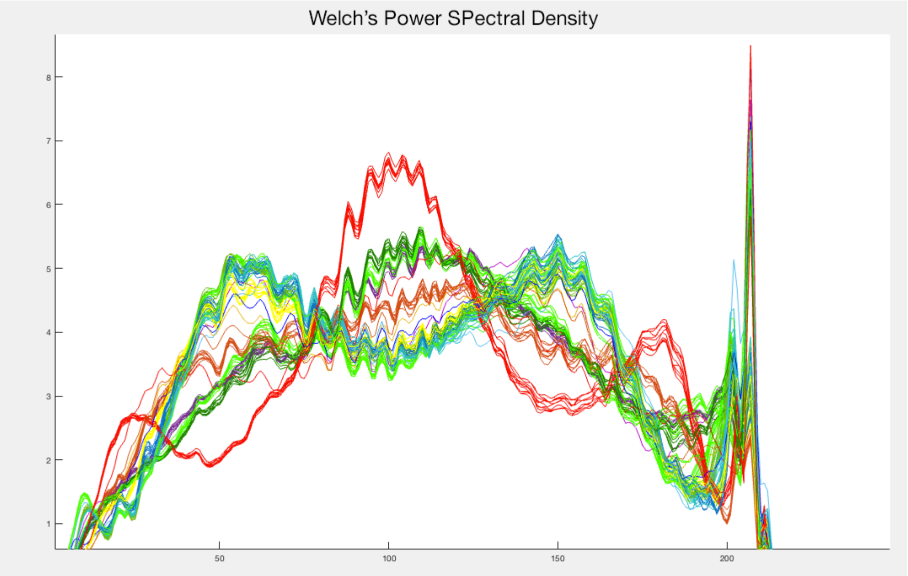


Figure 5.18: Overlapped plot of the Welch's power spectral density estimate for every signal.

To sum up, the 44 features extracted for each current data signal, which is related to one complete cycle of the robot's z-axis arm, and will be used as input for a Classification Model, are the following:

- Mean
- Standard deviation
- Variance
- Median
- First quartile
- Third quartile
- Skewness
- Kurtosis
- Peak to peak
- Root Mean Square (RMS)
- Minimum
- Maximum

- Root Sum of Squares (RSSQ)
- Peak to RMS
- Amplitude of the first peak of Welch's PSD
- Location of the first peak of Welch's PSD
- Amplitude of the second peak of of Welch's PSD
- Location of the second peak of Welch's PSD
- ...All the Amplitudes and Locations of the other twelve peaks extracted...
- Amplitude of the fifteenth peak of Welch's PSD
- Location of the fifteenth peak of Welch's PSD

Given that the Too Tight condition is very rare in practice, it has been taken out during model development phase. Accordingly, 100 random samples (78%) from the total amount of data available have been used to train the model and the remaining 28 (22%) samples to test the model once finished the training. To improve model performances and to have a preliminary measure of goodness of each trained model, 5-folds cross-validation has been adopted. ML models trained are: Decision Trees (Fine, Medium, and Coarse), K-Nearest Neighbour (Fine, Medium, Coarse, Cosine, Cubic, and Weighted), Linear and Quadratic Discriminant, Support Vector Machines, Naive Bayes, and Ensemble Classifiers.

Based on validation results, which will be shown later, the best performing trained model is the Ensemble Random Understanding Boosting (RUS) Boosted trees model. The RUSBoosted Ensemble classifier is especially effective at classifying imbalanced data, which means some class in the training data set has many fewer members than other classes. The data set collected is not heavily imbalanced, but still it is not balanced at all, reason why such model is suitable. Having taken the Too Tight class out of the focus, the model predicts to which of the three classes a current signal of one cycle belongs to. The model cross-validation results are resumed in Table 5.18, where model predictions are summarized for each Group. Specifically, predictions can be interpreted as True Positives (TP), which are the signal cycles correctly categorized in the specific group, True Negatives(TN), which are signal cycles belonging to another group effectively not classified as belonging to the specific group, False Positives (FP), which are the signal cycles wrongly associated to the group by the algorithm, and False Negatives (FN), which are the signal cycles wrongly not associated to the group. Therefore, focusing each time into a specific group the number of TP, TN, FP, and FN can be computed, and results are summarized into the table.

Group	TP	TN	FP	FN	GM	Se	Sp
Healthy	49	47	1	1	91.3%	98%	97.9%
Border-Line	15	81	2	2	92.8%	88.2%	97.6%
Loose	32	64	1	1	97.7%	97 %	98.5%

Table 5.18: Validation results of the Ensemble RUSBoosted trees model for three classes

Values of TP, TN, FP, and FN can be adopted for computing synthetic performance measures. The fact that classes are slightly imbalanced, i.e. there is a difference in number of samples belonging to different classes, has been taken into consideration, given that this can interfere with some performance metrics like the Accuracy [109] for example. Therefore, the performance metrics computed are those not imbalance sensible: Geometric Mean, that is a metric measuring the balance between classification performances on both the majority and minority classes, Sensitivity, that measures the accuracy of positive cases, and Specificity, that measures the accuracy of negative cases. They are computed according to following equations:

$$GM = \sqrt{\frac{TP}{TP + FN} * \frac{TN}{TN + FP}} \tag{5.6}$$

$$Sp = \frac{TN}{TN + FP} \tag{5.7}$$

$$Se = \frac{TP}{TP + FN} \tag{5.8}$$

5.4.4 Results and Conclusions

After choosing the best performing model based on validation results, it has been tested on data taken out of the training phase, which are 28 samples.

The results of the testing are resumed in Tab. 5.19. The three metrics suffer a decrease in their performances for what it concerns the Border-Line and Loose groups, while testing performances are perfectly comparable for what it concerns the Healthy group. This is quite important to be noted, since the very important discrimination that should be done by the developed model is between an healthy belt and a loose one. The capacity to understand the level of looseness is an extra capability which is not mandatory, even though can be useful for the maintenance managers. This lowering in performances achieved during testing respect to those achieved during training could be connected to the amount of data used for modeling. More data would help in achieving better performances.

Despite the performance degradation, in a concrete context, where every robot's cycle current data is analysed in real time, the trend of the prediction is considered, not the punctual prediction. I therefore expect that the trend of predictions will be more reliable than the single prediction that is analysed in this restricted testing set up.

Group	**TP**	**TN**	**FP**	**FN**	**GM**	**Se**	**Sp**
Healthy	12	11	0	2	92.6%	85.7%	100%
Border-Line	3	20	3	2	72.2%	60%	87%
Loose	8	15	2	1	88.6%	88.9 %	88.2%

Table 5.19: Testing results of the Ensemble RUSBoosted trees model for three groups

Concluding, a model specifically trained for predicting the belt calibration by using features extracted from the current data of one complete round-trip of the robot's arm has been proposed and tested. This model proved to be efficient during both validation and testing phases, especially if considering that the main discrimination that it should detect is between calibrated and loose belt. Model's goodness in predicting the level of looseness, acceptable for the Border-Line group or critical for the Loose group, is fair, while the capability of discerning between calibrated or not is excellent. One reason for the worse testing performances can be the lack of data, being the complete data set composed of only 128 samples of the three groups. Some improvements to the proposed method can be the reduction of the dimensionality of the features extracted through commonly adopted techniques like Principal Component Analysis, and features selection methodologies.

This work has been presented at the International Conference on Internet of Things and Intelligent Systems (IoTaIS), and the associated paper inserted in conference proceedings [194].

5.5 A Computer Vision System for Staff Gauge in River Flood Monitoring

Rivers close to populated or strategically important areas can cause damages and safety risks to people in the event of a flood. For this reason, such kind of disaster is part of the challenges of Society 5.0, that tries to exploit the enormous technological advance of the last decades for effectively dealing with societal problems, thus improving life quality of citizens.

5.5.1 Motivation

Therefore, we can set the problem of floods, which affects millions of people all over the world. Flash floods especially could be very dangerous for people living nearby rivers. For addressing this objective, measurements about river's height are essential. A camera based solution, versatile and efficient, has been developed and tested on a real data set collected through an IP cam installed in one river site relevant for the Marche Region in Italy.

Indeed, when dealing with flood monitoring, several attempts and solutions have been proposed over time, most of them focused on water-level monitoring. But traditional river flood monitoring systems like radar and ultrasonic sensors may not be completely reliable and require frequent on-site human interventions for calibration. This time-consuming and resource-intensive activity has attracted the attention of many researchers looking for highly reliable camera-based solutions. This research activity aims at proposing an automatic CV solution for river's water-level monitoring, based on the processing of staff gauge images acquired by a V-IoT device. The solution is based on two modules. The first is implemented on the edge in order to avoid power consumption due to the transmission of poor quality frames, and another is implemented on the Cloud server, where the frames acquired and sent by the V-IoT device are processed for water level extraction. The proposed system was tested on sample images related to more than a year of acquisitions at a river site in the Marche Region. The first module of the proposed solution achieved excellent performances in discerning bad quality frames from good quality ones. Also the second module achieved very good results, especially for what it concerns night frames.

5.5.2 State-of-the-Art

Despite technological advancements and efforts, river basins are often source of damages and risks, especially for the population living in the neighboring areas. The risk related to flash floods, which can be valued based on multiple factors such as local hazards, exposure, vulnerability, and emergency and recovery capabilities [195], is increasing over time and it is envisioned to get even worse due to climate change and atmospheric warming [196]. Several researchers attempted to develop models able to predict future flood hazards, highlighting also the correlation with climate changes [197, 198], but it is hard to develop area specific adaptation of such models. For this reason most of the time local public entities are predisposed to control the territory in which continuous monitoring mechanisms for the safeguard of citizens are used. In particular, continuous monitoring systems generally require human supervision and contribution, thus consuming strengths and resources that public administration has at its disposal, from both an economic and workforce point of view. Despite the costs associated to such kind of supervised monitoring mechanisms, the societal benefits have been estimated as higher [199]. However, to deal with such a source of inefficiency and waste identified, it is necessary to envision and implement smart and automatic solutions, by exploiting innovative technologies as Information Technologies, Sensing Technologies, and Artificial Intelligence, as some researchers already tried to address.

Automatic monitoring solutions are at the base of developing smart Early Warning (EW) systems for flood hazards, which usually exploit, among relevant input data, the water level of rivers [200, 201]. Nonetheless, the solutions proposed in the literature and focused on EW do not go into the details of how the water level is measured, apart from saying the type of instrumentation adopted [35, 202]. Commonly adopted technologies for monitoring river flood are pressure transducers, rangefinders, ultrasonic, radar as well as optical sensors [203]. Some of these technologies require frequent calibration, to ensure enough accuracy, particularly in the event of objects like wooden logs passing underneath, or waves caused by the wind. Moreover, these technologies are prone to measurement errors which could happen especially during dry riverbed and during extreme weather conditions like heavy rainfall, which are those conditions to be controlled more strictly for flood monitoring purposes. This has led many public entities to set up low-cost cameras for remote monitoring and visual inspection of river sites. In such sites the cameras can also frame the staff gauge which is generally installed to indicate the water level of the river. Using such cameras able to provide images related to the water level, it is possible to develop a Computer Vision (CV) system for flood hazards. Consequently, many researchers in recent years focused on using optical sensors like cameras to monitor the water level [203].

A camera equipped with remote transmission capability and eventually processing capability can be used as Visual-IoT device (V-IoT) for estimating the water level. Developing such V-IoT systems require less effort for calibration respect to using sonic and radar sensors, is economically viable, and allows the creation of a reliable sensing network, capable of being exploited for automatic monitoring solutions and on-demand remote visual inspection of river sites. For these reasons the application of V-IoT devices is spreading over time, but related criticalities should be taken into account when evaluating the creation of such a monitoring system [204]. In more details, when dealing with V-IoT systems, data transmission, processing and storage have a huge impact in terms of available bandwidth and energy consumption. V-IoT systems produce huge amounts of data in relatively short time, forcing to be mindful in managing them. In order to mitigate the transmission and storage constraints, Peng et al. [205] proposed an enhancement method to overcome the false contour and color distortion connected with bit-depth compression, given that this is a widely used solution. As a general suggestion, Ji et al. [206] highlighted the importance of optimising transmission, storage and processing, based on the specific system tasks to be completed, taking into consideration delay sensitive and context aware video services. Moreover, when V-IoT nodes are installed in natural contexts, like those of relevance for flood monitoring purposes, they are generally battery-powered thus forcing to be thrifty in the use of energy required for data transmission.

In the flood monitoring scenario the challenge is to develop a completely automatic solution capable of working 24 h a day in unconstrained natural landscape with possibly adverse weather conditions, and of easily adapting to multiple sites with easy to set adjustments. Focusing on the image processing side, Yang et al. [207] presented the development of a system tested in an indoor controlled laboratory, simulating rain. The development and testing configuration makes the proposed solution hardly applicable in unconstrained natural landscape, at least to the scenario under consideration in this study. Kim et al. [208] developed a method and tested it on 4 real sites. The proposed solution based on CCTVs is not able to work during night and two different approaches for computing the water level are proposed, one based on frame differencing, and another based on Optical Character Recognition (OCR). By looking at some sample frames, I noticed that during extreme weather the quality of captured images might become very low, thus making OCR not a viable nor reliable solution. Noto et al. [209] proposed a solution tested in a non-simulated scenario with some critical conditions of lighting and landscape. Their solution is capable of working 24 h a day but adopted a pole instead of a gauge. Moreover, water level estimation relies on the assumption that the pole is brighter than anything in the Region of Interest (ROI) framed, making this solution not versatile at all. Similarly, in [210] it is presented an automatic solution for detecting gauge's ROI, but it exploits the color and morphology of a specific kind of gauge, which is not the one commonly installed on generic sites. Zhang et al. [211] described a system whose performances have been tested during complex conditions. Main limitations of the proposed solution are connected to the gauge's ROI identification, which is not automatic and implies ROI setting during installation, but doesn't ensure reliability on the long run in case of camera motion. In fact, working in unconstrained natural landscapes, it is also necessary to use a solution capable of detecting the gauge's ROI if it changes due to any misalignment of the camera. In [212] the Authors proposed a 24 h a day monitoring system where the ROI is once again manually set. The solution is then tested on two sites, focusing on processing steps targeted at the extraction of the water level even under complex illumination conditions. Similarly, Hies et al. [213] proposed a solution capable of working h24 thanks to infrared camera, but the identification method of the gauge's ROI is manual. Royem et al. [214] proposed a method for one site, using one static ground camera. The proposed method is strongly dependent upon calibration procedures. Moreover, the gauge's ROI selection is done through color-based processing and requires a gauge that is chromatically distinguishable from the context in which it is immersed. Hasan et al. [215] presented a h24 monitoring solution, tested in multiple sites. In order to select the ROI of the gauge they installed a big white board near to it. In [216] the proposed solution uses multiple reference points to select the ROI, which is very ample respect to the contained gauge. Moreover, the system has not been tested during night. In the scenario under analysis, the gauges are already installed but it is advisable to avoid installing similar reference points. Bruinink et al. [217] proposed a portable solution, that can be implemented in mobile phones The solution has been successfully tested in 9 sites, but the gauge's ROI detection is performed using a textons-based approach which is not versatile at all. In fact, this approach is usable only when the gauge is highly distinguishable from the background, which is not always a true hypothesis. Jafari et al. [218] propose an advanced method which exploits CNN and leverages time-lapse photos and object-based image analysis. The methodology reaches very good performances in both the laboratory and two field experiments, nonetheless it relies on a strong site-specific adaptation phase. The aim is to propose a more versatile and adaptable solution. Isidoro et al. [219] propose a water surface measurement through image processing, still the proposed flowchart is quite easy and do not guarantee successful scalability to several diversified sites.

Concentrating on cases where the gauge is framed by a static ground camera, I propose hereafter a CV system for monitoring river flood based on the processing of images of the gauge installed in the rivers. In particular, the aim is the creation of a versatile and smart automatic water level measurement algorithm, to be applied in multiple sites with minimal adaptation effort, thus ensuring its scalability in the near future. By looking at past works, there are only attempts of automatizing the water level computation task, some of them reaching results in laboratories, or failing under complex conditions, which are very frequent in real river sites and should be addressed. Based on the reviewed literature the common steps of such a solution can be identified, but there are no past works that perfectly suits the considered scenario. Given the required versatility, advanced solutions based on Machine Learning (ML) are better than traditional Image Processing techniques. However, it must be pointed out that ML based solutions can be energy intensive, just like the transmission of images or videos. Therefore, I will present an important basic, fast and computationally light image processing methodology, capable of testing the quality of the image collected by the installed camera. This procedure becomes essential for V-IoT systems installed in unconstrained environments, even more so in those cases where energy consumption due to images transmission is a constraint.

The intention is to develop a versatile automatic solution, able to work in different sites, after a light and easy adaptation at the moment of installation. The presented works have pros and cons with respect to requirements set, and for this reason a new approach has been developed, mixing the strengths of the reviewed literature in order to develop a smart, flexible, scalable and reliable solution. The reviewed works are usually very site-specific, or incomplete respect to the identified requirements.

5.5.3 Materials and Methods

Hereafter an automatic CV solution capable of detecting and computing the water level of a river, taking as input a frame snapped by a V-IoT device, will be presented. The proposed solution has been created with the following requisites in mind, set together with the entity in charge of disaster management:

a. be fully automatic;

b. be able to detect the water level with an accuracy of ± 3 cm;

c. require minimum site-specific customization, except for the initial in-site installation;

d. be able to work day and night;

e. be reliable even during extreme weather conditions;

f. transmit to the central server high-quality data only;

g. be able to work in sites where the gauge is made up of multiple pieces, framed all together by the camera.

To develop and test the proposed CV solution has been exploited a data set composed of more than 10 thousands sample images collected using a cam framing the river gauge in one specific site of interest. The camera and the gauge were immersed in unconstrained environment, which increases the complexity of the proposed solution. The camera is installed in Senigallia (AN), Italy, near Garibaldi's Bridge, depicted in Figure 5.19 which has been captured during a day by the camera used for developing the solution, but using a different set-point for the acquisition respect to the one adopted for capturing frames of the gauge. From the picture it can be seen that the camera is installed inside a urban area, but during the night it does not require artificial illumination to work, thus being an hardware suitable for installation in completely natural sites where there is no artificial light available and only the IR could be exploited.

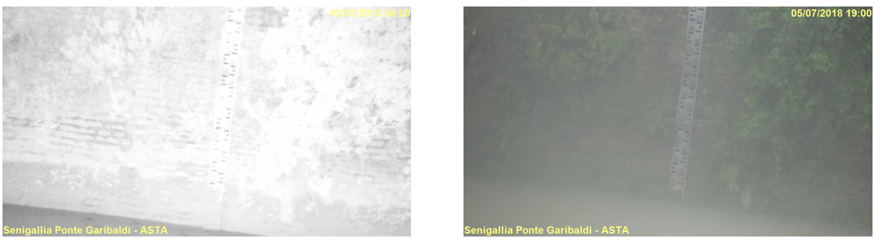
Figure 5.19: Panoramic view on the acquisition site.

The data collection architecture used indeed as static ground camera a Dahua DH-SD50C120S 1.3 Megapixel RGB 1280 × 960, with Auto ICR for day/night, and TCP/IP connection. The cam snapped one frame every 30 min and these data were uploaded on a dedicated server, which made them remotely accessible. All the acquired frames are RGB, even though night frames could seem gray-scale due to the fact that they are collected through the auto ICR function. Data were collected for more than a year, resulting in a collection of frames with almost every shade of picture linked to different seasons, light and weather conditions. Specifically, there are six extreme weather conditions events, resulting in more than twenty related frames. Going deeper into the data collected, night frames are quite similar to each other, while daily ones present differences caused by the different inclination of sun's rays. In Figure 5.20 the two main typologies of frames collected by the cam, day and night ones, are shown. Moreover, during the year, some samples were overexposed frames, and some others were blurred or bad quality ones due to extreme weather conditions, like the examples shown in Fig. 5.21.

(a) Day frame, collected by the cam 01/07/2018 at 11:00 a.m.

(b) Night frame, collected by the cam 01/07/2018 at midnight.

Figure 5.20: Example of two typical images collected by the system.



(a) One of the overexposed frames.

(b) One example of excessively blurred frame.

Figure 5.21: Example of overexposed and bad quality frames snapped by the camera.

The proposed solution must be able to process different typologies of frames collected by the cams, hence, a smart solution able to understand which kind of frame is the one under analysis, and to perform tailored computations to extract the water level, is required. In order to compute the water level during the entire day with an accuracy of ±3 cm, image processing should rely on good quality images but it is easy to have some bad quality frames, either due to bad weather or to contingencies connected to the unconstrained and non-standardised context of use. Therefore, a specific module of the solution has been created to be implemented on the edge. This module processes each collected frame as soon as it is snapped with basic image processing algorithms, with the aim of ensuring the collected frame is a good quality one. This module takes as input a frame snapped by a V-IoT device, and classifies it as either day, night, or bad quality (either overexposed, blurred, or with weather related artifacts), through light and fast computations suitable for edge implementation. In the proposed solution the good quality night frames, are pre-processed at the edge and only the grayscale version is sent to the server, while day frames, being more complex and less standardised, are sent in their original form. Specifically, for what it concerns night frames, only the image compressed in one color channel is sent to the cloud where the Water Level Computation module is implemented. By adding Image Quality Check at the edge, both data transmission and energy consumption of each V-IoT nodes would improve, thus increasing the overall reliability and performance of the network and system.

MODULE 1: Image Category Classification I started cleaning available data, 16'124 frames, from those samples not usable due to a different camera set point, which resulted in frames capturing the nearby landscape instead of the gauge. Exploring the resulting data set after upfront cleaning, 13'422 samples from the original set have been kept, and the search for quantitative metrics able to differentiate the distinct types of frames has been done. The following metrics, that are going to be called from now on with the synthetic abbreviation in brackets, have been evaluated:

- Mean of all pixels of RGB color channels (MN_{all});
- Mean of the saturation channel of the image converted into HSV color model (MN_s);
- Root Mean Square of RGB channels (RMS_{all});
- Root Mean Square of saturation channel (RMS_s);
- Maximum inter-pixel difference, computed as the maximum along all the pixel intensities, minus the minimum (*delta*);
- Variance of the image histogram (VAR_{ih});

I analysed the correlation between each of these metrics, and the image classes, finding some interesting strong relations. Specifically, MN_{all} is strictly discerning the overexposed frames from the other classes. MN_s and RMS_s were strongly different between day frames and the other classes, as could be expected since during the night the camera acquires through auto-IR cut filter and the resulting RGB image is like a gray-scale one. The night frames have very low saturation thus resulting very similar to frames snapped during bad weather or in case of bad quality images, where the saturation gets low. Another interesting connection has been found for the *delta* metric, suitable for discerning between bad quality, against good quality both day or night frames.

In order to develop a broad reference for understanding differences in the metrics between the distinct frame classes the three most discerning variables were plotted, specifically MN_{all}, RMS_s, and *delta*, by group, obtaining the graph shown in Fig. 5.22.

By analysing the 3D plot, it can be noted that group of images belonging to the same class, are quite well separable by using the three metrics plotted. Based on the analysis of the entire clean data set, a quantitative measure of frame class, distinguishing between night, day, and bad quality, can be obtained. Therefore, a multi-threshold based algorithm for discerning the class of the frame has been developed. The algorithm is integrated into a specific module able to discern bad quality frames, from good quality day and night ones, thus allowing to send only images from which it is possible to obtain useful information regarding the water level. This module should be implemented on the edge and is especially useful for battery-powered V-IoT devices, given that it was designed to save the energy consumption due to the transmission of unusable data. The proposed module is illustrated in the flowchart shown in Fig. 5.23, where the choice of the multi-threshold based algorithm for discerning frame category is due to its fast response and low computation load.

Once the module for image category classification analyses one snapped frame and understands its category, the frame may be classified as night, day, or bad quality. Bad quality frames, which can be connected to different kinds of causes, are discarded, whereas day and night frames are sent to the central server for further processing. In particular, in case of a day frame, the module sends directly the image to the central server. If the frame is a night one, the module sends directly the gray-scale image to the server, thus reducing the size of transmitted and stored data: from three color channels, to one.

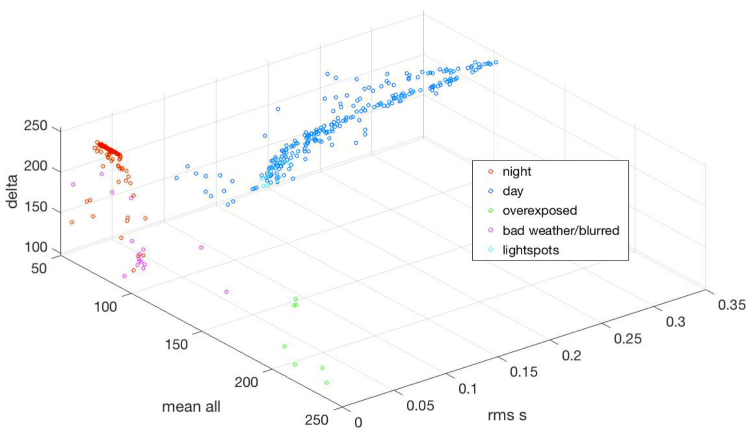


Figure 5.22: 3D plot of MN_{all}, RMS_s, and *delta*, coloured by group.

MODULE 2: Gauge Detection and Water Level Computation Once an image is sent by the V-IoT device to the server, it is temporarily saved for being

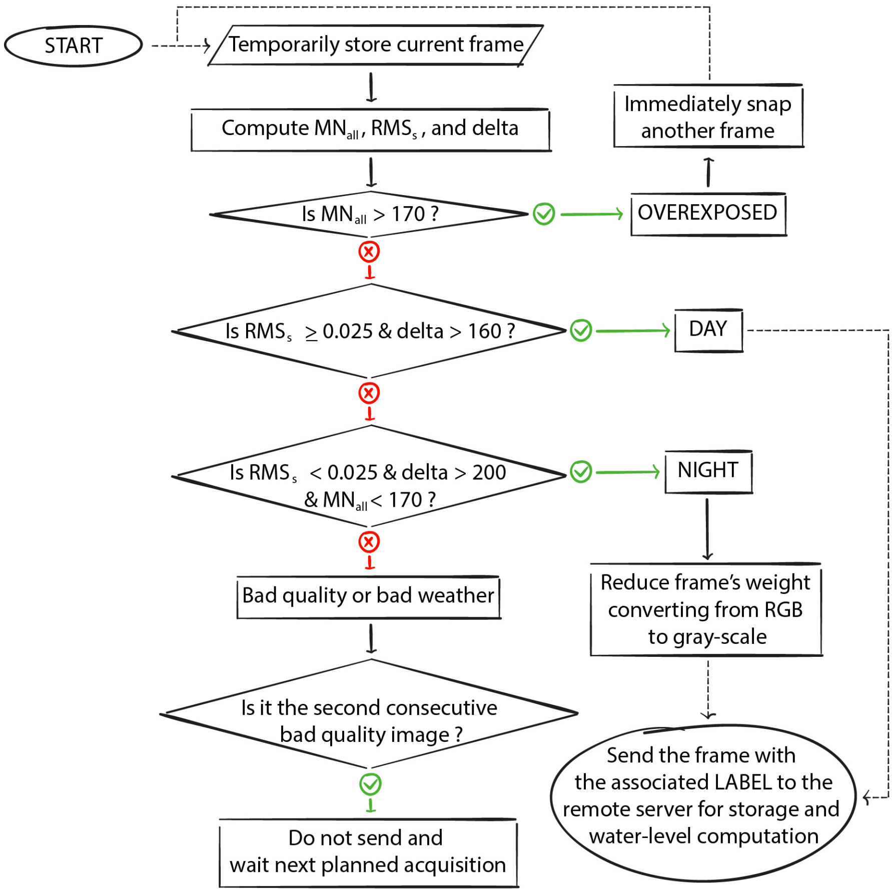


Figure 5.23: Flowchart of the image category classification algorithm.

processed by the second module. It is composed of two parallel algorithms, one for daily frames, and another for night ones. The first step is common to both day and night frames, and concerns the ortho-rectification of the image. Through this step, we pass from an image where the gauge is distorted, due to the relative perspective of the camera and the gauge, to a rectified image where the gauge seems frontally framed. Specifically, this procedure has to be set for each site, and starts with the identification of the four rectangle's vertices and the rectified rectangle associated to a perfect frontal view, as shown in Fig. 5.24. Once associated each corresponding vertex with its "correct" frontal position, image rectification can be performed. This solution is more than a simple rotation, and requires some portion of the image to be filled with a value since those pixels are not present in the original frame. As can be noticed by looking at Fig. 5.25, in the rectified image, the water level is an horizontal line, thus making the analysis easier.

Figure 5.24: The original frame with the desired gauge positioning, used to compute image rectification settings.

(a) The original frame sent by the V-IoT device

(b) The frame after ortho-rectification based on specific site's setting.

Figure 5.25: Image ortho-rectification example.

One sample frame has been used for setting the ortho-rectification parameters. Once defined, these parameters are fixed for the site under analysis and should be updated only if the system setup changes.

Then, if the image under analysis was classified as a daily one, the processing steps after rectification are the following:

d1. top hat filtering, using as structuring element a disk of 15 pixels radius;

d2. adjust image intensities, saturating top and bottom 1% of all pixel values;

d3. binarize the image using a fixed threshold (45);

d4. eliminate from the binary image those connected regions having area lower than 50 pixels, to reduce noise;

d5. fill the holes;

d6. perform morphological closing using as structuring element a line of 30 pixels;

d7. compute the percentage of white pixels for each row over the columns;

d8. compute the adaptive threshold as mean minus one standard deviation of the row percentages;

d9. start from the bottom and find the first line where the row percentage exceeds the threshold, which is the water level;

d10. draw a red line corresponding to the computed water level.

In Fig. 5.26 the outcome associated to each of the listed steps for the sample image already shown in Figure 5.25 is show. Additionally, even the plot of row percentages metric, used to find the water level.

If the image was a night one, the processing steps after image rectification are:

n1. detection of the gauge and cutting the image;

n2. median filtering the retained portion;

n3. extraction from it of 5 thresholds of intensity;

n4. sharpening by a factor of 1.4;

n5. clustering based on multiple thresholds computed before;

n6. clusters' edges extraction, using Canny algorithm;

n7. holes filling;

n8. morphological closing using as structuring element a rectangle of 4 by 15 pixels;

n9. eliminate from the binary image those connected regions having area lower than 50 pixels, to reduce noise;

n10. holes filling;

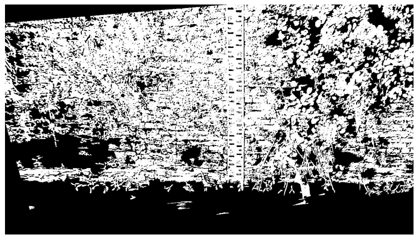
n11. compute the sum of black pixels for each row;

n12. assign to each row the value of 0 if the number of black pixels is lower than 70% of row pixels, 1 otherwise;

(d1) Outcome of top hat filtering.

(d2) Outcome of adjustment.

(d3) Binarized image.



(d4) White noise removed.

(d5) Holes filled.

(d6) Morphological closing outcome.

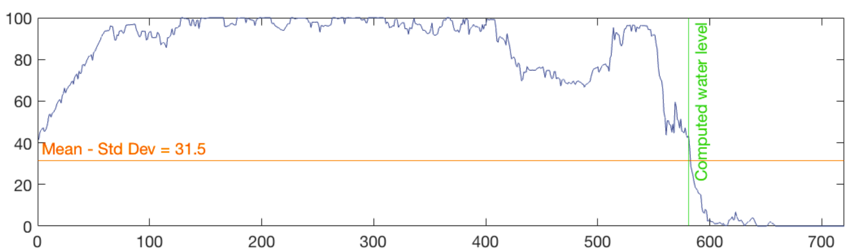


Figure 5.26: Day frames processing steps outcomes, according to the list of steps [di].

n13. find the water level which is the first non-zero line.

In Fig. 5.27 is shown the outcome associated to each of the steps, for a sample night image sent by the V-IoT device to the central server. The algorithm grounds on the fact that the night frames are very similar to each other: the water is darker than anything else, while the gauge is brighter, allowing us to compute the water line through simple computations. For what it concerns step n1, I decided to train an Aggregated Channel Features (ACF) [105] object detector on a small set of rectified images. This decision arose from the fact that due to wind and small relative movements between the rod where the cam is fixed and the gauge framed, the position of the gauge is not fixed over time. For this reason, the custom ACF object detector will be used given its easy training, accuracy, and speed of use [220]. Through this detector, the ROI is reduced coherently with the position of the gauge in the image under analysis.

5.5.4 Results and Conclusions

Results achieved by each of the modules using the data set previously described are going to be presented. In more details, among the 13’422 frames, we have 532 bad quality, 6’248 night, and 6’642 day frames. Results regarding correct classification one frame as day, night or bad quality will be shown. Then, the performances in computing the water level through the dedicated algorithms for respectively day and night frames will be discussed. Respect to the original data set, some images connected to camera set point errors (not framing the gauge, by the nearby landscape), and some others connected to the non-optimal system set up, have been removed. Based on these two categories of frames, that are not usable for the sake of computing the water level, improved guidelines for the installation of the V-IoT devices in other sites of interest have been defined.

To begin with the first module, among all the available frames, the algorithm found 487 of them to be low-quality. By screening these frames, 464 were effectively non-optimal, and some unusable even by the human eye, like the two shown in Fig. 5.28. The remaining 23 bad quality images were overexposed like the one previously shown in Figure 5.21, hence not analysable. For what it concerns images classified as either day or night frames of good quality, 24 day and 21 night frames are not good quality at all, while all the detected as day frames are actually day, the same for night frames. Removed those that turned out to be of bad quality, the frames categorized as either day or night, were all correctly classified and hence processed each by the dedicated algorithm. Results regarding the first Module are summarized into Table 5.20.

To present the results of the second Module, I decided to divide between “correct water level”, if the computed line is no more than 3 cm apart from the actual water line, “small errors” if the computed line is 3 cm to 10 cm apart

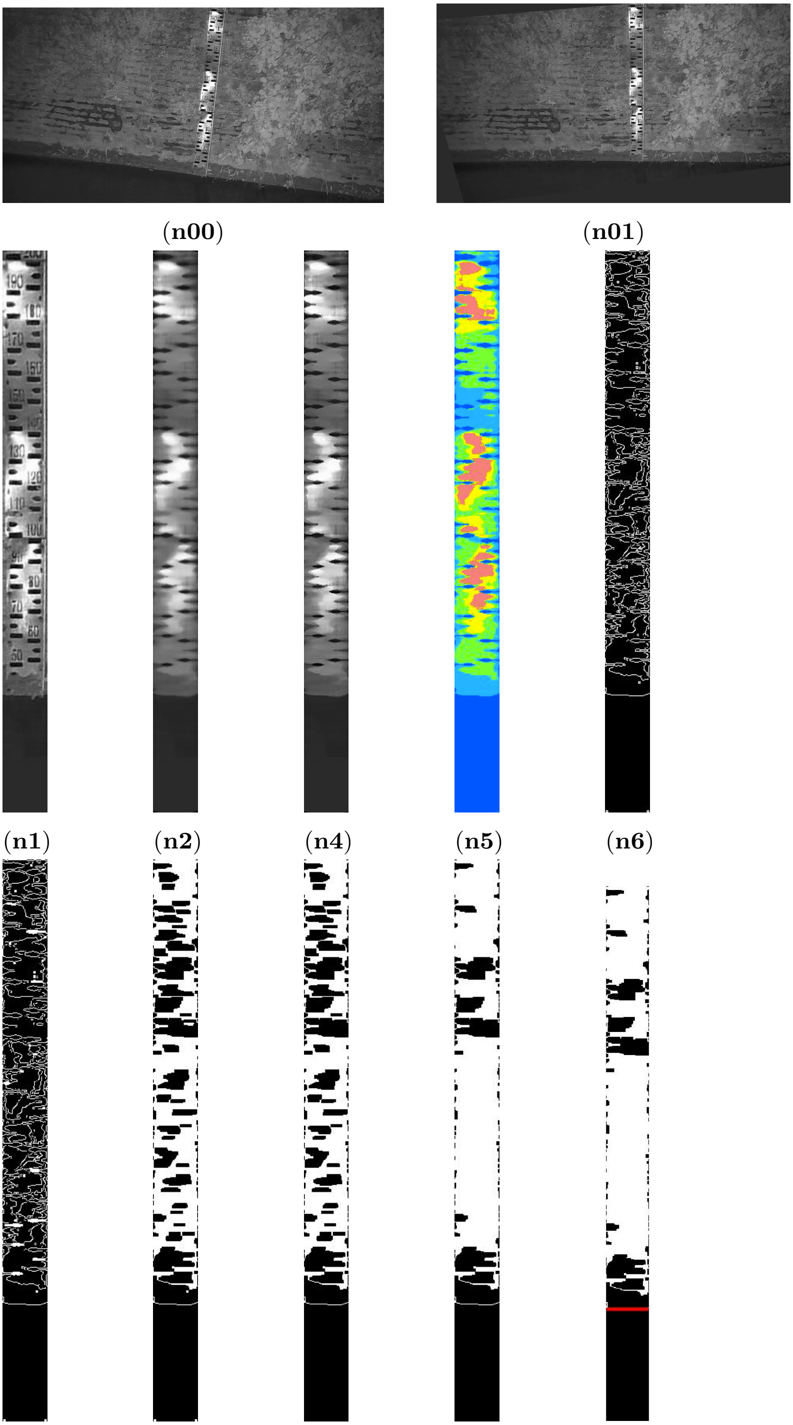


Figure 5.27: Night frame processing steps outcomes, according to the list of steps [ni].

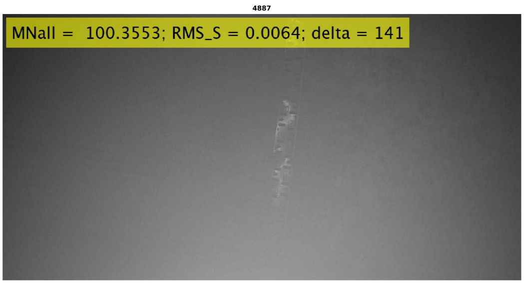


Figure 5.28: One of the worse bad quality images detected by the first Module.

	Actual	**Detected**
Night	6628	6652
Day	6348	6369
Bad Quality	532	487

Table 5.20: Summary of the Results of Module 1.

from the actual water line, and "heavy errors" otherwise. The frames with the computed water level shown have been compared with their original version and visually inspected, with the aim of assessing the goodness of computed water level. Focusing on night frames, 6545 have been further analysed to compute the water level with success, other 35 resulted in small errors, and in 48 the algorithm made heavy errors. Focusing on day frames, 5300 have been further analysed and the computed water level was correct, 465 were the small errors, and in 483 frames the algorithm made heavy errors. I would like to specify that among heavy errors, there are two samples for which the algorithm made a big mistake, as shown in Figure 5.29. Anyway, the fact that only two times this kind of error happened, can foster thinking that it might be caused by a wrong threshold. I therefore expect from more advanced solution, like a semantic segmentation network, to be more reliable. Results of Module 2 are summarized into Table 5.21.

	Correct Water Level	**Small Errors**	**Heavy Errors**
Night	6545	35	48
Day	5300	465	483

Table 5.21: Summary of the Results of Module 2.

Going deeper into the scalability requirement set for the system, I tested the algorithm on additional frames related to other sites respect to the one of development and tests presented until here. Specifically, the algorithm without any kind of adaptation has been applied to images related to thirteen sites,

Figure 5.29: One of the two big errors done by the algorithm.

(a) Frame of Misa River and resulting water level.

(b) Frame of Chienti River with computed level.

Figure 5.30: Results achieved for two of the additional sites analysed.

each very different from the others. Some sites are characterised by a multi-pieces gauge, other are characterised by a very high staff gauge, thus being a small but very diversified data set. Results achieved show very good capability of being applied in those sites with similar perspective of camera and gauge, like those presented in Fig. 5.30.

Results achieved suggest that we can move to the next step: validation in the field, in multiple sites. During data set development phase an interval of 30 min between frames has been adopted. Given the tested reliability of Module 1, which allows to be sure about the quality of frames sent to the central server, thus optimizing transmission bandwidth utilization, the plan is to put the system in place setting 3 minutes interval between acquisitions. In this way the solution will be sensitive to sudden flood events through this more frequent frame snapping, without burdening transmission and processing.

Respect to the reviewed literature, a solution that goes from the RGB image, to the one with computed water level without any need for human intervention has been proposed. Some of the reviewed works, presented a solution able to deal with day frames only. The developed solution is able to understand if the frame under analysis is a day or night one, and then apply a customized step of image processing. Respect to [207], where the solution is developed and tested inside a laboratory, in this work the solution is tested on a very large real data set. Respect to [208] I took care of the night frames. Being flood monitoring a continuous task, I believe that it is essential that a solutions takes night-operation into consideration, as it has been done here. Generally, this system is going to be installed into unconstrained and not-standardised contexts, hence, it can't rely on strong chromatic assumptions, like the solutions proposed by [209], which requires the gauge to be brighter than its background, by [210], whose processing steps rely on color and morphology of the gauge, by [214] that exploits color for extracting gauge's ROI. The proposed solution is not based on chromatic assumptions. Other works proposed solutions based on the manual definition of gauge's ROI. By analysing available data, I found out that oscillation of the camera can happen, mostly due to weather conditions like strong wind. Hence, solutions based on an a-priori gauge's ROI (like those presented in [211, 212, 213]) are not reliable at all.

For what it concerns reliability during extreme weather, six events happened during the period of acquisition, resulting in tens of frames analysed and all water levels correctly computed, thus proving the goodness of the proposed solution. Moreover, one problem that can interfere with the correct functioning is the clearness of the water, that could make the underwater content visible. Even though it is very rare in the site analysed, it happened sometimes over the year of acquisition, and thanks to refraction and reflection it did not cause computing errors.

Furthermore, the proposed algorithm allows the adaptation in multiple sites with minimal effort, as proved by applying it on some samples related to thirteen additional sites, for which only few images collected by volunteers are available. Once the V-IoT device is installed, a frame is snapped and rectification parameters for the site under analysis are set in few seconds. Then, some images are added to the ACF detector for adapting it to the additional site. After one or two days of data collection, site-specific thresholds for Module 1 and Module 2 are defined. Therefore, The adaptation required to the proposed solution is mostly regarding the initial system setup and, subsequently, the algorithm will be able to work on the new site autonomously and continuously. However, it is very important to set additional data collection campaigns, able to enlarge the data set to multiple sites, thus allowing us to test the reliability of the proposed solution in similar yet distinct contexts.

Based on results achieved and discussed, the proposed solution solved main limitations found in existing literature. It is therefore possible to move on to the next step, which is putting into operation in several sample sites. The work carried out proved to be very reliable, and an essential part is Module 1, the Image Category Classification. It is particularly necessary for V-IoT systems, especially for battery powered nodes, where data transmission is among the most consuming activities, and may be related to unusable data resulting in an energy waste. Ensuring the quality of data to be transmitted with a light and fast algorithm will help for having good data while extending system life.

Focusing on the second Module, results achieved are satisfactory, especially for what it concerns night frames as expected, since this category of frame is characterised by a strong standardisation of key characteristics. Day frames, connected to a very broad range of different light rays inclination respect to the camera objective, are more diversified and therefore critical to be analysed. For this reason, in the near future additional possibilities dedicated to improving the reliability on day frames will be developed and tested. Respect to past works reviewed, the proposed algorithm has been tested on an extremely wide data set, which allows to be sure about its overall reliability respect to the task of measuring the water level.

5.6 Dynamic Energy Consumption Rationing in Oil Refining Plant based On ML

During the third year I have been able to collaborate for seven months with Prof. Potekhin Vyacheslav, Associate Professor of the School of Cyber-Physical and Control Systems at the Peter the Great St.Petersburg Polytechnic University (SPbPU). Research fields of Prof. Potekhin's lab are the following:

- Advanced manufacturing technologies
- Technological processes and systems automation
- Mechatronics
- Intelligent robotics and Cyber-Physical Systems
- Intelligent control systems and industrial networks

5.6.1 Motivation

Our collaboration focused on the modeling of an oil refinery consumption data set, in order to evaluate possible ML based solutions that could bring to energy consumption rationing. Energy rationing is necessary for high-quality production planning, and allows optimization of energy consumption itself. Specifically, if we consider the oil refining process, it is essential to optimise the management of energy consumption, for avoiding waste and reducing overall costs in cost-intensive processes. Innovative technologies allow the implementation of a wide monitoring network, made of sensors and other devices able to collect an extremely wide amount of data, which can be used as predictors for modeling energy consumption rations. Through such models, optimisation can be achieved respect to the actual situation which grounds on guidelines fixed a priori, that cannot take into consideration the actual situation of the plant.

The development and test of a Data Science-based solution will be presented to answer this objective. After an initial data preparation and exploration phase, some approaches have been applied for testing viability of the theoretically defined insight. Specifically, basic ML algorithms like Regression models have been implemented as a baseline reference for comparisons, and more advanced modeling until DL like Neural Networks have been trained and tested, with the aim of finding the best model.

5.6.2 State-of-the-Art

The oil refining industry is an exemplary sector where the active integration of new technologies aiming at the optimization of processes, will increase the quality of the final product and reduce its production costs in a non negligible manner. Digital Twins have been largely exploited by researchers in this field for improving overall efficiency [221, 222, 223]. A Digital Twin is a virtual representations of manufacturing assets, characterised by near real-time synchronization between the cyberspace and physical space, that can be used for monitoring, control, diagnostics, prediction, and simulation [28]. Among processes which can be embodied in Digital Twin, we find rationing of energy consumption. Consumption rationing digital model could allow to count the necessary and sufficient resource consumption for a specific scenario hypothesized. One of the key purposes will be the capability of analysing the deviations in energy consumption and the associated improved cost management.

It should be highlighted how much energy consumption is affected by a wide variety of internal and external factors in these non-trivial and very complex industrial processes like oil refining. To name few, process parameters, input materials characteristics, weather conditions, time of day and many others are the influencing factors. Energy consumption regulation algorithms available are prescriptive and generally defined, thus being not optimal at all for highly digitized contexts where a customized solution, able to exploit monitored data, could reach better performances. Indeed, thanks to the profuse adoption of monitoring and sensing technologies, a large amount of real-time updated data is available through Digital Twins. As Mantravadi et al. [224] pointed out, ML is a precious resource for solving plenty of manufacturing related problems: energy efficiency of industrial processes and plants, rescheduling strategies optimization, sustainability improvement, and many other.

Energy consumption rations are the computed values of maximum allowable expenditure of certain resources with the aim of forcing energy conservation as an alternative to price mechanisms in energy markets. The norms determine the calculation basis for planning the consumption of fuel and energy resources, and also allow you to control their expenditure and identify any potential saving reserves. In the industrial consumers context, ration is an indicator of the planned consumption for the production of a unit of final product. The focus of this research has been the rations of resources consumption, associated with the provision of the main production process only, namely, fuel and energy resources. They are measured in Tones of Equivalent Fuel (TEF) per unit of production.

Consumption rations estimation models adopted so far are experienced method, analytical method, and statistical method. The first methodology grounds on experiments whose results allows the definition of individual rations. Any deviation of the analysed system from the settings used in the experiment cannot be managed, thus making this method inconsistent. Moreover, experiments could be very costly respect to the obtainable results. The second is the computational and analytical methodology, based on a thorough study of technical regulations and design and engineering documentation. The object under analysis is divided into separate sub-objects at first, then, interactions between sub-objects are modeled. The quality of the computed values is strictly dependent upon the quality of object description and technical documentation available. Therefore, this method also is not able to dynamically adapt values to actual object conditions. The third methodology ground on computation and statistics thus allowing the determination of rations, based on the reports of the actual consumption of fuel and energy resources during the past periods. Interpolation is exploited for characterizing the relation between operating conditions and the amount of energy consumption.

The main goal of this research has been the development of a pilot insight for determining methods and models able to dynamically ration energy consumption. An oil refining process has been used as experimental setup for the creation and validation of modeling approaches. For the specific use case considered, the existing approaches to energy consumption rationing have been analyzed, and new methods based on ML algorithms, were developed and tested. Being data-driven and real-time models, they are able to dynamically recalculate rations of energy consumption while the system and its environment are evolving. This timely adaptation done by models is a source of process optimization.

5.6.3 Materials and Methods

First of all, mathematical formulation of the energy consumption process has been defined according to the following equation:

$$Y = f([X_1^{<in>}(T_1), ..., X_N^{<in>}(T_N)], [X_1^{<out>}(T_{N+1}), ..., X_K^{<out>}(T_{N+K}), \tau, \dot{X}]) + \epsilon(\tau) \quad (5.9)$$

where $X^{<in>}$ are the values of interior industrial process parameters, $X^{<out>}$ are values of the outer parameters, T is the timestamp of the different parameters, τ is current date and time, $\dot{X}$ are parameters not considered in manufacturing, ϵ is measurement noise.

The proposed approach is universal and widely applicable for various objects. Moreover, it is also more flexible respect to other alternatives described earlier. Nonetheless, model development should be done with care and rigorousness in order to reliable when used for very complex systems like the one under analysis, i.e. a oil refining process. Modern oil separation relies on piping crude oil through a sequence of hot furnaces. The resulting liquids and vapors are discharged into distillation units. Final products of the process include diesel fuel, kerosene, gasoline, and other. The refining unit under analysis receives crude oil coming from oil pumping stations, and then separates it into different products thanks to boiling point differences. These products are given to following refining units.

Rationing values were defined using the experimental method, specifically, taking the norm as reference and updating it on a yearly basis, proportionally to actual load of the system. The consequent energy consumption is not optimized, because the accuracy of computed consumption rates, which do not consider any real-time updated parameter, is very low.

Having an adaptive model able to dynamically update rations based on detection of actual consumption deviations from the planned values would strongly improve process management performances. Here comes into play the digital twin, which would be able to provide real-time data about the technological process under analysis, thus enabling the implementation of dynamic rations definition.

It is important to define three variables, y'' is the consumption rations computed based on estimations of parameters, y' is the consumption rations computed based on measured values of the parameters, finally y is the real consumption value. Dynamic rationing models can be fruitful for the calculation of the planned y'' energy consumption rations, thus allowing the comparison of them with the actual values y'.

Factor analysis, a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors, would be exploited for understanding the degree of influence of each parameter on the total difference between planned and actual consumption values. One requisite for the dynamic rationing model in order to be usable at all, is to be interpretable. Specifically, if the degree of influence of each parameter with respect to the energy consumption is known, it would be possible to understand in which measure each parameter is responsible for the deviation detected.

ML and DL models are highly performing only if good quality data is used for training them. Data pre-processing is hence an essential step in model development. To begin with, data collected for one year and a half by the widespread sensors installed on the unit under analysis have been downloaded from the server. This amount of data can be considered appropriate given the fact that during an entire year several behaviors happen. Going deeper into the type of data, there are technological process information (temperatures, pressures, flows, etc.), production data (plant load, quality characteristics), as well as environmental parameters (external temperature, wind directions, etc.). The total fuel consumption was taken as an energy resource for rations modeling. Being a work conducted in collaboration with an oil company which own the data, their practical meaning inside this manuscript has been made anonymous by generically calling the parameters with the label "tag_n" and the targets with "y_m". For the same privacy issue, parameters values have been scaled to the [0,1] interval through min-max scaling.

The energy consumption control and monitoring is performed on hourly averaged values. Therefore, the dynamic rationing model should also be structured in hourly average indicators of energy consumption. However, data from the sources was downloaded with a sampling rate of 1 minute, making it necessary to clean and average values within every hour. Averaging is also beneficial to the possible problems connected to sparse anomalies in the data, which could be caused by functional failures of measuring instruments, breakdowns and production interruptions. Consequently, the Elliptic Envelope algorithm, a high-pass filter, and a moving average filter were applied to achieve the best anomaly detection efficiency. Evident outliers, clearly connected to measurement anomalies, have been effectively leveled up, thus proving the efficiency of the pre-processing performed.

The volume connected to the available data relevant, being 1083 parameters with 780 thousand values each (being measured every minute). The hourly basis aggregation makes the number of values decrease until around ten thousands samples for each parameter. Nevertheless, dimensionality reduction methodologies like Principal Components Analysis are not applicable if we are willing to have an interpretable model. For this reason correlation based methodology has been applied to further reduce dimension of the data: those parameters having Spearman and Pearson correlation with the target variables higher than 0.9 have been removed in order to avoid interference with the modeling phase; those parameters having Spearman and Pearson correlation with the other parameters higher than 0.9 have been removed in order to reduce multicollinearity. After this additional data cleaning, 562 parameters, with almost ten thousands samples each, are available for modeling the target variables.

Turning now to the modeling phase, first of all cleaned data have been split into training and testing sub-sets, respectively composed of data regarding twelve months and two months. One peculiarity of the modeled process is that some parameters can affect power consumption with some delay. To handle such delays, time lag parameters $tag_n^{<}tk >$ have been inserted into the model. By analysing the characteristics of the process, a maximum lag of 8 hours has been set. Going deeper into the kind of models to be implemented, first of all linear regression has been applied. Then, model based on tree boosting, and lastly a one-dimensional Convolutional Neural Network (1D-CNN).

Linear regression is a simple modeling technique, characterised by a high degree of interpretability that can reach very good performances but lacks a strong generalizing capability. It has been used as baseline model, for comparisons with more advanced models trained later on.

For what it concerns modeling based on tree boosting. The idea behind ground on the fact that creating an ensemble of models and finding the final output based on some voting criterion respect to the different predicted output of all the models is better than using one single model. In other worlds, the majority of a group of models is more prone to behave correctly respect to one model alone. Through the Catboost library in Python it has been able to train the model and assess the importance of each feature. The parameters have been used as features, together with their lagged version for caring about the delay effects as previously said.

Lastly, Artificial NN (ANN) have been considered as models to be trained. By adopting an ANN we are lowering the performance respect to the interpretability criterion, but those models proved to be very good at both generalizing and predicting in an extremely wide set of applications. First of all a simple sequential fully-connected NN, for which all the time deltas were flattened into one input layer, has been trained and tested. followed by a 1-D CNN. The convolution is used to convolve time series data with several filters without having the need to a priori define the time lag dependency. Time intervals can be folded and transferred to deeper layers.

Hereafter, results are going to be shown and discussed.

5.6.4 Results and Conclusions

Given that a variety of models have been trained and tested, it is essential to define one or more performance metrics which allow the comparison between different models. The Mean Absolute Percentage Error (MAPE) has been chosen. It is computed according to the following equation:

$$MAPE = \frac{100\%}{n} \times \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \tag{5.10}$$

where n is the number of samples, A_t is the actual value, and F_t is the forecasted value.

In Tab. 5.22 MAPE obtained by the different models during the validation phase and the testing phase are resumed.

Looking at the values, it is evident how much also simple linear models like Linear Regression could perform well, reaching the best MAPE during the validation phase. Nonetheless, the metrics suffers a strong decline during testing, suggesting that its generalizing power is not optimal. This result suggests that linear models could be attempted again if empowered in some ways, for example by adding regularization which should increase testing performances.

Focusing now into the Ensemble Tree CatBoost model, it reached good per-

Model Type	**Model**	**Valid. MAPE (%)**	**Test. MAPE (%)**
Linear	Linear Reg.	1.013	2.422
Ensemble Tree	CatBoost	1.304	1.282
ANN	Perceptron	2.621	2.305
	CNN	1.476	1.503

Table 5.22: Summary of MAPE metric for the models trained, validated and tested.

formances, obtaining both validation and testing MAPE lower than 2%. Moreover, this model is very good for the analysis of deviation cause, given that it computes the significance for each parameter used as predictor.

Lastly, focusing on ANN, the Perceptron did not behave well either during validation or testing. On the other hand, the CNN reached satisfactory results during both validation and testing. Nonetheless, it should be highlighted how much these methodologies are dependent upon the specific architecture defined, hence, Network Architecture Search (NAS) could be applied rigorously for finding better performing CNN versions. Moreover, a lot of parameters - if compared with other Linear and Ensemble models - should be tuned when dealing with Neural Networks, thus suggesting that also having more data at disposal could be beneficial.

Summarising, three types of models, for a total amount of 4 different models, have been adopted for modeling energy rationing based on a wide variety of process parameters measured inside a unit which works in an oil refining plant. Weaknesses and strengths of the models have been deeply analysed, especially with regard to model interpretability, model adaptability, and model performance during validation and testing. Even though results achieved are satisfactory, ways to improve the models already tried have been proposed and will be implemented in the future. Moreover, new families of models, especially those belonging to the wide world of DL, could be tried out (e.g. Long Short-Term Memory network, GRU).

Chapter 6

Discussion and Conclusions

A wide variety of research activities has been presented, analysed and addressed in this manuscript. The technological focus of all of them is IoT and/or AI, which have been addressed using a bottom-up approach: starting from several use cases each focused on specific sub-parts of the whole, a broad comprehension of IoT and AI technological paradigms has been built. The conceptual reference scheme introduced in Chap. 2, and reported hereafter for convenience of the reader, aims at the organization of the broad process that allows to evolve into a smarter society: put in place smart systems, pushed by the technological advance and pulled by societal needs. These systems should be able to collect data from the reality under consideration, eventually transmit, and process these data through advanced analytic, for the final creation of meaningful knowledge and wisdom.

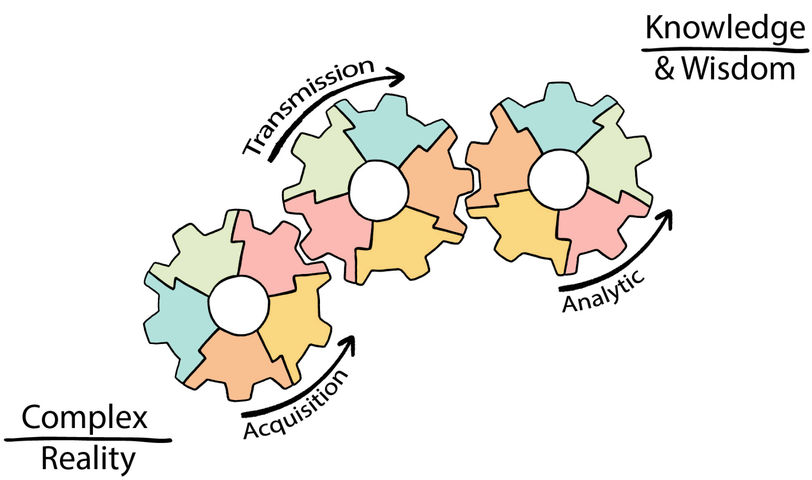


Figure 6.1: Conceptual reference reported from Chap. 2.

Use cases addressed emerged from the collaboration with either the PhD funding company, iGuzzini Illuminazione S.p.A., or by activities planned inside National and International projects where I have been involved. Therefore, the domains of application range from the industrial to the consumer and societal contexts. The output of the researches is directly beneficial for the actors involved and could be usually extended to higher value.

To begin with, I report here the first research question: how can we customize and optimize IoT devices based on specific tasks at hand? Based on the e-Health system and on the IoT device for building monitoring, we can conclude that different domains of application imply very different hardware and software solutions. When dealing with SHM of buildings, high performances for a reasonable price guided the accelerometric sensor selection, and timeliness of data transmission forced to use specific protocols suitable for real-time applications. On the other hand, frailty assessment is less critical with respect to the real-time, thus implying a different system architecture.

How communication protocols and networks should evolve in order to meet requirements of next generation IoT and Web of Things? The cross-protocol proxy is an example of useful solutions in the realm of IoT. Being a context which grew rapidly, several communication protocols emerged, thus making compatibility-solutions, like the proposed cross-protocol, essential for allowing non-experts deal with IoT solutions, and for making these IoT solutions really inter-operable in view of home and work environments permeated by a wide variety of different devices.

Which smart analytic, technologies and systems are suitable for dealing with complex and previously unsolvable tasks? CV and MV proved to be very versatile and reliable solutions, able to deal with very complex tasks, like counting manually moved pieces (a context where traditional light barriers failed), or computing the water level through images of river's gauges.

How can the maintenance of industrial equipment be optimized through advanced technologies and analytic? A lot of effort has been done in this direction. It is important to highlight that each context of use has its own peculiarities, which require an in-depth comprehension for setting up a PdM solution. Sensors selection, data collection campaigns, and analytic creation each have their own complexities. By delving into several use cases, a broad understanding of most relevant criticalities in the realm of PdM has been gained.

Are ML and DL techniques able to support in managing extremely complex situations? The answer, as expected, is yes. Several domains are characterised by model and experts-based modeling, which could be very performing, but still it is usually expensive and completely lacks adaptability and versatility. A dynamic energy rationing data-driven model, which exploits DL and ML algorithms, proved to reach satisfactory performances with very little effort, if compared to the same solution developed by domain experts through experiments. Moreover, even in case of system changes, by iterating the training phase a new ad-hoc model could be quickly developed.

Can innovative systems be sustainable enough for the future of industry and society? All research activities addressed this question in some ways. E-Health solutions enormously improve sustainability of the healthcare system. By having critical buildings monitored automatically in real-time, maintenance and repair actions could be optimized, thus improving citizens' security and reducing costs respect to the system in place, which usually grounds on preventive maintenance, hence, does not guarantee security neither lower cost. Through innovative solutions able to deal with complex situations inside manufacturing environments, digital twins of production systems can be created, with all the positive effects in terms of production optimization. Being able to maintain manufacturing assets only when needed, is a huge source of sustainability from the economic and environmental point of view, as the useful life of the components is fully utilized. Not-value adding activities, like assessing the water-level of rivers, can be managed in a reliable way through innovative systems. Energy related tasks can be addressed efficiently through data-driven methodologies, which allows better results and imply less model development costs. Nonetheless, particular care should be given to the fact that data collection, transmission, storage and modeling are not cost-less.

Therefore, as a general take-away, the wide variety of cases addressed and the results achieved, suggests that edge-AI, also called tiny-ML or edge-intelligence is the key for successful achievement of S5.0. By putting diffused intelligence at the edge, data intensive solutions become feasible, sustainable, and reliable (respect to their cloud implementation where heavy transmission of data is required). Moreover, the real-time capability, autonomy, security, data quality and privacy are also improved thanks to edge computing and in-network computing. This concluding reflection, should be carefully taken in mind for the prosecution of research activity.

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