Automation and information approaches to support maintenance and production management in the construction industry

Published version
Politecnico di Bari
DOI:10.60576/poliba/iris/parisi-fabio_phd2023

Department of Electrical and Information Engineering
ELECTRICAL AND INFORMATION ENGINEERING
Ph.D. Program
SSD: ING-INF/04–System and Control Engineering

Final Dissertation

Automation and Information Approaches to Support Maintenance and Production Management in the Construction Industry

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Course n°35, 01/11/2019-31/10/2022

LIBERATORIA PER L'ARCHIVIAZIONE DELLA TESI DI DOTTORATO

Al Magnifico Rettore
del Politecnico di Bari

Il sottoscritto PARISI FABIO nato a BITONTO (BA) il 03/02/1988

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ed essendo stato ammesso a sostenere l'esame finale con la prevista discussione della tesi dal titolo: AUTOMATION AND INFORMATION APPROACHES TO SUPPORT MAINTENANCE AND PRODUCTION MANAGEMENT IN CONSTRUCTION INDUSTRY

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To my wife Margherita’s heart, brain and arms, because she is the only one that made this possible.

To my parents and family, colossal foundations during battles and safe bay during storms.

To my friends, relief valve from rationality.

Acknowledgements

I would like to acknowledge the numerous people that encouraged me to study this topic and write down this thesis.

My supervisors and the LCA research team at Politecnico di Bari for the precious theoretical and practical support in this work. In particular, my acknowledgements go to Professor Maria Pia Fanti and Professor Agostino Mangini for their never-ending effort in improving to the best of all our results; to the LCA team, senior and junior members, that always shared bright and dark moments with me.

I am extremely grateful to my supervisor Professor José Adam and the ICITECH research team at the Universitat Politècnica de València, for the opportunity to experience strong academic and personal bonds and relations.

My gratitude goes to my second family, the Fablab Bitonto and Fablab Poliba, where inevitably this journey began and where my heart persistently remains.

Abstract

The construction industry is a wide industrial sector ranging from the design and management of major infrastructures, such as bridges, to civil dwelling construction. It is worldwide acknowledged as a fundamental driving sector for the Gross Domestic Product, but it is also among the less performing and delayed ones in the adoption and exploitation of technological improvements. These limitations are inducing stakeholders to borrow and integrate many enhancements from other industrial fields into the sector. This digitalization trend is spreading through the entire life cycle of the construction process and identifying a challenging approach because of the paradigm shift needed from physical to cyber-physical systems. The *Industry 4.0* concept boosted this trend so that both in the academy and in the construction industry it has been specified as *Construction 4.0*. It borrows from the *Industry 4.0* the adoption of many key enabling technologies such as Internet of Things, Artificial Intelligence and Additive Manufacturing. This thesis investigates specifically this technological integration, focusing on the application of such enabling technologies in the construction field and considering different stages in the life cycle in varying infrastructure typologies. Starting from a literature investigation on "holistic" intelligent systems in Intelligent Buildings construction, in a Digital Twin fashion, the influence and the application of enabling technologies and related operative ICT tools such as Internet of Things and Big Data are studied, from a perspective of the whole constructions' life cycle. The maintenance phase of major infrastructures is studied concerning structural safety and fault detection, by developing a method to detect damages in railway steel truss bridges via artificial intelligence. An innovative additive manufacturing technology for high-rise constructions is then presented. It consists of an improvement with a custom extruder of standard tower crane technology, while the whole system is driven by an artificial intelligence agent.

We conclude that Construction 4.0 is still at its embryonic stage. More advanced results are obtainable for the operation and maintenance management of existing

infrastructures because of the already mature approach related to sensorization and data analysis. Innovation in the design/construction phase remains more challenging, because of the need for a completely new paradigm and industrial innovations in many different fields.

* * *

L’industria delle costruzioni è un vasto settore produttivo che spazia dalla progettazione e gestione di grandi infrastrutture come i ponti fino alla costruzione di civili abitazioni. È riconosciuto a livello mondiale come un settore trainante fondamentale che concorre al Prodotto Interno Lordo, ma è anche tra quelli meno performanti e restii all’adozione ed allo sfruttamento delle innovazioni tecnologiche.

Queste limitazioni stanno inducendo gli stakeholder coinvolti a mutuare nel settore molti miglioramenti riscontrabili in altri ambiti industriali. Questa attività di trasferimento si sostanzia principalmente in una tendenza alla digitalizzazione, si applica all’intero ciclo di vita del processo di costruzione e rappresenta una grande sfida a causa del necessario cambio di paradigma nel passaggio dai sistemi fisici a quelli cyber-fisici. Il concetto di *Industria 4.0* ha dato impulso a questa tendenza tanto che il termine specifico di un termine specifico di *Costruzione 4.0* è stato adottato sia nell’accademia che nell’industria. Questo concetto prende in prestito dall’ Industria 4.0 l’adozione di molte tecnologie abilitanti come l’Internet of Things, l’Intelligenza Artificiale e la manifattura additiva. Questa tesi indaga in modo specifico questa integrazione tecnologica, concentrandosi sull’applicazione di tali tecnologie abilitanti nel campo delle costruzioni e considerando le diverse fasi del ciclo di vita in diverse tipologie di infrastrutture. Partendo da un’indagine di letteratura sui sistemi intelligenti "olistici" nella costruzione di edifici intelligenti, in chiave Digital Twin, sono studiate l’influenza e l’applicazione delle tecnologie abilitanti e dei relativi strumenti operativi ICT come Internet of Things e Big Data dalla prospettiva dell’intero ciclo di vita delle costruzioni. Si approfondisce la sicurezza strutturale e del rilevamento dei guasti nella fase di manutenzione delle grandi infrastrutture, sviluppando un metodo per rilevare i danni nei ponti ferroviari a traliccio tramite l’intelligenza artificiale. È quindi presentata un’innovativa tecnologia di produzione additiva per manufatti di grandi dimensioni: la tecnologia standard delle gru a torre è integrata con un estrusore custom, mentre l’intero sistema è guidato da un agente intelligente.

È possibile concludere che la Costruzione 4.0 è ancora al suo stadio embrionale. I risultati più avanzati sono ottenibili sulle infrastrutture esistenti in fase di gestione della manutenzione grazie alla relativa semplicità della sensorizzazione e alla conseguente analisi dei dati. L'innovazione nella fase integrata di progettazione/costruzione rimane invece più sfidante, per la necessità sia di un paradigma completamente nuovo che di innovazioni tecnologiche in diversi campi industriali.

* * *

La industria de la construcción es un amplio sector industrial que abarca desde el diseño y la gestión de grandes infraestructuras como puentes hasta la construcción de viviendas civiles. Es mundialmente reconocido como un sector impulsor fundamental del Producto Interno Bruto, pero también se encuentra entre los de menor rendimiento y retraso en la adopción y explotación de mejoras tecnológicas. Estas limitaciones están induciendo a las partes interesadas a tomar prestadas e integrar muchas mejoras de otros campos industriales en el sector. Esta tendencia de digitalización se está extendiendo a lo largo de todo el ciclo de vida del proceso de construcción e identifica un enfoque desafiante debido al cambio de paradigma necesario de los sistemas físicos a los ciberfísicos. El concepto *Industria 4.0* impulsó esta tendencia por lo que tanto en la academia como en la industria de la construcción se ha concretado como *Construcción 4.0*. Toma prestada de la *Industria 4.0* la adopción de muchas tecnologías habilitadoras clave como Internet de las Cosas, Inteligencia Artificial y Fabricación Aditiva. Esta tesis investiga específicamente esta integración tecnológica, centrándose en la aplicación de tales tecnologías habilitadoras en el campo de la construcción y considerando diferentes etapas en el ciclo de vida en diferentes tipologías de infraestructura. A partir de una investigación bibliográfica sobre sistemas inteligentes "holísticos" en la construcción de Edificios Inteligentes, a la manera de Gemelos Digitales, se estudia la influencia y la aplicación de tecnologías habilitadoras y herramientas TIC operativas relacionadas, como Internet de las Cosas y Big Data, desde una perspectiva de todo el ciclo de vida de las construcciones. Se estudia la fase de mantenimiento de grandes infraestructuras en materia de seguridad estructural y detección de fallos, mediante el desarrollo de un método de detección de daños en puentes ferroviarios de celosía metálica mediante inteligencia artificial. Luego se presenta una innovadora tecnología de fabricación aditiva para construcciones de gran altura. Consiste en una mejora de la tecnología de las grúas torre estándar con una extrusora personalizada, mientras que todo el sistema está controlado por un agente de inteligencia artificial.

Concluimos que la Construcción 4.0 aún se encuentra en su etapa embrionaria. Se pueden obtener resultados más avanzados en la implantación tecnológica sobre infraestructuras existentes para su gestión de operación y mantenimiento debido al enfoque relacionado principalmente con la sensorización y análisis de datos. La innovación en la fase integrada de diseño/construcción sigue siendo más desafiante, debido a la necesidad de un paradigma completamente nuevo e innovaciones industriales en muchos campos diferentes.

* * *

La indústria de la construcció és un ampli sector industrial que abasta des del disseny i la gestió de grans infraestructures com a ponts fins a la construcció d'habitatges civils. És mundialment reconegut com un sector impulsor fonamental del Producte Intern Brut, però també es troba entre els de menor rendiment i retard en l'adopció i explotació de millores tecnològiques. Aquestes limitacions estan induint a les parts interessades a amprar i integrar moltes millores d'altres camps industrials en el sector. Aquesta tendència de digitalització s'està estenent al llarg de tot el cicle de vida del procés de construcció i identifica un enfocament desafiador a causa del canvi de paradigma necessari dels sistemes físics als ciberfísics. El concepte Indústria 4.0 va impulsar aquesta tendència pel que tant en l'acadèmia com en la indústria de la construcció s'ha concretat com a Construcció 4.0. Ampra de la Indústria 4.0 l'adopció de moltes tecnologies habilitants clau com a Internet de les Coses, Intel·ligència Artificial i Fabricació Additiva. Aquesta tesi investiga específicament aquesta integració tecnològica, centrant-se en l'aplicació de tals tecnologies habilitants en el camp de la construcció i considerant diferents etapes en el cicle de vida en diferents tipologies d'infraestructura. A partir d'una investigació bibliogràfica sobre sistemes intel·ligents "holístics" en la construcció d'Edificis Intel·ligents, a la manera de Bessons Digitals, s'estudia la influència i l'aplicació de tecnologies habilitants i eines TIC operatives relacionades, com a Internet de les coses i Big Data, des d'una perspectiva de tot el cicle de vida de les construccions. S'estudia la fase de manteniment de grans infraestructures en matèria de seguretat estructural i detecció de fallades, mitjançant el desenvolupament d'un mètode de detecció de danys en ponts ferroviaris de gelosia metàl·lica mitjançant intel·ligència artificial. Després es presenta una innovadora tecnologia de fabricació additiva per a construccions de gran altura. Consisteix en una millora de la tecnologia de les grues torre estàndard amb una extrusora personalitzada, mentre que tot el sistema està controlat per un agent d'intel·ligència artificial.

Concloem que la Construcció 4.0 encara es troba en la seua etapa embrionària. Es poden obtindre resultats més avançats en la implantació tecnològica sobre infraestructures existents per a la seua gestió d'operació i manteniment degut a l'enfocament relacionat principalment amb la sensorització i anàlisi de dades. La innovació en la fase integrada de disseny/construcció continua sent més desafiadora, a causa de la necessitat d'un paradigma completament nou i innovacions industrials en molts camps diferents.

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Chapter 1

Introduction: Construction 4.0

The term Industry 4.0 first appeared at Hannover Messe in 2011 during one of professor Professor Wolfgang Wahlster's speechs, the Director and CEO of the German Research Center for Artificial Intelligence. It was then introduced in [1] and both the academy and the industry started to provide huge effort in investigating its potential application in numerous research fields. Some foundation concepts such as the vision, the basic technologies, the idea aims as well as some selected scenarios were initially described by the key promoters of the idea, the "Industry 4.0 Working Group" and the "Platform Industry 4.0" [1]. At the base of this new industrial paradigm there was the concept of Cyber-Physical Systems enhanced by Internet of Things, in which the digital and physical worlds were strongly bound and put in communication. It was originally expected that industry, market and economy would have been affected by production processes and product lifecycle improved, productivity increased, new business models created and work environment with labour marked completely renewed and restructured [2]. The expert estimated considerable effects on social life after its conceptualization. In a report prepared by the World Economic Forum [3] eight hundred experts outlined recommendations and findings regarding the digital transformation. If the increase in the number of robots was predicted up to 2.4 million by 2018, on the other hand, technologies and applications such as wearable electronics, machine-to-machine communication, intelligent systems and learning machines assumed a realistic perspective of feasibility. Additive manufacturing started to gain more interest due both to its widespread diffusion and the high-specialized tasks in which it was involved, such as metal of biological 3d printing. 1 trillion sensors were expected to be used in human life by

2025. The related technologies were supposed to enable Smart cities' progression and spread with at a high speed all over the world. Global spending on big data was assumed to be well over 200 billion dollars in 2020. By 2020 %59 US manufacturers were predicted to be using some sort of robotics technology [3].

Despite the huge potential predicted, the actual implementation and adoption of Industry 4.0 technology in supporting the digital transformation of European industry are far from the previsions. In [4] authors state that *Despite extensive discussion on the potential impact of AI and robots, there is almost no systematic empirical evidence on their economic effects*; for Artificial Intelligence, Machine Learning and smart robots that *there is still a gap between the expectation and implementation possibly due to lack of adequate Technology Readiness Levels (i.e. the level of applicability of the technology) and of the investments required*, that *European companies need to invest around €1.35 trillion into Industry 4.0 over the next 15 years*; they conclude that *in general, there is still little awareness about Industry 4.0 outside a key group of stakeholders*. In conclusion, the paradigm is substantially far from being completely exploited and investigated and its economic potential.

Industry 4.0 has gained much interest also in the construction industry, even if it is globally acknowledged to be resistant to technology improvement and generally delayed in the adoption of upgrades [5]. Despite its resistance to changes, Information and Communication Technologies (ICT) deeply pervaded the industry after the advent of the Industry 4.0 framework [6].

If in [7] the EU refers to the digitization of the construction economic sector as "Smart Construction", in the academic literature the concept of Industry 4.0 is usually specified as Construction 4.0, even if there is no wide acceptance of its specific meaning [6]. Some authors state that Construction 4.0 instantiates the Industry 4.0 concept in the construction industry [8] [9], while others state that "*the industry specific definition of Industry 4.0 for construction comprises a wide range of interdisciplinary technologies and concepts which enables the digitisation, automation and integration of the construction process at different stages"* [10].

There are many studies in literature translating concepts from Industry 4.0 to Construction 4.0 and investigating Construction 4.0-involved technologies. To summarize the main concepts, it is possible to refer to many review papers already present in the literature, and Tab.1.1 summarizes the technologies according to different researches. In particular, the first column highlights Industry 4.0 technology listed in eminent literature studies, while the second reports the Construction 4.0 technologies resulting from academic review papers also employing content analysis.

Table 1.1 Industry 4.0 and Construction 4.0-related technologies.

Industry 4.0 technologies [11] [12] [13]	Construction 4.0 technologies [10] [6]
Cyber-physical systems (CPS)	Cyber-Physical Systems (CPS)/Embedded systems
	Human-Computer-Interaction
Cloud systems	Cloud Computing
	Mobile Computing
Machine to machine (M2M) communication	Product-Lifecycle-Management (PLM)
Smart factories	Robotics
Augmented reality and simulation	Virtual, Augmented and Mixed Reality
Big Data/Big Data analytics	Big Data
Internet Of things	Internet of Things
	Radio-Frequency Identification (RFID)
Enterprise resource planning (ERP) and business intelligence	
Virtual Manufacturing/Computer-Aided Design and Manufacturing (CAD/CAM)	Building Information Modelling
	Smart Factory
	Modularisation
Intelligent robotics	Robotics
Additive Manufacturing	3D Printing / Additive Manufacturing
Artificial Intelligence	Artificial Intelligence

A useful indicator of the interest gained by the different technologies is the numerosity of the investigation in the literature. To this aim, Fig.1.1 and Fig.1.2 show the results of a content analysis of review papers performed by following the methodology in [14] and [5]: research strings such as "Industry 4.0 construction review", "industry 4.0 construction survey" and "Construction 4.0 review" have been searched in major databases such as ScienceDirect, Emerald, Taylor& Francis, Wiley, ASCE, IEEEXplore. Fig.1.1 and Fig.1.2 highlight technologies consistent with Tab.1.1, but also show the occurrence of concepts in the literature.

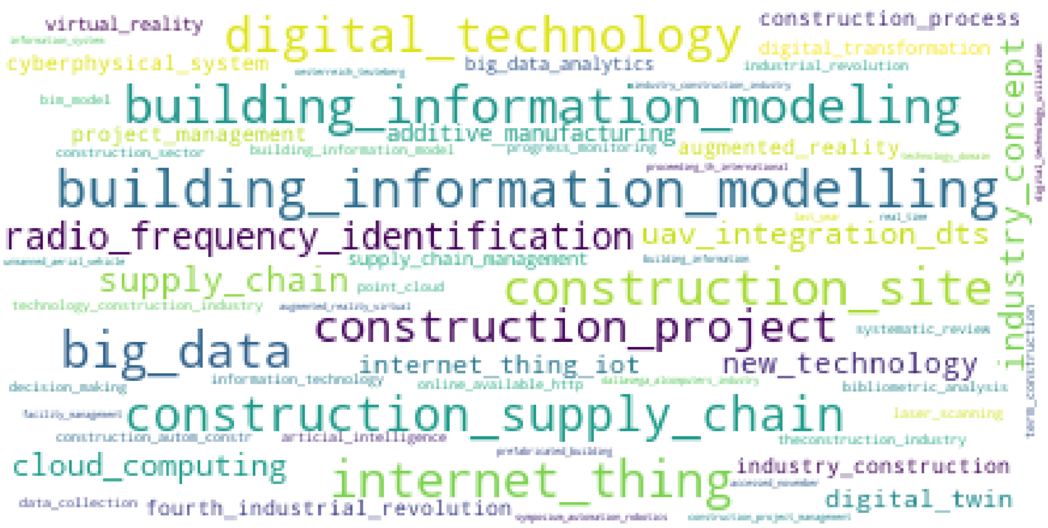


Figure 1.1 Wordcloud with bi-grams and tri-grams in related review papers

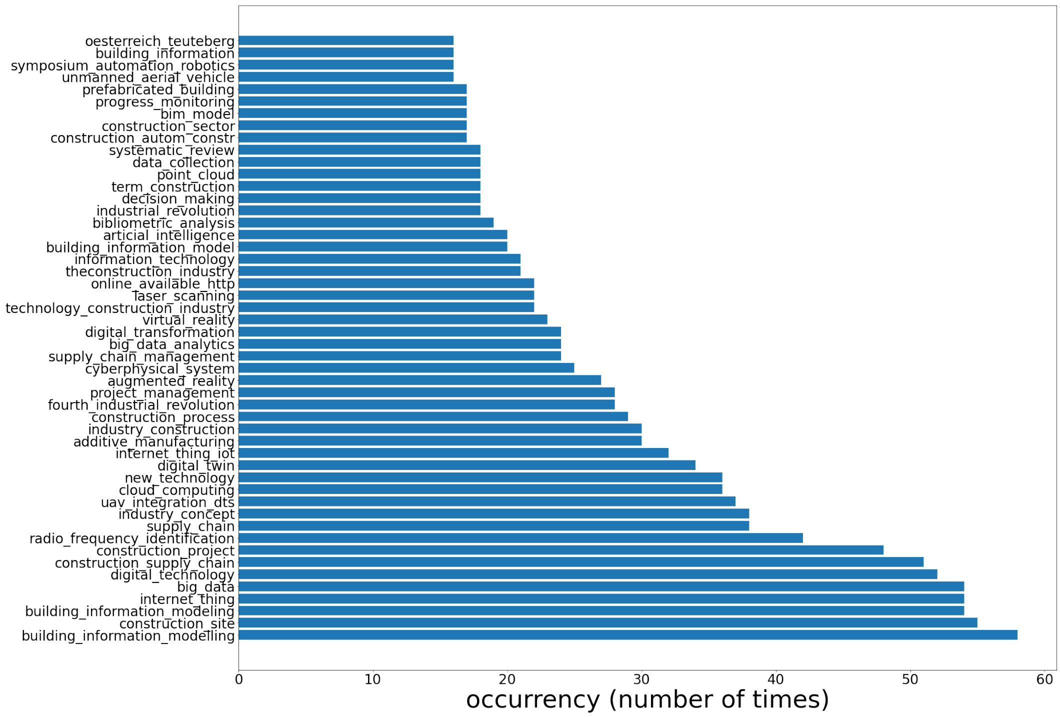


Figure 1.2 Bi-grams and tri-grams occurrency in related review papers

The results in Fig.1.1 and Fig.1.2 are also consistent with [6], in which authors analyse the evolution of enabling technologies' occurrences in the related academic literature with a systematic review. The result is that Big Data (and thus Artificial

Intelligence), Internet of Things, 3d printing and additive manufacturing show an increasing interest in the research, while the role played by BIM and simulation technologies is prominent above all the technologies.

It is widely acknowledged that the construction industry plays a major role in the economy, which can be addressed by analysing investments amount and contributions to the GDP of countries. The EU represents an important player in the construction industry, in which Germany, France, United Kingdom, Italy and Spain are the major actors: from 2014 to 2016, the total construction investment raised from 1.37 [15] to 1.43 trillion euros [16]. Despite the huge impact on the GDP of countries, the investments in research and developments (R& D) result still limited. According to [17], in which authors ranked industry sectors by their research and development intensity, the construction industry appears in a low position, with less than 1% of net sales.

The actual implementation of Construction 4.0 and, thus, its related technologies, is still at its early stage and there are many reasons for this lag with other industries. As reported in [10], the construction industry has to face many challenges to reach an acceptable implementation of Construction 4.0: hesitation to adoption, high implementation cost, organisational and process changes, need for enhanced skills, knowledge management, acceptance, lack of standards and reference architectures, higher requirements for computing equipment, data security and data protection, enhancement of existing communication networks, regulatory compliance, and legal and contractual uncertainty.

This perspective justifies the attempt to enlarge the investigation in Construction 4.0 and to further study possible applications and approaches exploiting technologies resulting from literature and industry state of the art.

1.1 Research Problems

In recent years, the construction industry has undergone numerous attempts to digitize and innovate the built environment life cycle management with tools and strategies borrowed from other industrial fields.

Urban buildings (such as residential and commercial ones) play a central role in terms of numerosity and global energy employed during the life cycle management

[18]. Despite such importance, the life cycle management process is still conducted with anachronistic approaches featuring poor automation and real-time control of the construction process relation, poor inter-relation between automated construction and constructions technologies, poor data collection of the whole construction system during its operative condition and consequent comparison with the estimated behaviour during the design phase, no formalization of the knowledge extractable from the whole built environment and no consequent reuse [5].

On the other hand, major strategic infrastructures (such as bridges) are of great importance because of their role in the social and economic development of countries. If the design and construction phase is affected by the same issues highlighted for civil constructions and can benefit from modern designing tools, the already built ones are approaching their estimated end of life so a safety issue is rising all over Europe [19]. Innovative strategies and technologies could still improve the prevention and early damage detection capability of state-of-the-art monitoring systems.

To face the limitations highlighted, there is a further need to integrate innovative approaches and strategies from other industrial fields into the construction industry. The knowledge gaps presented are discussed and investigated in this document.

1.2 Research Objectives

The research proposed aims at investigating solutions to fill the gaps described in Section 1.1, and thus develop further innovative strategies to improve the built environment life cycle management. In particular, it is proposed to integrate the control theory approach, robotics and artificial intelligence, at the base of the system and control engineering, into the construction process, both to already existing constructions and not.

The general objectives of the thesis are further specified in the following specific objectives:

1. the investigation on the most eligible Industry 4.0 technologies for the construction industry:
    - state of the art and analysis of their applications both in the industry and academic research field;

- identification of the specific gap and the main development directions.

2. The application of artificial intelligence (AI) and machine learning (ML) to the control and management of the built environment: structural health monitoring featured by sensors analysis with ML algorithms.

3. Robotics technologies as improvement in the life-cycle construction phase: design and application of innovative additive manufacturing technologies for the construction scale.

1.3 Thesis Outlines

This work investigates Construction 4.0 by contributing to the exploitation of many of the related technologies reported in the literature. It consists of published and submitted research articles constituting the attempt to fill some gaps in the state of the art, contributing to the conceptualization of technologies and monitoring strategies and methodologies. In particular:

- In Chapter 2 introduction notions related to the investigated Construction 4.0 technologies are presented. Big Data and Internet of Things are briefly discussed in relation to their practical applications and their main operative tools such as specific technologies. Then, supervised learning and reinforcement learning paradigms in artificial intelligence are introduced, with a focus on deep learning basic concepts. In conclusion, additive manufacturing and its information flow in the construction industry are described.

- In Chapter 3, Big Data, semantic technologies and Internet of Things integrations into BIM environment are studied in relation to Intelligent Buildings. The literature is reviewed researching for integration approaches of these technologies, and the specific tools involved are investigated. The aim is the analysis of the state of the art of intelligent systems supporting intelligent buildings in the whole lifecycle, the identification of the main approaches, the specification of technologies used, and the statement of future directions for its implementation.

- In Chapter 4, artificial intelligence integrated with simulation strategies is used to develop a methodology for fault detection of structural systems. In particular, strain signals from a railway bridge damaged in different portions are collected through a series of simulations. Without any feature extraction, the signals are used to train a Convolutional Neural Network classifier able to assess both the location and the severity of the damages.

- In Chapter 5, an artificial intelligence-based control methodology is investigated and applied to additive manufacturing at the construction scale and the conceptualization of a novel additive manufacturing technology is provided. A tower crane is equipped with an aeropendulum extruder featured with propellers controlled to stabilize the swinging effect. The whole system is controlled by a Deep Reinforcement Learning controller that aims at minimizing the extruder swing effect and at maximizing the speed on the trajectory describing the geometry to 3D print.
- In Chapter 6 the global results of the investigations are presented, highlighting novelties, limitations and future works.
- Chapter 7 summarizes the conclusions of the work.

Chapter 2

Construction 4.0 technologies

2.1 Introduction

In this section, the research methodology and the main 4.0-related technologies investigated in the thesis are introduced. Starting from the investigation on Intelligent Buildings, technologies such as BIM, Big Data, Internet Of Things and Semantic web are first contextualized. Artificial Intelligence is then described in its basic concepts, by presenting two different paradigms: supervised learning and reinforcement learning. Some particular examples of algorithms of interest belonging to these classes are elaborated on. In conclusion, basic concepts regarding the information flow in additive manufacturing and main features that characterize its use in the construction industry are presented.

2.2 Methodology

Objective (1) in Section 1.2 is investigated with a literature review of the state of the art in the application of Industry 4.0 technologies to the construction industry. Since the wideness of the topic, the review phase uses automated text retrieval procedures and natural language processing tools to extract resuming statistics from the analysed literature. This analysis is then used to conform a framework to analyze the searched papers which are then studied in terms of technological operative tools employed in the development of the strategies proposed.

Objective (2) is pursued by studying the application of machine learning and artificial intelligence algorithms to support built environment management in the operational phase. Coherently with the research motivation highlighted in Section 1.1, the case of the damage detection of a major strategic infrastructure such as a bridge is considered. In particular, Deep Learning is used to analyze sensor data from structures to propose an innovative strategy for structural health monitoring. Finite elements analyses are used to collect feasible data representative of the damaged conditions of the bridge studied: due to the large amount of data required, automated finite element analyses are performed by ad hoc routines. Commercial software is used in order to verify the usage of the methodology also outside of the academy.

Objective (3) is pursued by investigating robotics applications in the design and construction life cycle phase of constructions and an innovative conceptualization of additive manufacturing technologies is proposed. The robotised production processes and the dynamic behaviour of the machines are mathematically modelled and simulated in a software environment. An intelligent agent exploits the deep reinforcement learning paradigm and is then trained to control the machines while fulfilling accuracy requirements for the additive manufacturing procedure. The trained agent and the machine behaviour are then validated and the tolerance reached is assessed.

2.3 ICT Technologies

The evolution of software towards systems integrating artificial intelligence-powered capabilities is enhancing their capability and their technological developments. In the specific, their needs for data, communication and processing are highly increasing. In the construction industry, Building Information Modeling (BIM) software are considered the state-of-the-art environment to upgrade by these ICT-enhanced capabilities [5]. The National Building Information Model Standard [20] defines BIMs as a *"digital representation of physical and functional characteristics of a facility. As such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle from inception onward."* In this case, BIM technology has a wide perspective of usage, and does not focus only on the first stages of the building process (design and construction phases), but has a key role also in the management stage.

BIM is a massive source of information about the construction process during the life cycle since it allows the collection of data and information regarding geometric description, material composition, but also procedural information for the construction process. In a cloud-based architecture, BIM can acquire data also from remote sources and repositories such as weather data, Geographical Information Systems data and seismic data, as well as from Internet of Things (IoT) infrastructure. Semantic and ontology technologies (ST) can offer strong support for formalizing and reusing acquired knowledge about life-cycle processes. Moreover, big data (BD) infrastructure is improving its support for ST, which is also playing a relevant role in IoT-driven data semantic enrichment and in BIM platform exchange information capabilities. Such a perspective induces to investigate and highlight the noticeable features regarding BD, Iot and ST in the following sections.

2.3.1 Big Data

The introduction of the BD concept is related to the continuous generation of large data volumes, of different typologies and format, at unprecedented rate [21], and these multi-source data are considered effective information sources for knowledge extraction. [22] presented the *HACE theorem* to describe BD features and the consequent challenge to extract consistently knowledge from it: *BD starts with large-volume, heterogeneous, autonomous sources with distributed and decentralized control, and seeks to explore complex and evolving relationships among data*. Another important model was also specified in the Doug Laney 3V model [23], in which BD features many specific characteristics such as "Volume", i.e., huge data size, "Velocity", i.e., data speed of generation and "Variety", i.e., different formats. A further feature like "Veracity" considers the authenticity and trustworthiness, and "Value" is the *"added-value that the collected data can bring to the intended process"* [24]. The greatest BD-related limitation specified in the literature and industry is the unsuitability of most of the standard data analytics for knowledge extraction with these data [25].
BD analytics involves the processes of searching a database, mining, and analyzing data, also in real-time [26]. More precisely, different BD analytics can be applied according to the time requirements:

- Streaming or Real-time analytics is performed on data collected from continuous streams (such as sensors). Due to memory constraints, small data portions of the stream are stored and examined to determine potential knowledge from the approximated patterns. Some examples of platforms supporting streaming analytics [27] are Spark [28], Storm [29], and Kafka [30].

- Batch/off-line analytics is used when a real-time response is not required [31], and differently from real-time data analytics, it analyzes data after storing. MapReduce is the most widely used batch processing method [32] and Hadoop [33], Kafka [30] and Chukwa [34] are examples of off-line analytics architectures [26].

- Hybrid computation [35] where the combination of batch and real-time processing is required. This approach is described as Lambda Architecture [36], and consists of the combination of queried batch and real-time data.

In Fig.2.1 BD analytics paradigms are represented. In case of batch processing BD analytics, a standard pipeline consists of : i) a data acquisition phase, ii) a data storage phase, iii) a data analysis phase and iv) a data exploitation phase. Differently, in the case of real-time analytics the pipeline can consist of different phases [37]: i) an ingestion stage, that buffers and optionally pre-process data streams before they are consumed by the analytics application; ii) a storage phase, where typically pre-processed and buffered data directly from the ingestion stage or from the processing stage are stored; iii) a processing stage, that analyses data from the ingestion stage.

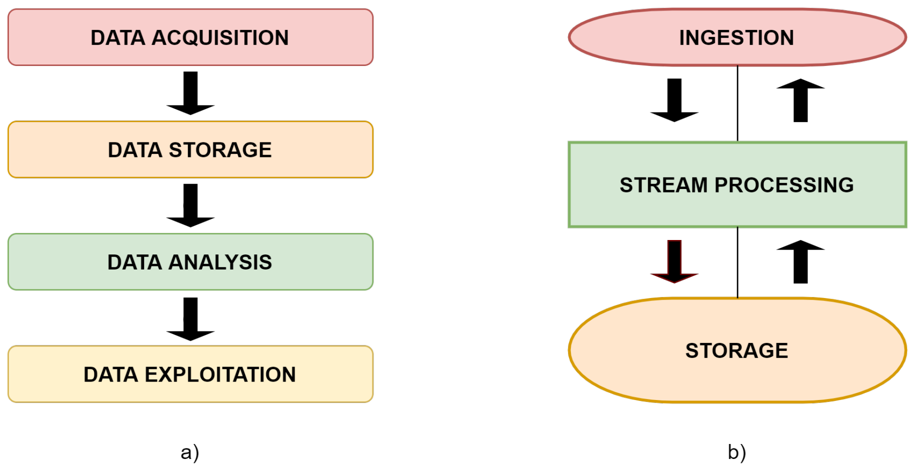


Figure 2.1 BD analytics pipelines: a) batch [35] and b) real-time [37].

BD analytics capabilities are enhanced by the technological stacks composed of different layers. If we consider a generic stack as in Fig.2.2, the layers highlighted can be specified by common technologies used in academy and industry [38][35].

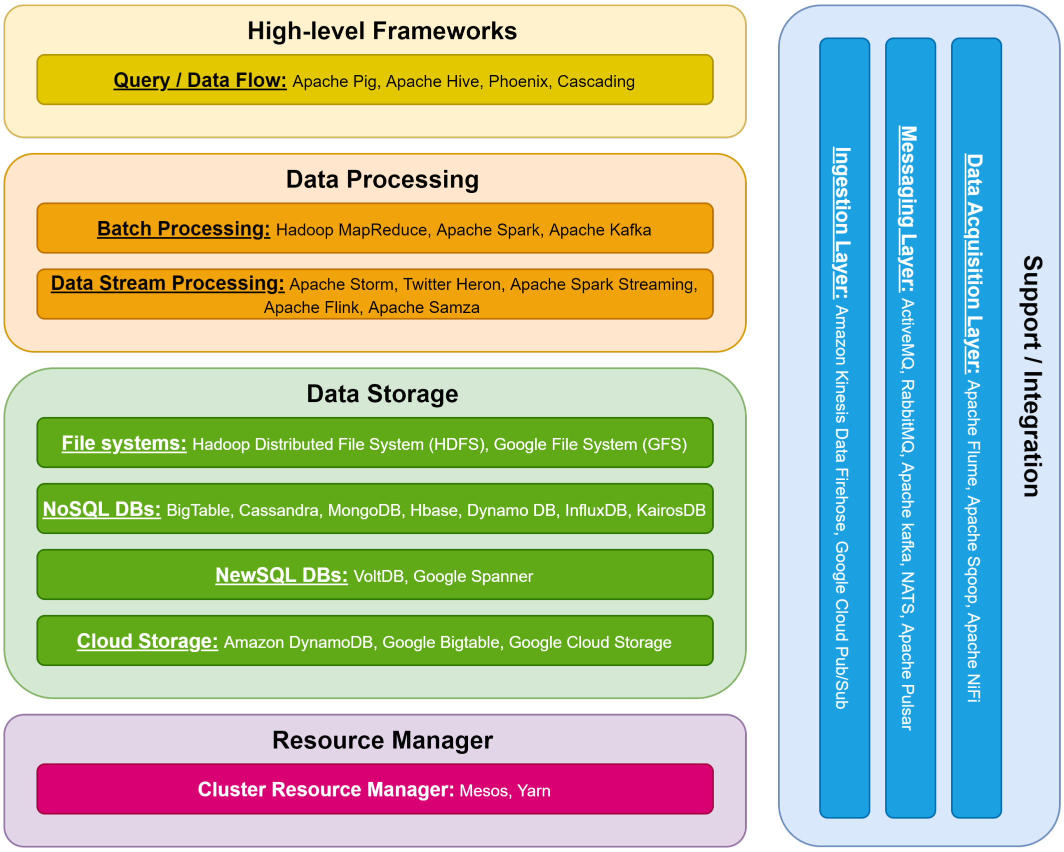


Figure 2.2 Generic BD stack [38] and related examples of technology used [38][35]. The list of technologies is not meant to be exhaustive.

Currently, there is no generic standard architecture available for analytical BD systems [39]. The most used, depending on the different analytics types mentioned before, are [27] [40]:

- *Apache Hadoop* is a framework consisting in a collection of libraries dedicated to all tasks involved in big data analytics.
- *Apache Spark* is a general-purpose open-source distributed cluster-computing framework, supporting both stream data processing and batch processing.

- *Apache Storm* allows to build real-time, highly scalable, low latency distributed processing systems.
- *Apache Kafka* is defined as a distributed streaming platform, characterized by the three key capabilities of publish and subscribe streams of records, the storing in fault-tolerant durable way of streams of records and the processing of these streams of records.
- *Apache Flink* is a framework and distributed processing engine for stateful computations over unbounded and bounded data streams. Flink allows both stream and batch processing, state management, event-time processing semantics, and consistency guarantees for state.

2.3.2 Internet of Things and enabling technologies

There isn't a single accepted definition of Internet Of Things [41]. As reported in [42], *"the semantic origin of the expression is composed of two words and concepts: Internet and Thing, where Internet can be defined as the world-wide network of interconnected computer networks, based on standard communication protocol, the Internet suite (TCP/IP), while Thing is an object not precisely identifiable. Therefore semantically, Internet of Things means the worldwide network of interconnected objects uniquely addressable, based on standard communication protocols"*. There are numerous IoT applications that can be grouped into various domains such as health, traffic, logistics, retail, agriculture, smart cities, smart metering, remote monitoring, process automation. IoT is an umbrella concept covering many different research and industrial fields, and can be specified by considering its influence in the real implementation of cyber-physical systems. Common architectures to develop cloud-based intelligent computing systems implements the following layers (Fig.2.3):

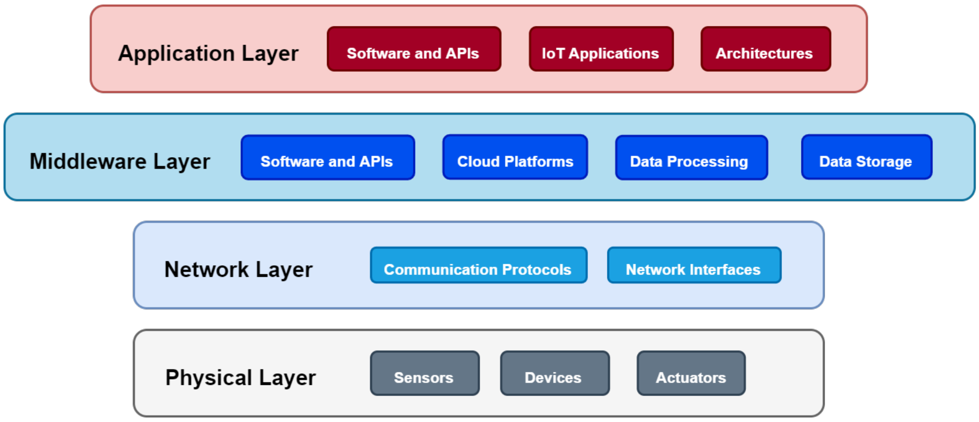


Figure 2.3 IoT architecture layers [43] [44]

- *Physical layer*: IoT sensors and devices aiming at collecting data from the environment. This sensing layer is devoted to the implementation of the connections between the physical and the digital world [45], in both directions: data are collected from the physical word, but the systems can also act on it by actuators.

- *Network layer*: the configuration of the network infrastructure for data transmission. In particular, data can flow both from and to the sensing/physical layer. Important requirements regard communication and security issues, and the main components of this layer consist of communication technical specification, such as communication protocols and network interfaces.

- *Cloud-based Big Data Management layer*: internally divided into sub-modules, is devoted to the Big Data-related tasks, such as data acquisition, integration, storage and mining [46]. It can be identified by the architectural stack presented in Sec.2.3.1 and in Fig.2.2.

- *Application Layer*: it specifies the lower layers architecture to the field investigated, such as intelligent buildings, health, traffic, logistics, retail, agriculture, etc. It exposes services to the end users, both client and admin.

In such common layer architecture, IoT the enabling technologies are classifiable depending on the layer in which to apply them, and by the scale of the IoT network [43]:

- *Low Power Wide Area Network (LPWAN)* is a communication scheme that can achieve the long-range Machine to Machine (M2M) communication by using low power energy with low data transmission rate [47]. The main enabling technologies for LPWAN are:
  - SigFox is a low power technology used for M2M applications and designed to transfer low data transfer speed (up to 1000 bps).
  - Low Range WAN (LoRaWAN) is a supported upper layer of LoRa physical layer technology.
  - LTE-M is a cellular technology standardized for IoT. It is based on Long Term Evolution (LTE) technology services requiring only a narrow bandwidth, compared to the bandwidth of a normal LTE carrier.
  - NarrowBand IoT (NB-IoT) is also integrated into the LTE technologies like LTE-M, aiming at minimizing energy consumption and lowering devices prices[47].
- *Short Range Network*:
  - *IPv6 over low-power wireless personal networks (6loWPAN)* is among the most commonly used standards in IoT communication protocols, in which every device is identified by a unique IPv6 address [48].
  - *ZigBee* is a standard for data communications that works on top of IEEE 802.15.4 network standard.
  - *Bluetooth Low Energy (BLE)*, also known as Bluetooth smart, is a significant protocol for IoT application aiming at minimizing power consumption in low data rate applications differently from previous Bluetooth Classic.
  - *Radio-frequency Identification (RFID)* is characterized by a variety of standards, and consists of a reader device and a small radio-frequency (from 3 to 30 GHz) transponder called RF tag.
  - *Near Field Communication (NFC)* is similar to RFID technology, it differs for available more elaborated two-way communication between devices.
  - *Z-Wave* has been developed to support small data packets (up to 100 kbps) and low speeds up to 30-50 nodes. It is characterized by masters and

slaves nodes, with slave nodes that cannot initialize the communication and can only reply and execute commands by masters node.

– *Message Queuing Telemetry Transport Protocol (MQTT)* is a publish/subscribe, extremely simple and lightweight messaging protocol, designed for constrained devices and low-bandwidth, high-latency or unreliable networks [49].

– *The Constrained Application Protocol (CoAP)* is a web transfer protocol for constrained nodes and networks (e.g., low-power, lossy). It provides a request/response and also a resource/observe as a variant of the publish/subscribe and is designed to interface with HTTP [50] [51].

– *Advance Message Queuing Protocol (AMQP)* supports both request/response and publish/subscribe architecture [52]. AMQP communication system requires that either the publisher or consumer creates an "exchange" with a given name and then broadcasts that name [53].

2.3.3 Semantic Technologies

Ontologies in Construction Industry

The ontology is a fundamental concept in dealing with knowledge usage applications, together with formalization and representation concepts. In [54] the ontology is defined as *"a formal, explicit specification of a shared conceptualization"*, i.e.,*"simplified view of the world to represent"*. In some cases, the conceptualization aims to organize concepts into hierarchical tree structures. The entities of the structure are characterized by super-classes, sub-classes and relationships, and their semantic descriptions enable automated query and reasoning.

In the construction-related literature, these concepts are applied mainly in information extraction by BIM software and in automated flows of data in cloud computing environment [55]. In particular, Industry Foundation Classes (IFC) is a data model widely applied in the semantic-oriented description in the construction industry. IFC data model is defined as *"a standardized, digital description of the built environment, including buildings and civil infrastructure. It is an open, international standard (ISO 16739-1:2018), meant to be vendor-neutral, or agnostic, and usable across a wide range of hardware devices, software platforms, and interfaces for* *many different use cases"* [56]. The data model language EXPRESS [57] is formally used in IFC format and proprietary platform owners are implementing it in BIM models.

Even if IFC has a prominent role in the BIM model description, it can not be defined as an ontology in the architecture, engineering and construction industry domain, due to the problems in its practical applications. In [58] and [59] authors identify the main limitations of the IFC approach: limited expression range, difficulty in partitioning information, ambiguity deriving from the multiple possible descriptions of the same information, limited reuse and interoperability. Hence, ST can be considered a valid tool to integrate and model information in an ontology-based environment in order to overcome the IFC limitations.

Semantic Web Technologies in constructions

The semantic web is an information space able to integrate different knowledge, expressed in compatible meanings/forms and expand the isolated source of knowledge [60]. According to the W3C [61], the *"semantic web is a web of data to provide a common framework that allows data to be shared and reused across applications, enterprises, and community boundaries".*

In particular, Semantic Web Technologies are devoted to the exploitation of the semantic web potential, and the translation of the ontology-based knowledge representation paradigm, to allow the reuse of formalized knowledge. The World Wide Web Consortium identifies [62] some core technologies of the Semantic Web environment:

- *Resource Description Framework (RDF)* is *"a framework for representing information in the Web"* [63]. In RDF, data and information are expressed as directed labelled graphs, that allow the description of the information in Semantic Web as a set of "triple", composed of subject, predicate and object.
- *Web Ontology Language (OWL)* is a semantic web language designed to represent ontologies in the web. *"It is a computational logic-based language such that knowledge expressed in OWL can be exploited by computer programs, e.g., to verify the consistency of that knowledge or to make implicit knowledge explicit"*[62].

- *SPARQL query language for RDF* is a language used to query data stored as RDF graph across different data sources [64].

Other important data web technologies are the linked data, introduced in [65], defined as *"a set of best practices for publishing structured data on the Web"* [66]. A vision that underlines their important role asserts that they are*"to spreadsheets and databases what the Web of hypertext documents is to word processor files [66]."*

Semantic Sensor Web

Also for sensor data there is a strong effort to enhance web automation capabilities, by replicating the data approach of configuring a common web information infrastructure to improve their reachability [67]. The two main organizations that are leading the standardization process are the Open Geospatial Consortium (OGC) and the World Wide Web Consortium: the sensor web is described by the OCG as a *"Web-accessible sensor networks and archived sensor data that can be discovered and accessed using standard protocols and application program interfaces"*. Sensor Web Enablement is acting to reduce the poor standardization aiming at reaching deeper automated data exploitation by adopting these technologies. There are many ontologies developed to semantic enrichment and formalization of sensors and sensors data [68]: semantic sensor web ontology from W3C Group [69], IoT-A model and IoT.est [70], Sensor Model Language [71], Observation and Measurements [72] and OneM2M [73].

2.4 Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) or Machine Learning (ML) enable achieving many different tasks by detecting patterns in data [74]. The concept of "learning" is central, and it is specified for a computer program by [75]: *"a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improve with experience E"*. The tasks to perform are characterized by the final aim of the ML process, i.e. what it is necessary to achieve by processing the data collected from the event or system studied. The form of the dataset, i.e. the data collected, depends on the task to perform.

It is acknowledged that three different paradigms can be considered in relation to these tasks T:

- *Supervised Learning* deals with labelled training data and consists on classification or regression tasks;
- *Unsupervised Learning* deals with unlabelled data as input on which to draw inferences;
- *Reinforcement Learning* identifies the agents' learning process of sequence of actions in an environment and driven by cumulative reward.

ML builds its potential on the function approximators, that are available in different types: linear models [76], Support Vector Machines (SVMs) [77], decision tree [78], Gaussian processes [79], Artificial Neural Network [80]. In recent years, the massive increase of computational power allowed by GPUs, the availability of powerful open programming environments such as Tensorflow and methodological breakthroughs have driven exponential enhancement of ML applications. Also, the construction industry is benefiting from this disruptive evolution.

As tools adopted in the present study, in the following, supervised and reinforcement learning (SL and RL) are briefly introduced in their main theoretical aspects. SL gives a perspective and a brief introduction to Deep Learning (DL) basic concepts.

2.4.1 Supervised Learning

By abstracting to some extent the concept of SL, it can be defined as the formalization of the idea of learning from examples [81]. One famous example of SL is represented by the Iris dataset [82] in which three different species of iris plant are classified depending on the measurements of different parts of the plant, such as sepal length, sepal width, petal length and petal width. A straightforward application of SL on such a dataset would consist of an algorithm that learns to recognize to which of the three species an unknown example belongs only depending on the measurements of the parts of the plant to recognize. This capability is acquired by the algorithm experiencing and learning from the 150 examples already classified in the dataset.

In its general form, supervised learning aims at finding a function $f : X \rightarrow Y$ that takes as input $x \in X$ and gives as output $y \in Y$:

$$y = f(x) \tag{2.1}$$

Traditionally, researchers and practitioners refer to SL for tasks such as regression, classification and structured output problems [80]. In general, in supervised learning the dataset D is composed of instances consisting of the vector of features $\boldsymbol{x}$ (i.e. the input of the system and quantities measured affecting the process to study) and a target, i.e. the information to compute as the output of the system, y so that $D = [(\boldsymbol{x}, y)]$. $\boldsymbol{X}$ represents the entire features for all the instances in D, while $\boldsymbol{Y}$ the output vector. A usual way to describe a dataset D is with a design matrix, containing instances in each row and features in columns. Depending on the task T, dimensions of both $\boldsymbol{X}$ and $\boldsymbol{Y}$ may vary. A supervised learning algorithm is thus a function mapping D into a model [83].

The ability of the model to represent consistently the data needs to be measured by the performance P introduced. It differs in the case of different task T, e.g. the accuracy for a classification task. The generalization capability is the main aim of ML algorithms, and it consists of good performance on new and previously unseen inputs. Generally, a dataset D is partitioned so that a portion of data (the training set) is used during the training phase, while another resulting part is used for testing the generalization capability (the test set). During the training phase, the training error measures how good the algorithm is learning on the training data, while, during the test phase, the test error instead measures how good the algorithm works on new data. For our model to behave the best, we need to:

- make the training error small, that results in reducing *underfitting*;
- make the gap between training and test error small, that results in reducing *overfitting*;

By controlling its *capacity*, i.e. informally defined as its ability to fit a wide variety of function [80], we are able to drive a model's trend to overfit or underfit: by modelling complex problems with low capacity models can lead to underfitting, but too complex models can drive to overfitting.

Deep Learning

Deep learning relies on a function $f : X \rightarrow Y$ parameterized with $\theta \in \mathbb{R}^{n_\theta}$ with $n_\theta \in N$ so that:

$$y = f(x; \theta) \tag{2.2}$$

Artificial Neural Networks (ANN) are the function approximators used to model f in Eq.2.2. Generally, they consist of computational units called Neurons organized in layers stacked one after the other. Depending on many features, each layer consists of a non-linear transformation, allowing learning different levels of abstraction [84]. To briefly highlight how an ANN works, we can analyse a simple feedforward fully connected neural network made of a single hidden layer (Fig.2.4).

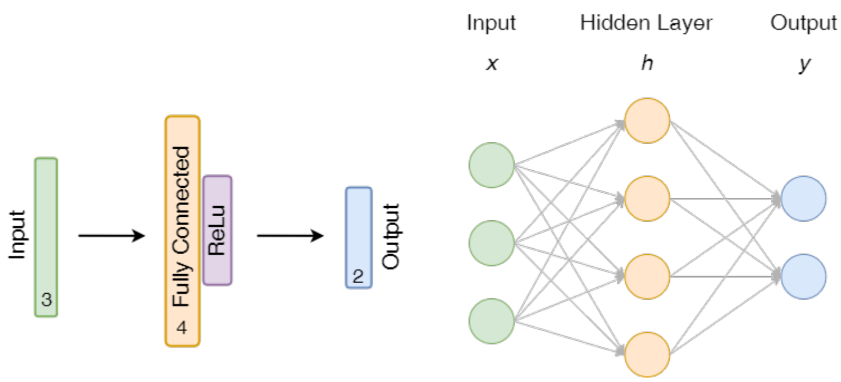


Figure 2.4 Two different representations of a one hidden layer feedforward Neural Network

Given a dataset $D = \{(\boldsymbol{x}_i, y_i)\}$ with $i = 0, 1, \ldots, n_i$, $\boldsymbol{x}_i$ is the input vector of features for the instance i and y_i is the "ground truth" target for the instance i. The output of the hidden layer h is computed by non-linearly transforming $\boldsymbol{x}$ following Eq.2.3:

$$\boldsymbol{h} = A(\boldsymbol{W_1} \cdot \boldsymbol{x} + \boldsymbol{b_1}) \tag{2.3}$$

where $\boldsymbol{W_1}$ is a weight matrix, $\boldsymbol{b_1}$ are the bias terms and A is the activation function, which makes each layer transformation non-linear. The output of the network consists then in Eq.2.4:

$$\hat{\boldsymbol{y}} = A(\boldsymbol{W_2} \cdot \boldsymbol{h} + \boldsymbol{b_2}) \tag{2.4}$$

with $\hat{\boldsymbol{y}}$ the output of the network computed with the available weights and biases. The training consists in optimizing the weights and biases of all layers that minimizes a loss function $L(y,\hat{y})$ which depends on the task T. The most famous approach for this optimization task is the gradient descent via the backpropagation algorithm [85]: the parameters $\boldsymbol{\theta} = (\boldsymbol{W}, \boldsymbol{b})$ are iteratively update to fit the desired function:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \gamma \nabla_{\theta} L(y,\hat{y}) \tag{2.5}$$

where γ is the learning rate.

The design of an ANN strongly depends on task T and the data available. Further than choosing the loss function and the optimizer to use during the parameters optimization, there is a massive availability of ANN different architectures. Many different types of layers appeared since the abrupt development of this technology, and each one characterizes advantages and features related to specific tasks.

Among many examples, Convolutional Neural Networks (CNN) plays a central role in image and sequential data processing. Their main feature is the use of the Convolutional Layer (CL) [86]: for example, for a two-dimensional signal I as an input, the convolution with a two-dimensional kernel K is given by Eq.2.6 [80]:

$$S(i,j) = (I \star K)(i,j) = \sum_{m}\sum_{n} I(m,n)K(i-m,j-n) \tag{2.6}$$

The layer's parameters consist of a set of learnable kernels or filters K that allow focusing locally by scanning the entire input, applying the convolution operation and then computing the output to the following layer. The output of the CL is usually referred as features or activations map, with a size that depends on three different hyperparameters called the *depth*, *stride* and *zero-padding* [87].

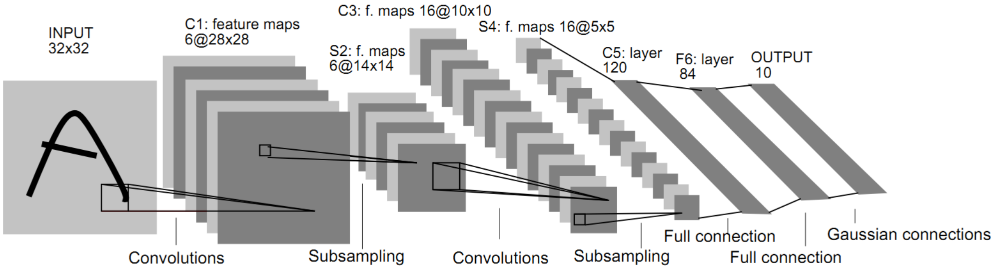


Figure 2.5 LeNet-5 Architecture [88].

The general overall architecture of a CNN is shown in Fig.2.5 by representing a famous CNN called LeNet-5 [88]. Generally, a CNN does not comprise only the CL. The input first feeds a CL: six kernels are considered in Fig.2.5 because six feature maps are obtained as output by passing the output of the CL to a non-linear activation function (such as ReLU). The subsampling operation is then performed by feeding a *pooling layer* (PL) that aims at further modifying the output by replacing it with summary local statistics of the nearby outputs. The remaining part of the architecture is obtained by stacking subsequently CLs and PLs, while, for general classification tasks with CNN, in the end, it is usually found a *Fully Connected* (FC) layer.

2.4.2 Reinforcement Learning

Reinforcement Learning (RL) is an area of machine learning that deals with sequential decision-making, considering artificial agents that learn by interacting with their environment, similarly to biological agents. The artificial agent uses the experience gathered to optimize objectives given in the form of cumulative rewards. The key aspects of RL are the agent's ability to learn good behaviour, modify and acquire new skills incrementally, and the trial-and-error experience approach. The RL agent thus does not require complete knowledge or control of the environment, it only needs to be able to interact with the environment and collect information [83].

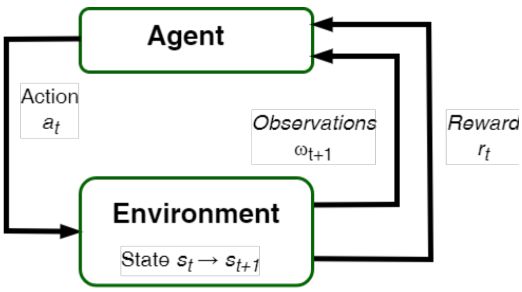


Figure 2.6 Agent-environment interaction in RL.

The RL problem is formalized as a discrete time stochastic control process in which an agent interacts with its environment in a discrete time Markov decision problem in which the future of the process only depends on the current observation and not on the full history process. A discrete time Markov process is defined as a 3-tuple (S, A, R) where:

- $\mathscr{S}$ is the agent *state space*;
- Ω is the *observation set*;
- $\mathscr{A}$ is the set of *action space*;
- $R : \mathscr{S} \times \mathscr{A} \times \mathscr{S} \rightarrow \mathscr{R}$ is the reward function, where $\mathscr{R}$ is set of real positive numbers in the range $[R_{min}, R_{max}]$.

The agent starts in an initial state $s_0 \in \mathscr{S}$ within its environment, by gathering an initial observation $\omega_0 \in \Omega$. At each time step t, the agent has to take an action $a_t \in A$. As shown in Fig. 2.6, the system behaviour is the following at each time t [89] [90] [91]: i) the agent is in state $s_t \in S$; ii) the agent takes an action $a_t \in \mathscr{A}$ from the set of available actions; iii) the agent obtains a reward $r_t \in \mathscr{R}$, iv) the agent updates its state from state $s_t \in \mathscr{S}$ to $s_{t+1} \in \mathscr{S}$, v) the agent obtains an observation $\omega_{t+1} \in \Omega$.

The objective of DRL is to find a policy as a function $\pi : \mathscr{S} \rightarrow \mathscr{A}$ that maximizes the cumulative reward. The cumulative reward is expressed by a Q-value function $Q^{\pi}(s,a) : \mathscr{S} \times \mathscr{A} \rightarrow$ R that is defined as follows:

$$Q^{\pi}(s,a) = E[\sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t = s, a_t = a, \pi] \tag{2.7}$$

representing the expected future cumulative reward by taking action a in state s by following policy π. In Eq.2.7, $\gamma \in [0,1)$ is the discount factor, which emphasizes the importance of the nearest rewards over future rewards in the further future, while k counts the future time steps. The *optimal $Q-$value function* $Q^*(s,a)$ maximizes the Q-value function following policy π and can be defined as:

$$Q^*(s,a) = \max_{\pi \in \Pi} Q^{\pi}(s,a). \tag{2.8}$$

The Bellman optimality equation allows calculating $Q^*(s,a)$ ([91]):

$$Q^*(s,a) = E[r_t + \gamma \max_{a'} Q^{\pi^*}(s_{t+1}, a_{t+1}) | s,a]. \tag{2.9}$$

In particular, $Q^*(s,a)$ is computed as the sum of the immediate reward r_t gained by the agent in the time step t and the optimal future reward thereafter $\gamma max_{a'} Q^{\pi^*}(s_{t+1}, a_{t+1})$.

The possibility of estimating the optimal future reward allows the cumulative reward at the current time to be calculated [92].

The specification of the optimal Q-value function $Q^*(s,a)$ allows calculating the optimal policy π^*:

$$\pi^*(s) = argmax_{a\in A}\left(Q^*(s,a)\right). \tag{2.10}$$

In DRL, $Q^\pi(s,a)$ and $\pi(s)$ are obtained by neural networks which are updated during the agent's interaction with the environment.

2.5 Additive Manufacturing

Additive Manufacturing (AM) is defined as *"the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies, such as traditional machining"* [93]. Additive manufacturing systems (or 3D printers) are classified into seven categories according to the ISO/ASTM 52900:2015 [93]: i) binder jetting, ii) directed energy deposition, iii) material extrusion, iv) material jetting, v) powder bed fusion, vi) sheet lamination and vii) vat photopolymerization. Originally, AM main use was the formal prototyping to investigate custom and performative solutions for different types of products, in many industrial fields; it allowed the formal testing phase without implying expensive subtractive machining yet during the testing phase. Because of its enhanced performance in terms of accuracy, available aesthetic possibility and numerous printable materials, AM used directly in the production phase is highly increasing [94, 95]. Some fundamental features driving the technological adoption are resumed in [8]:

- No need for tooling, which significantly reduces production time and costs;
- Possibility to quickly change designs;
- Product optimization for function;
- More economical custom product manufacturing (mass customization and mass personalization);
- Potential for simpler supply chain, shorter lead times and lower inventories.

2.5.1 Information flow in AM processes

Each AM process consists of a specific information flow throughout different phases, e.g. Fig.2.7 describing the case of a bench printed with raw earth material by a WASP 3MT Industrial Concrete 3D printer.

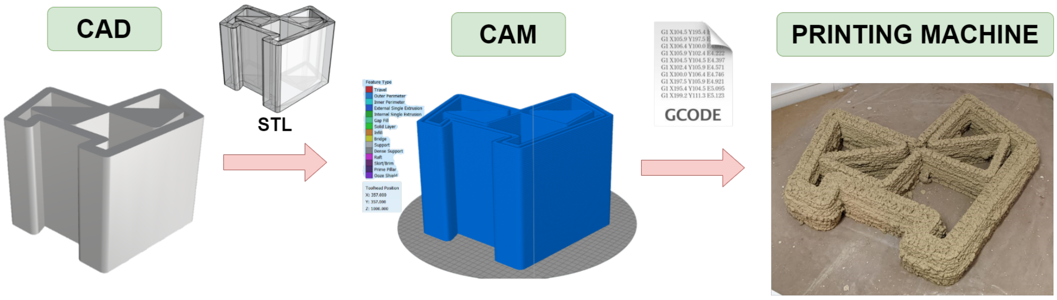


Figure 2.7 Usual information flow in additive manufacturing processes.

An idea conceptualized needs to be first represented as an informative model using a Computer Aided Design (CAD) system. In many standard processes, the model needs to be described as a volume in CAD, then represented as a triangular mesh and converted into the Standard Tasselation Language (STL) format. A Computer Aided Manufacturing (CAM) software environment employs the STL as input and outputs the machining file that depends on the features of the machine used. In AM, within the CAM, the STL is sliced into a number of layers, and the resulting machining files (usually called "gcode") consist of a toolpath describing the path the extruder has to follow, its speed and other printing-related information such as extrusion flow. As the technologies are not fully developed and widely commercialized in the construction field, the process is not uniquely addressable.

2.5.2 AM in the construction industry

Of the seven technologies specified in the ISO/ASTM 52900 (2015) [93], the most popular additive manufacturing category in the construction industry is extrusion-based 3D printing, in which a viscous material (e.g. cementitious material, clay or raw earth) is deposited in layers as a continuous filament from a nozzle [96]. The AM application in the construction industry is challenging because of numerous issues classified by [97] in three macro-features:

- Printable feedstocks: the choice of the material to print and of its characteristics;
- Geometry: the characteristics of the objects to obtain, both in terms of geometry, precision and constructive technology;
- Printer: all the issues strictly related to the printing process, considering the machine technology and, thus, the printing parameters related, such as feedrate and material flow.

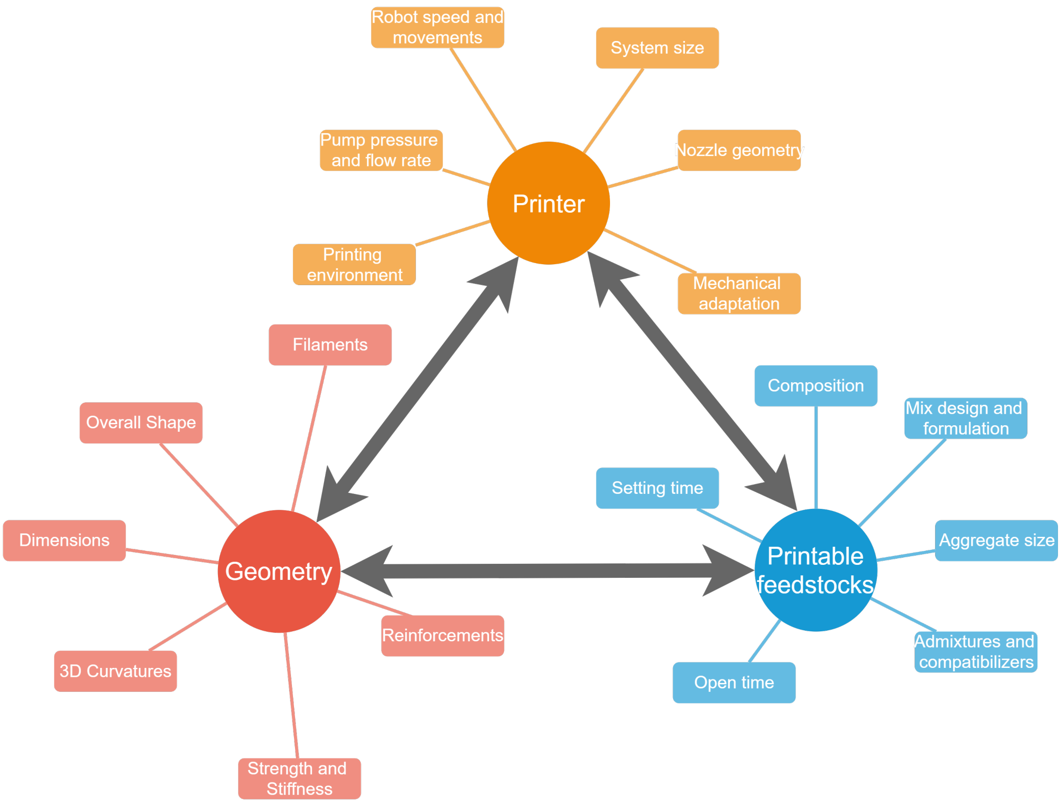


Figure 2.8 AM features in the construction industry [97]

For what concerns the printable feedstocks, the concrete is the printing material of greatest interest to companies and researchers (extrusion-based 3D concrete printing) and is still widely studied in recent research projects [98] because of its uses and lower costs [99, 100]. Sustainability of additive manufacturing with clay and raw earth material is also investigated in many application because of its great potential [101–103].

Freedom in obtainable geometries is the AM main feature in the construction industry. Examples of hard-to-achieve geometries are already present in the industry, and examples are shown in Fig.2.9a and Fig.2.9b.
However, this freedom is influenced by technological limitations concerning printing machines available. Among the most diffused technologies is possible to identify gantry systems or robotic manipulator, but all of them suffer from limited build volume, their main concern. Attempts to overcome this issue are done in literature trying to turn already widespread construction machines into 3D printers [104, 105]. Another attempt is also done in this thesis in Chapter 5.

(a) Apis Cor, Dubai [106]

(b) WASP, Tecla [107]

Figure 2.9 Two examples of challenging geometries obtained with AM in the construction industry

2.6 Conclusions

In this chapter, the main Construction 4.0 technologies investigated during the next chapters are introduced. Note that the discussion of the topics is not meant to be exhaustive of all the theoretical aspects involved, since there are plenty of high-quality books investigating in detail each of them. In this case, only a brief introduction of the main aspects is given to the reader, and examples of specific applications are left for the following chapters.

Chapter 3

Information and Communication Technologies Applied to Intelligent Buildings

Partially published in *Fabio Parisi, Maria Pia Fanti, & Agostino M. Mangini (2021). Information and Communication Technologies applied to intelligent buildings: a review. J. Inf. Technol. Constr., 26, 458-488.*

3.1 Introduction

The recent development of Information and Communication Technologies (ICT) is favouring the intelligent modelling and management of many systems engineered.

Also in the architecture, engineering and construction (AEC) industry, the availability of ICT fosters a deep transformation of the approaches for modelling, designing and managing Intelligent Buildings (IBs) and, generally, constructions.

There is not a single acknowledged definition of IBs. Some first definitions pointed attention mainly to performance aspects, e.g. the definition of the Intelligent Building Institute of U.S.: an IB "provides a productive and cost-effective environment through optimization of its four basic elements including structures, systems, services and management and the interrelationships between them” [108].

With the evolution of the IB concept, different topics and factors are taken into account and the importance of users and environment becomes central. In [109], the authors identify four Key Performance Indicators (KPIs) to assess and classify the IB main features considering two levels as shown in Fig. 3.1: i) smartness and technological-driven awareness, ii) economical and cost efficiency, iii) social sensitivity, iv) environmental responsiveness. More in detail, the KPI-1 of the top level focuses on technological aspects that are specified in different contexts at the bottom level by considering KPIs that evaluate economical and cost efficiency (KPI-2), social sensitivity (KPI-3) and environmental responsiveness (KPI-4).

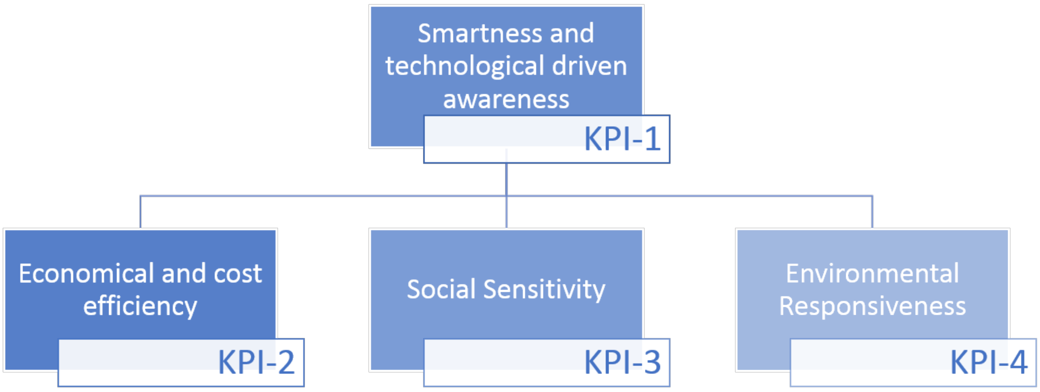


Figure 3.1 KPIs in Intelligent Building definition [109].

This paper reviews the ICT tools and strategies presented in the related literature and implemented in the IBs, by considering the specific applications in the different building life cycle phases.

The novelty of the presented review is twofold.

First, starting from the specification of the KPIs, this paper performs a IB literature review on the basis of a defined framework, involving the usage of a hierarchical two-layer framework for specifying the IB technological contexts. The first top layer of the considered conceptual framework is constituted by the evaluation layer inspired by the KPIs reported in Fig. 3.1 and specified in research sub-domains about IB. The second layer consists of the ICT construction-related technologies and is divided in two sub-layers: an ICT construction sub-layer and a generic ICT tools sub-layer.

Second, the main operative technological tools to be investigated in the second layer are not determined a priori but they derive from a text analysis of the IB review papers. Such text analysis performed on the literature related to the ICT applications allows identifying the main technological tools employed in the IB paradigm and not sufficiently discussed.

By Natural Language Processing approach [110], we automatically retrieve and analyse the review papers from the most important scientific archives. The results of the analysis point out that in the review papers about the IB field, innovative technologies such as Big Data (BD), Internet of Things (IoT) and Semantic Technologies (ST) are worthy of further study.

Hence, on the basis of such an outcome, the paper performs a review analysis of the application of BD, IoT, ST in the context of the IBs by locating them in the building life cycle. Moreover, considering the basic importance of the implementation of Building Information Modeling (BIM) in the IB design and management, the proposed review also deals with the possible integration of such ICT tools in the BIM environment.

The chapter is structured as follows: Section 3.2 introduces the IB review framework; Section 3.3 recalls the IB applications; Section 3.4 discusses the results and 3.5 draws the conclusions.

3.2 Intelligent buildings review framework

In this section we specify in detail the framework according to which the review has been performed, starting by considering the two layers in Fig.3.2, the evaluation layer and the IB ICT layer.

The evaluation layer includes the technological performance areas reported in Fig. 3.1 characterizing the different domains of the IB construction and maintenance.

The IB ICT layer describes the specific ICT construction tools devoted to model, designing and managing IBs during the complete building life cycle. We consider this layer divided into two sub-layers: the ICT construction sub-layer including the information tools adopted in the construction industry and the generic ICT tools sub-layer including the ICT tools that are relevant for supporting the construction sub-layer tools development.

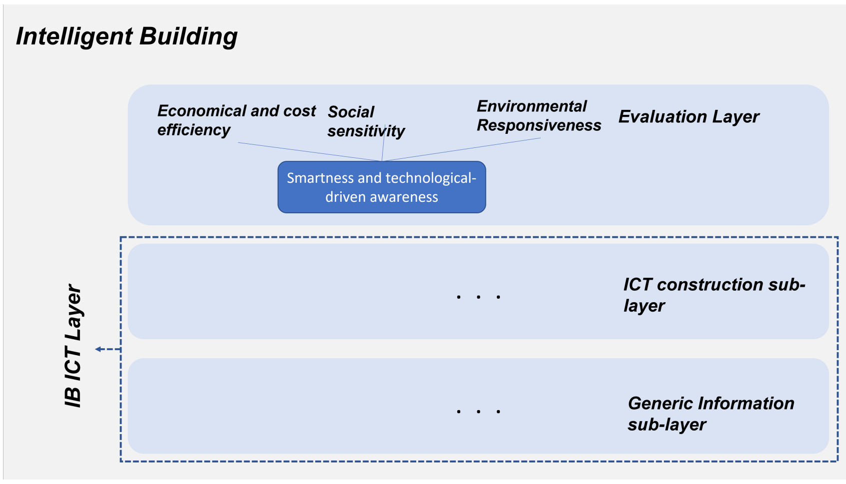


Figure 3.2 Intelligent Buildings General Conceptual Framework to specify.

The following sub-sections specify the components of the two technological sub-layers on basis of the analysis of the contributions in the related literature.

3.2.1 The ICT construction sub-layer components

The description of buildings and in general constructions' life-cycle, helps to identify which construction-specific informative tools are considered strategic in the construction industry, and also the specification of related research fields and domains can contribute. Thus, this helps us in specifying the ICT construction sub-layer in 3.2. Fig. 3.3 shows four phases of the building life-cycle and their relative research domains according to [111, 112].

In informative-driven-fashion management of constructions, the four phases of the life cycle are supported by dedicated ICT construction tools that can be characterized by the following main three systems: Building Management System (BMS), Facility Management System (FMS) and Building Information Modelling (BIM).

- The *BMS* aims at the computerized control and management of buildings, characterized by a distributed infrastructure [113]. The usual architecture of this distributed system is structured into three levels: (i) the field level that includes the interaction with sensors and actuators (field devices); (ii) the automation level, where processing activities are performed, like measurements

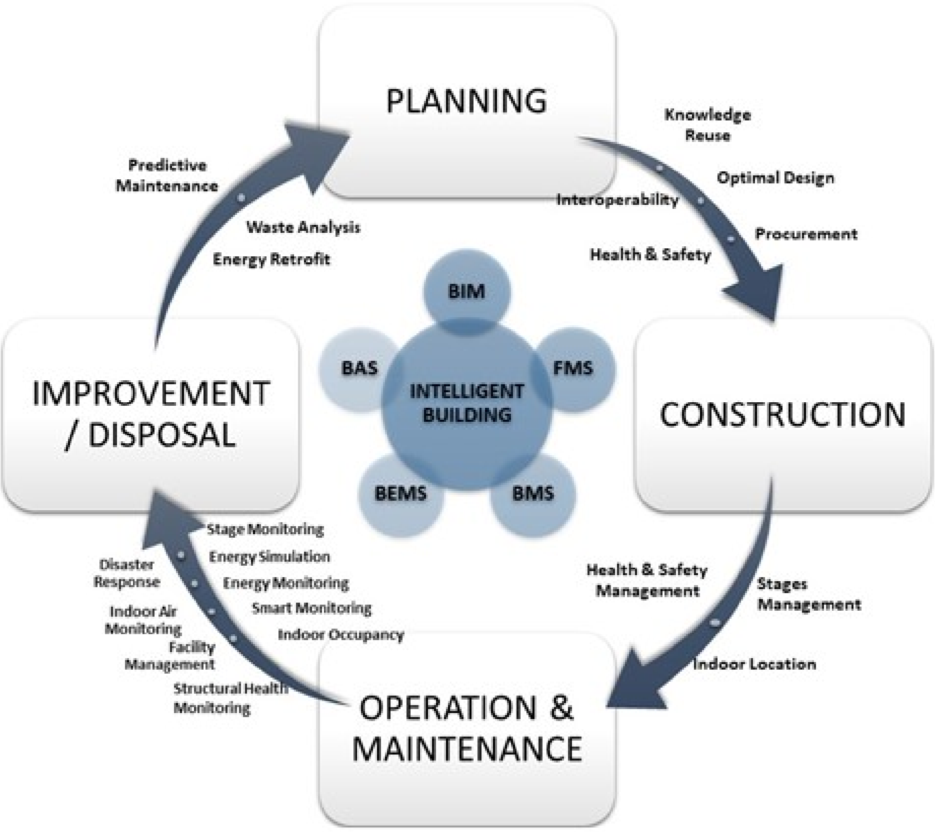


Figure 3.3 Building life cycle phases and research sub-domains.

processing, control loops execution and alarms activation; (iii) the management level where data elaboration activities are performed, such as system data presentation, forwarding, trending, logging, and archival. As reported in [114], BMS includes some related systems such as building control systems and building automation systems.

- *FMS* is an umbrella term covering many topics ranging from financial management to facilities maintenance [115]. In [116] different definitions presented in the related literature are provided. A definition that is consistent with this study is in [117] where the author defines FMS as *"a supporting tool to obtain sustainable and operational strategy for an organisation over time through management of infrastructure resources and services"*. Moreover, an additional system named Energy Management System (EMS) includes tasks partially shared with the FMS and the BMS. In particular, the EMS involves strategies and methods aiming at building performance, efficiency and energy utilization improvement [118]. This sub-system is focused on key energy management tasks like the demand-response strategies, energy costs prediction, energy use anomalies detection, and management of energy use information [119].

- Depending on the literature and context, *BIM* can be defined in a *narrow sense* or in a *broad sense* [120].
  - BIM in *Narrow Sense*: it is seen as a "tool" strictly used for the creation process of a building's model, i.e., a technology to manage information related to buildings' design. The contents' visualization and representation capabilities are strong features of the management process, being the description of construction strongly geometric-driven. In BIM, visualization models are enriched with interdisciplinary design information: these models become a visual representation and integration of cross-field time-dependent data [112]. BIM's historical role allowed a large interoperability amount different stakeholders involved in the design, construction and management process [121]. Despite this, there are still limitations in BIM usage [122]: i) proprietary platforms are strongly pushing towards the development of further features in their own software environment, implying high dependency on proprietary data format; ii) even if information exchange open data format are available (like Industry Foundation Classes), the information flow suffers consequences; iii) even if official Application Programming Interfaces (API) and scripting environments are largely diffused, custom features integration remains tricky.
  - BIM in *Broad Sense*: the National Building Information Model Standard [20] defines BIMs as a *"digital representation of physical and functional characteristics of a facility. As such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle from inception onward."* In this case, BIM technology has a wide perspective of usage, and does not focus only on the first stages of the building process (design and construction phases), but has a key role also in the management stage.

The gradual evolution of the BIM concept from the *Narrow Sense* to the *Broad Sense* is observable in the progressive introduction of features and functionalities in BIM software. This BIM evolution is also highlighted by the growing number of "dimensions" considered in the model [123]:

- 2D models: 2D CAD model application;
- 3D models: modelling and visualization of the third dimension, also with parametric modelling, object oriented approach and automated digitalization;
- 4D models: scheduling and sequencing of operations to plan project and construction execution;
- 5D models: cost estimation, i.e., the budget estimation and control of the construction phase;
- 6D models: sustainability, i.e., impact control of construction and operation;
- 7D models: facilities management, including operation, maintenance, planning and execution of building life-cycle.

In these “n-dimensions” BIM applications, the trend to the integration of BIM with the BMS and the FMS is quite evident.

The new challenge for the future development of the potentialities of the BIM in the broad sense is represented by the Cloud-BIM. Indeed, as in other industrial fields where the cloud-based software and platforms boost applications' potential, also BIM environments are being developed toward web services and cloud-based applications. In [124] some examples of cloud-based applications and services are highlighted, like GRAPHISOFT BIM Explorer, ONUMA System, BIMServer.org, Autodesk BIM360, Trimble Connect and xBIM.

3.2.2 Generic ICT sub-layer components identification

In order to identify the technological components of the generic ICT sub-layer, a preliminary analysis of existing review papers on the topic "Intelligent" and "smart" "buildings" is performed, following a methodology proposed in [14]. This preliminary study has two objectives: i) determining the research fields already deeply analyzed, and the most prominent topics already speculated in the field of the IB literature; ii) identifying the emerging technologies that are applied in the IB research areas but not still deeply reviewed in the related literature.

Preliminary review papers analysis methodology

In-depth research of the review papers about the IB and smart building concept is performed to single out the most reviewed research fields. The database used in this analysis and the related results are shown in Table 3.1.

Table 3.1 Intelligent and Smart Buildings Review papers

Journal/Database	Searching	References
Elsevier	15	[125] [126] [127] [128] [129] [130] [131] [132] [133] [134] [135] [136] [137] [138] [139]
IEEEXplore	10	[140] [141] [142] [143] [144] [145] [146] [147] [148] [149]
Taylor & Francis Online	5	[150] [151] [152] [153] [154]
ResearchGate	13	[155] [156] [157] [158] [159] [160] [161] [162] [163] [164] [165] [166] [167]
Emerald	1	[168]

The research is performed by an automatic procedure consisting of the following steps:

- Research: both Application Programming Interfaces (APIs) provided by databases maintainers and *Web-Scraping* techniques [169] are applied. The research is performed by searching for all paper titles in which the words "intelligent" or "smart" together with "buildings" and "review" or "survey" are present.

  APIs allow us to obtain a response from the APIs server directly in form of analysable text data (JSON or XML format). If APIs are not provided, a web-scraping approach is used. This methodology implies the analysis and the parsing of web pages in order to detect automatically desired information.

- Collection: once papers corresponding to the research are identified, full texts are automatically retrieved and stored locally, in order to create the corpus on which to perform the preliminary analysis.

  By the APIs approach, the full texts are retrieved by Digital Object Identifier directly as text data and stored locally in the software script in order to be analysed. By the web-scraping approach, the texts are retrieved in PDF file format and stored locally. A subsequent phase is necessary to read the content of these files, and put them together with the ones obtained by the APIs approach, obtaining only one "corpus".

- Analysis: raw text data are not directly analysable. The entire corpus obtained in the previous collection phase is pre-processed and analyzed in Python development environment. The preliminary pre-process is necessary to put the corpus in a form usable as input for natural language processing or machine learning algorithms. In this stage the Python library Natural Language ToolKit (NLTK) is used. The following steps are applied to the corpus:
  - tokenization is the process of dividing the corpus on the elementary units [170]; in the present study, the used token units are the words. In particular, the Treebank tokenizer [171] implementation in NLTK is applied;
  - stopwords removal allows removing tokens that bring no informative content about the text from the corpus. Example of stopwords to delete are articles and prepositions [172];
  - lemmatization aims at expressing tokens into their dictionary form, by using vocabulary and morphological analysis to remove inflectional endings. It also helps in matching synonyms by the use of a relational thesaurus [173];
  - the corpus is then re-built in the form of a continuous text composed by the pre-processed tokens;
  - after the text is pre-processed and re-built, analytical methodologies are applied to extract the frequency (the number of occurrences) of the concepts the corpus contains. The concept is expressed by an n-gram, i.e., a sequence of n words that appears with a specific order in the corpus. The analysis method assumes that important concepts are more often present in the text [14]. In this investigation, the n-grams composed of two and three words are analysed.

Results of the review paper analysis

In Fig. 3.4 a graphical visualization of the most important topics and contents obtained from the presented procedure are shown in a "Word Cloud" representation.

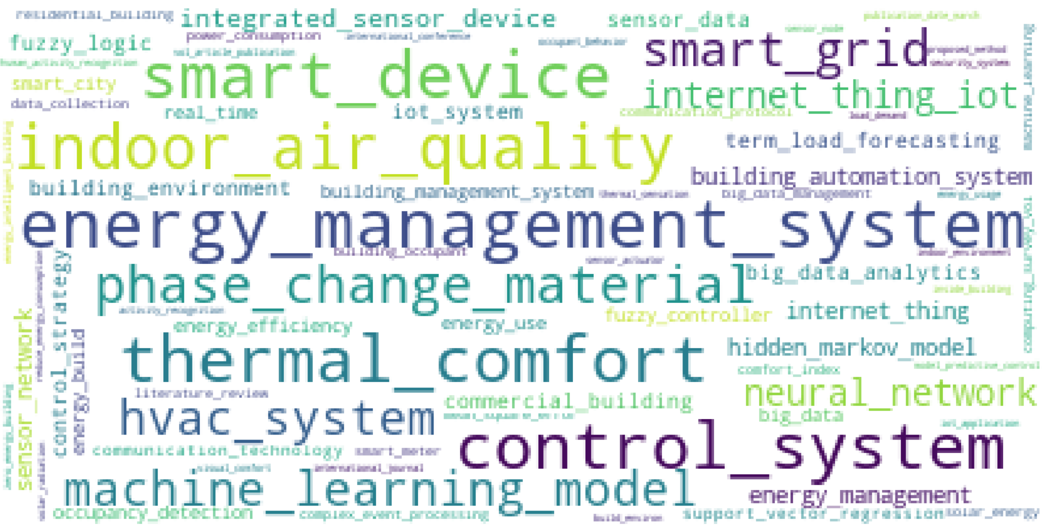


Figure 3.4 Bigrams and trigrams reviews World Cloud

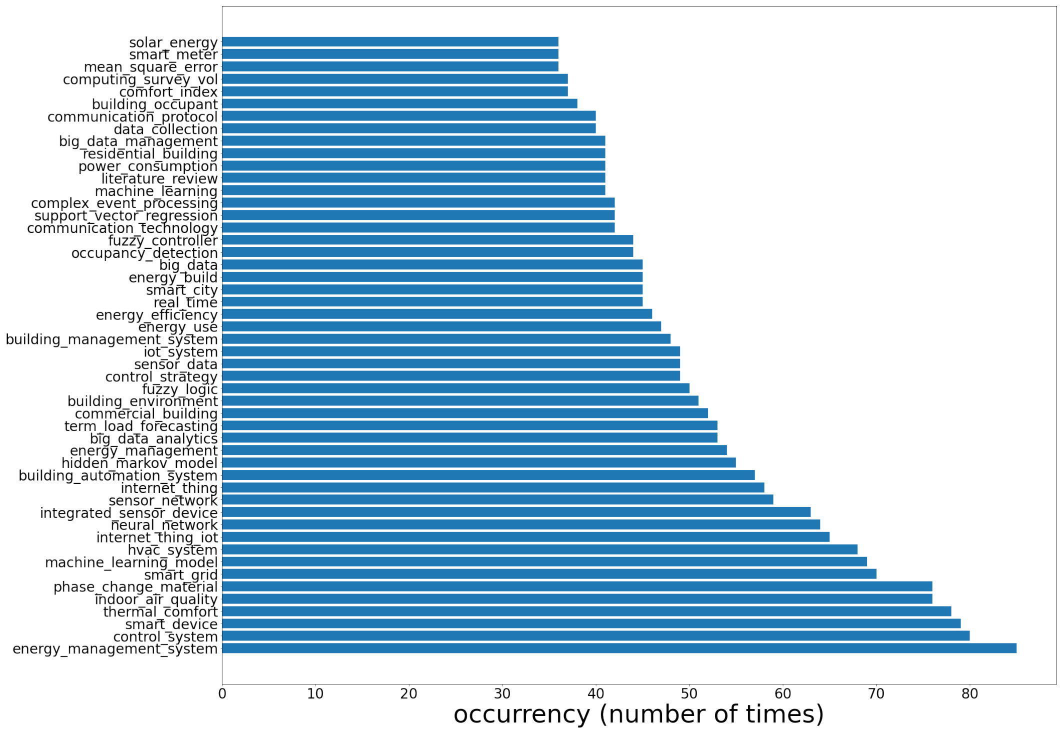


Figure 3.5 Bigrams and trigrams World Cloud Frequency [first 50]

In the used "BagOfWords" approach bi-grams and tri-grams are considered because of their capacity to be more consistent in content representation in the text corpus [174]. The metric that supports the generation of Fig. 3.4 and Fig. 3.5 is the frequency distribution of bi-grams and tri-grams in the whole corpus text, defined as the number of times each bi-grams or tri-grams appears in the considered corpus text.

The first evident outcome is that the most investigated field concerns energy efficiency and indoor comfort management supported by automatic control systems. Indeed, in Fig. 3.5 the bi-grams and tri-grams "indoor air quality", "thermal comfort", "HVAC system", "control system" and "energy management system" are the most frequent in the corpus text.

After these main topics, the most relevant ICT technologies enlightened by the analysis are the tools that support such systems: Internet of Things (keywords highlighted by "smart device", "Internet Of Thing", "Sensor Network" and "IoT System"), Big Data ("Big Data Analytics", "Big Data") and Artificial Intelligence ("Neural Network, "Artificial Neural Network", "Machine Learning").

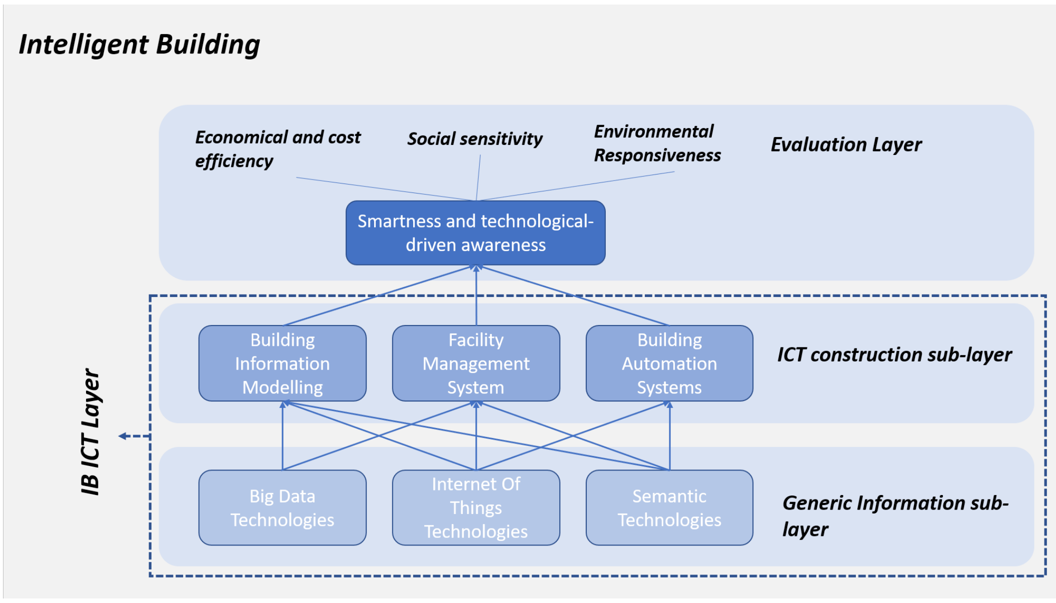


Figure 3.6 Intelligent Buildings General Conceptual Framework.

By the presented analysis results, it is possible to specify the generic ICT sub-layer as it is shown in Fig. 3.6: the new emerging technologies that are changing the design and management of IBS are BD including the semantic concepts of "Big Data Analytics", "Big Data Management", "Neural Network, "Artificial Neural Network", "Machine Learning Model" and "Machine Learning"; IoT including the semantic concepts of "Sensor network", "IoT system".

Moreover, considering the basic importance of BIM in the IB applications, in this chapter we also investigate one of the main ICT strategies recently used in BIM: the ST.

3.3 Applications of ICT to the Intelligent buildings

In this section, the literature is reviewed by adopting the hierarchical framework introduced in 3.2. In particular, the ICT technologies adopted for the implementation of the IB ICT layer inner components are analyzed. The analysis is conducted by considering the building life cycle phases and the related domains in Fig. 3.3.

The review results are summarized in Tables 3.2, 3.3, 3.4, 3.5, 3.6. In each table, the following information is reported: the first column shows the reference of the considered paper; the second column shows the BIM-related technologies that characterize the ICT construction sub-layer (denoted Middle Layer) of the framework in Fig. 3.6; the third, fourth and fifth columns describe technologies related to the generic information sub-layer (denoted Low Level) consisting of BD, IoT and ST; the last column reports the domain of application in the building life cycle (Fig. 3.3).

3.3.1 Planning / Design

Table 3.2 focuses on the "planning/design" stage and summarizes the ICT technologies mentioned in the reviewed papers according to the proposed framework.

In [55] the authors propose a framework based on linked data for BIM defects detection. The system aims to convert defect data to an ontology-based linked data format to link and search defect data between different data sources. In [175] a cloud-BIM approach is proposed to achieve an optimized leadership in energy and environmental design project delivery and certification. In [176] ST have been applied for building component descriptions by using linked data from different sources available on the Web. Moreover, the data sources are made available and accessible in the product catalogue to end-users working with BIM models via web services. In [177] the authors propose an automated approach to identify and prevent potential safety hazards by using a rule-based checking system integrated with BIM. The hazard identification is implemented in the early design stage. In

[178] an evaluation, analytics and prediction platform is presented for BIM in order to collect, store, process, and analyze BIM data in integrated approach. BIM is used as an "entry point" for user information that is automatically converted into ontology, characterized by web-scale expandability.

Table 3.2 Adoption of analyzed technologies in planning/design stage

	Middle Layer	Low Layer			
Ref.	**BIM**	**BD**	**IoT**	**ST**	**Sub-areas**
[55]	Autodesk Revit	-	-	RDF Converter, SPARQL, Protege, Linked Data	Knowledge reuse
[175]	Autodesk Revit, Stratus	-	-	-	Optimal design
[176]	Revit	-	-	D2RQ	Knowledge reuse
[177]	Tekla	-	-	IFC	Health and Safety
[178]	WebGL, General BIM	Hadoop, Spark, MapReduce	-	OWL	Interoperability

3.3.2 Construction

Table 3.3 focuses on the "Construction" phase and summarizes the ICT technologies that are mentioned in the reviewed papers.

Table 3.3 Adoption of analyzed technologies in construction stage

	Middle Layer	Low Layer			
Ref.	**BIM**	**BD**	**IoT**	**ST**	**Sub-areas**
[179]	Autodesk Revit, Navisworks	-	-	SWRL, OWL , Protege	Health & Safety
[180]	WebGL	-	RFID	-	Stage monitoring
[181]	Autodesk Revit, Dynamo	Azure	BLE, RFID	BIMtoIFC	Indoor localization

[182]	Autodesk Revit	-	TelosB	-	Safety & Health
[183]	General BIM, Unity	-	RFID	-	Indoor localization
[184]	Autodesk Revit, Naviswork, BIM360	-	-	-	Stage monitoring
[185]	Autodesk Revit, Naviswork	SQL Database, MongoDB	-	-	Stage Monitoring

In [179] the authors introduce an organized, stored and reusable construction risk knowledge, by combining the strength of BIM, ontology and semantic web in an ontology-based methodology. More precisely, a risk map representing this risk knowledge allows capturing and semantically inferring interdependence between risk and risk paths. A tool is implemented to allow the reuse of the knowledge. In [180] a centralized BIM platform powered with IoT applications provides features both for integrating information from previous construction stages and for real-time locating prefabricated components by improving decision-making among stakeholders. In [181] an application of IoT together with the lean and injury-free construction management approach is presented. Firstly, a framework to integrate into an existing system the proposed application and then a prototypical example are described with validation in a field-like work setting. In [182] the authors propose CoSMoS, i.e., a system that aims at improving the health and safety of workers on construction work-site by integrating real-time sensors monitoring in a BIM environment. The solution is applicable in the construction and maintenance stages. Paper [183] proposes a solution for monitoring the construction site, based on RFID protocols by locating construction workers and providing real-time visualization with a cloud server architecture. The visualization capability is based on BIM technology. In [184] authors apply BIM360 technology to a real-case scenario to extend BIM potentiality of the progress monitoring from the design phase to the construction site. In [185] authors aim at solving the full life cycle data management by implementing a cloud architecture.

3.3.3 Operation/Maintenance

Table 3.4 focuses on the "Operation/Maintenance" phase summarizes the ICT technologies that are mentioned in the reviewed papers. In [186] the authors develop a tool to reduce building hazards in the facility management stage. BIM technologies, sensors and Hadoop architecture are integrated to gather real-time data about temperature, activities in the facilities and water monitoring. The data are then aggregated and exposed by cloud services. In [187] a platform named *Otaniemi3D* is proposed to provide information about energy usage, occupancy and user comfort by integrating BIM, IoT devices, IFC and open messaging standards. In [188] an IoT software infrastructure integrating heterogeneous data from IoT devices into BIM and geographical information systems are presented. The validation of the building energy model with real data and the simulation of building energy behaviour is strengthened by the usage of real weather data from third-party services. The system can be employed to check near-real-time bad usage of building resources. In [189] the integration of information between BIM and sensor data is obtained by a linked data approach. The work aims at the performance analysis of the energy demand of the facility manager's building. In [190] authors integrate a semantic sensor network with the IFC standard in a prototypical wireless structural health monitoring system. Paper [191] presents an IoT BD analytics framework for storing and analyzing real-time data generated by IoT sensors inside the IB. A real-case analyzing the automatic management of the oxygen level, luminosity and smoke/hazardous gases in wide areas is conducted. Linked data for implementing cloud-based data services are proposed in [192]. A real-time energy awareness system and an audit-style energy tracking system are implemented using the merged data. A middleware for ambient intelligence systems is presented in [193]. It is based on the Service-Oriented Architecture, and the work includes a real-scenario application in a smart university system, a prototype board server, and a sample client application. In [194] the authors present an architecture named *Building Big Data*, i.e., a distributed system for storing and processing building data. In the platform, ICT tools for data analytics and software applications development are implemented; also insight on scalability is given to aggregate data from different smart buildings. The support of intelligent water management is the topic in [195], where sensing, analytics, services and interfaces are implemented to optimize the water network at the home scale. An innovation of the work is using a domain ontology on a web service to integrate heterogeneous data sources and analytics, and visualization components. An intelligent context-awareness building energy management system aiming at identifying particular energy waste causes is presented in [196]. In [197] a foundation study for the development of a cloud-based platform for the integration of BIM and FMS platforms is presented. A tool is implemented for data analytics, and complex predictive and classification modelling. Also, data visualization issue for managers is analyzed. A framework for managing information in the operational stage of buildings is implemented in [198]. In this BIM-based system, the integration of different data sources is used to improve building conditions linked to user behaviours. The authors present a framework based on BIM and IoT technology for monitoring IB in [199]. BIM is used to manage the 3D data and a prototype is developed and tested in an office building. In [200] authors integrate sensor data, BIM and structural analysis. In the paper, they develop a prototypical data transfer model that integrates modelling, visualization and structural analysis tools. A first step in using semantic web technologies in building automation systems is presented in [201]. A reference designation system is integrated into a BIM environment. A proof-of-concept prototype for embedded real-time information from sensors in BIM is presented in [202]. In [203] authors develop a fire visualization and warning system by integrating BIM, fire simulation and IoT technology. In [204] authors propose an augmented reality-based smart building that focuses on fire emergencies and integrates different sensors in a cloud-based environment. A software allowing real-time energy monitoring and simulation and integrating BIM and IoT sensors is developed in [205]. Implementation of Bluetooth devices for indoor location and customizable pathfinding solutions for building modelled by BIM technologies is described in [206]. In [207] authors develop a wireless sensor network by ZigBee technology to efficiently monitor energy consumption in an integrated BIM environment. A cloud-based BIM application for visualizing and managing facility tasks is developed in [208], while an automatic integration of BIM and FMS information is obtained with ST in [209].

Table 3.4 Adoption of analyzed technologies in management stage

	Middle Layer	Low Layer			
Ref.	BIM	BD	IoT	ST	Sub-areas
[186]	Autodesk Revit	Hortonworks Hadoop - Tableau	TelosB motes	-	Health and Safety
[187]	WebGL, X3DOM	-	O-MI, O-DF	Ifc Open Shell	Indoor occupancy
[188]	Autodesk Revit	-	ZigBee	-	Energy monitoring
[189]	Autodesk Revit	-	-	Apache JENA RDF Api, IfcOWL, SAREF, SPARQL, IFCtoRDF	Energy monitoring
[190]	-	-	802.15.4 / ZigBee	IFC, SSN	SHM
[191]	-	Flume, HDFS, Spark	TCP	-	HeS - Indoor air monitoring
[192]	-	-	-	Linked Data - Semantic Sensor Network	Energy monitoring
[193]	-	-	ZigBee, Z-wave	-	Smart Monitoring
[194]	-	Kafka, Flink, MySQL, Cassandra	-	-	Indoor monitoring
[195]	-	-	MQTT	Apache Jena	water management
[196]	Open Smart Building Simulator	-	-	-	Energy simulation, monitoring
[197]	Revit, Dynamo	kafka, spark, Cassandra	-	IFC	Facility Management
[198]	Autodesk Revit	-	Z-wave	Autodesk BIM-IFC	Indoor occupancy, air monitoring

[199]	Revit	MongoDB	MQTT	IFC	Indoor air monitoring
[200]	ArchiCAD - Solibri	-	-	IFC	Structural Health Monitoring
[210]	Revit	-	Zigbee	-	Indoor air monitoring
[201]	General BIM, gbXML	-	OPC UA, Obix, 6LoWPAN	OWL, SPARQL	Indoor air monitoring, Energy monitoring
[202]	Autodesk Revit API	-	-	IFC Converter	Automated As-built details updating e performance monitoring
[203]	Autodesk Revit	MySQL	BLE	-	Disaster and emergency response
[204]	Unity	-	ZigBee	-	Disaster and emergency response
[205]	Autodesk Revit, gbXML	-	ZigBee	-	Energy monitoring, simulation
[206]	Autodesk Dynamo	-	BLE	-	Indoor location
[207]	General BIM	-	ZigBee	IFC Conversion	Energy Monitoring
[208]	Unity	-	-	-	Facility Management
[209]	Autodesk Naviswork	-	-	Apache Jena, SPARQL	Facility Management

3.3.4 Improvement / Disposal

Table 3.5 focuses on the "Improvement/Disposal" phase and summarizes the ICT technologies that are mentioned in the reviewed papers.

Table 3.5 Adoption of analyzed technologies in improvement/disposal stage

	Middle Layer	**Low Layer**			
Ref.	**BIM**	**BD**	**IoT**	**ST**	**Sub-areas**
[211]	Autodesk Revit	-	Z-Wave	IFC conversion	Energy Retrofit
[212]	Revit	Flume, Spark, HDFS, Neo4J	-	-	Waste analytics
[213]	Autodesk Revit	Autodesk Forge	RFID	-	Predictive maintenance
[214]	Revit API	-	BACNet	IFC	Predictive mainteinance

A "cognitive" concept applied to the building is elaborated in [211], where a monitoring framework is used for energy retrofit in a real-case application. In [212] the authors propose a BD architecture for construction waste data analytics based on a waste analytics life cycle. The authors in [214] focus on BIM and IoT integration for improving predictive and long-term dynamic maintenance strategies. Finally, [213] presents an approach to managing and predicting corrosion in mechanical and electrical plumbing BIM by integrating RFID and cloud-based tools in the Autodesk environment.

3.3.5 Full Life-Cycle

Table 3.6 summarizes the ICT technologies that share applications in all the IB life cycle phases.

Table 3.6 Adoption of analyzed technologies in full life-cycle stage

	Middle Layer	**Low Layer**			
Ref.	**BIM**	**BD**	**IoT**	**ST**	**Sub-areas**

[112]	CloudBIM (WebGL)	Apache Hadoop - HBase	-	IFC converter	data visualization
[215]	WebVR	Apache Accumulo	-	-	Data management
[216]	BIMsurfer	BIMServer, MariaDB, Apache Tomcat	-	-	Data visualization
[217]	Autodesk Revit	NoSQL Apache Cassandra	-	IFC	Data management
[218]	BIMTriSer	MPI, Spark	-	IFC Splitter	data management
[219]	Developed Visualizer	-	-	IFC	data visualization
[220]	General BIM, BIMRL	-	-	IFC	Compliance audit
[221]	BIMSurfer	BIMServer	-	IFC	Data management

In [112], features such as viewing, storing and analyzing massive BIMs are implemented in a cloud-based system by using: i) Apache Hadoop as cloud computing technology, ii) WebGL 3D as display technology, iii) and HTML5 as web page technology. The online services provided by the systems allow uploading BIM models to involve both the project and the visualization capability. In [215] authors propose a hybrid storage architecture including a NoSQL database, distributed peer-to-peer storage, and spatial database engine to store remotely BIM geospatial data. An open source BIM platform based on cloud computing technology to handle geospatial data is presented in [216]. In [217] a tool named *Social BIMCloud* facilitates the storage and partial exchange of integrated BIM to study inefficiency in data transfer speed and inconsistency in a distributed environment. The result is achieved both by using IFC technology and a cloud-based NoSQL database. In [218] authors deal with the visualization of geometrical BIM big data, and propose a novel scalable BIM triangulation service named *BIMTriSer*: the service can decompose the original IFC description into several IFC files. BIMTriSer enables scaling of IFC geometric triangulation thanks to a parallel computing framework. Also in [219] complexity and challenges involved in visualizing large BIMs are addressed. The main contribution is the development and validation of a prototypical BIM viewer to handle detailed and large building models. In [220], a web service based on the Representation State Transfer (REST) protocol is used to integrate BIM Rule Language into an automated compliance audit framework named *ARCABIM*. In [222] the authors deal with IFC relationship entities for integration of the federated BIM model. The work focuses on the modification of BIM tools for supporting references during model splitting into smaller (federated models) without compromising the integrity of the relationships. An example of an integrated cloud-based BIM platform for BMS issues is presented in [221]. The paper focuses on the data management related to a building during its life cycle.

3.4 Discussions

3.4.1 Research findings

A synthesis of the distributions of the considered technologies in the reviewed papers is performed in the current subsection.

In particular, Fig. 3.7a shows the number of times ST, IoT and BD are utilized in the 49 analysed papers employing the BIM in the different life cycle phases. The bar diagram shows that ST is the most used technology followed by IoT and BD.

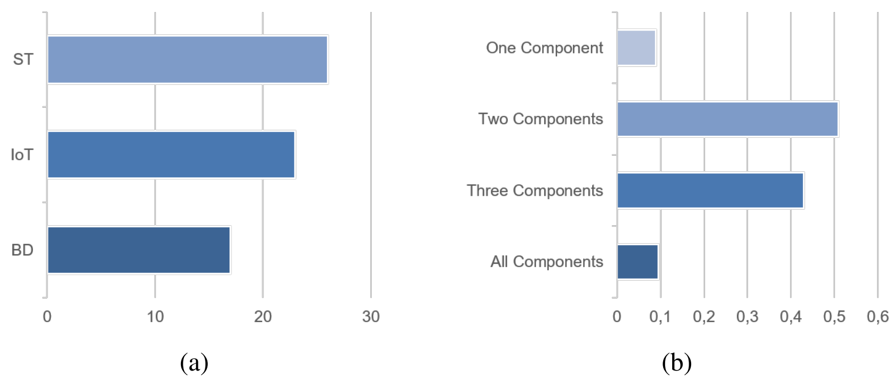


Figure 3.7 ICT IB components and integration in references

Moreover, Fig. 3.7b shows that most of the analyzed papers adopt two (51%) or three (43%) of the components of the IB ICT layer in Fig. 3.6. Only a few papers employ one component or all the components. More precisely, Fig. 3.8 specifies Fig.

3.7b by listing the number of papers that integrate the different technologies. As expected, the most diffused applications regard the BIM-IoT integrated usage. On the other hand, few papers consider IoT, BD and SW without integrating them into a BIM component.

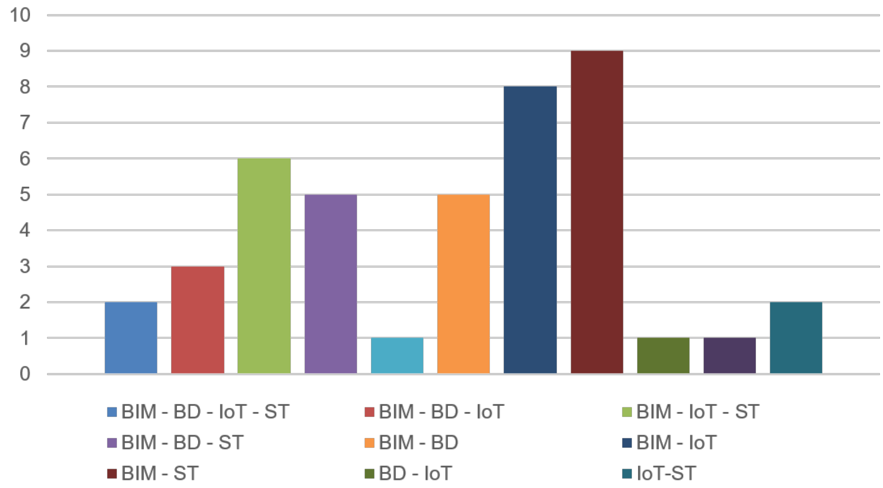


Figure 3.8 Framework components integration in references.

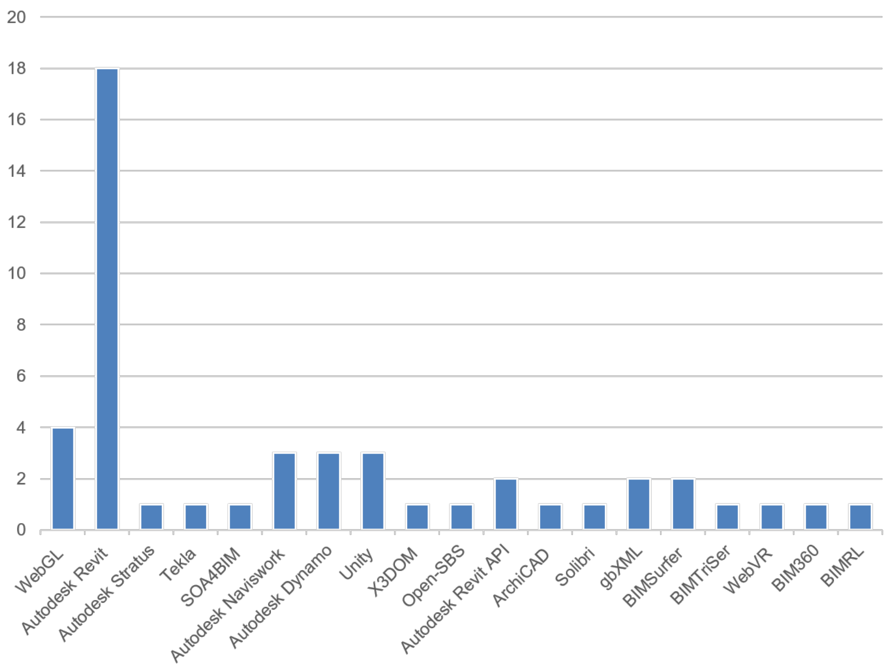


Figure 3.9 BIM-related technologies adoption.

In Table 3.7 the specific BIM-related technologies adopted in the researched papers are reported. In this context, BIM-related technologies refer strictly to BIM features that characterize proprietary software, but also to all cloud-based data visualization tools and software libraries. Fig. 3.9 shows the number of times in which the mentioned BIM technologies are applied in the 49 considered papers. Autodesk Revit is the most used technology in BIM integration strategies. Also, other Autodesk-related technologies like Dynamo, Naviswork and Revit API are applied, because of their flexibility and potential in services and applications customization. Moreover, libraries for cloud visualization (like WebGL) are also applied in 4 papers.

Table 3.7 BIM-based adopted technologies

Technology	Functionality	Description
WebGL	cloud visualization	*Web standard for a low-level 3D graphics API based on OpenGL ES, exposed to ECMAScript via the HTML5 Canvas element* [223].
Autodesk Revit	design, visualization, management	Software for integrated BIM, also able to export to IFC4 format.
Autodesk Stratus	design, visualization, management	Autodesk Revit add-on which leverage mechanical and electrical plumbing together with fabrication issue.
Tekla	design, visualization, management	BIM software focused on structural construction activities.
Autodesk Naviswork	management	Project review software that improve the BIM project obtained by integration of different projects.
Autodesk Dynamo	design	Parametric and generative modeling tools in Autodesk Revit environment.
Unity	cloud visualization	Game engine to create web-based dynamic models.
X3DOM	cloud visualization	*open-source framework and run-time for 3D graphics on the Web* [224].
Open Smart Building Simulator (Open-SBS)	visualization, simulation	A proposed platform integrating the possibility to simulate different senarios for smart home.
Autodesk Revit API	development	Software development kit to develop plug-in and software application in Revit environment.
ArchiCAD	design, visualization, management	BIM software.
Solibri	design, visualization, management	BIM software.
gbXML	cloud visualization	A standard supported from industry for sharing and storing building data.
BIMServer	management	A system to manage BIM projects on cloud.
BIMSurfer	cloud visualization	Open source WebGL viewer for IFC in browser.
BIMTriSer	service	A proposed online BIM triangulation service to obtain triangular meshes.
WebVR	cloud visualization	Specification to allow experience of Virtual Reality in browsers.
BIM360	Construction management	Platform for managing construction workflows.

BIMRL	Database schema	Used to convert IFC into relational database management systems [225]

Table 3.8 Cloud computing-based adopted technologies

Technology	Functionality	Description
Hortonworks	distributed storage / distributed processing	Open source framework for cloud distributed storage and processing for Big Data.
Tableau	data visualization	A platform for visual analysis of data [226].
Apache Kafka	distributed storage / distributed processing	A distributed streaming framework used to build data pipelines for real-time data streaming among systems [30].
Apache Flink	distributed processing	A framework for data stream management. It can deal both with online and offline stream, state management, event-time processing semantics, and consistency guarantees for state. Like Spark, Flink can run on various resource providers such as YARN, Apache Mesos, and Kubernetes. Most common types of application developed by using Flink are event-driven application, data analytics applications and data pipeline applications [227]
Apache Hadoop	distributed storage / distributed processing	A libraries collection that configure a framework for all Big Data-related tasks.
Hadoop Distributed File System (HDFS)	distributed storage	Distributed file system for storage in Hadoop environment.
Apache Hadoop YARN	resource provider	Hadoop environment resource manager and job scheduler.
Apache HBase	Distributed Storage	Open-source database for Big Data based on Google BigTable
Microsoft Azure	Cloud Computing	Platform that offers products and cloud services

Apache Spark	distributed storage / distributed processing	General-purpose open-source distributed cluster-computing framework, supporting both stream data processing and batch processing. It integrates ApacheSparkSQL, GraphX, MLib, and Spark streaming components and can access data from various data sources and run on various platforms such as Hadoop, Mesos, and Yarn. It is considered cost effective compared to Storm even if Storm has shown superiority in terms of latency [27].
Apache Flume	streaming data service	A framework for managing stream of large quantities of data, modeled as events [228].
Apache Cassandra	Distributed storage	Open-source distributed NoSQL database solution for Big Data.
MongoDB	Distributed storage	Document-based NoSQL distributed database.
Apache Accumulo	Distributed storage	Key/value NoSQL distributed database.
MariaDB	Storage	SQL Database technology.
Apache Tomcat	Web server	Open Source software for powering large-scale application over the web.
Neo4J	Distributed storage	A graph database technology to leverage also relationships between data.
Autodesk Forge	web-service API's	Environment to improve Autodesk data formats interoperabilities.

Table 3.9 IoT-based adopted technologies

Technology	**Functionality**	**Description**
Crossbow TELOSB	Platform/device	Platform published to research community with IEEE 802.15.4/ZigBee compliant RF transceiver sensors.
O-MI/O-DF	communication protocols	A Messaging standard text-based protocol [229].
ZigBee	Communication protocol	Protocol on top of IEEE 802.15.4 network standard. It allows the creation of personal area network application that requires a low data rate, longer battery life, and secure networking devices [230].
BACNet	Communication protocol	Standard data communication protocol for building automation and control networks [231]

Z-wave	Communication protocol	Low speeds, network up to 50 nodes and small data packets characterize this technology. Masters and slaves nodes network, with only masters node able to initialize the communication and force slaves to execute commands.
Message Queuing Telemetry Transport Protocol (MQTT)	Communication protocol	A publish/subscribe, simple and lightweight messaging protocol, designed for constrained devices and low-bandwidth, high-latency or unreliable networks[49].
Open Platform Communications Unified Architecture (OPCUA)	Service Oriented Architecture	An Interoperability platform-independent standard, for data exchange in industries. [232]
Open Building Information Xchange (oBIX)	Web service	XML web service-based mechanism for building control systems. [233]
6LoWPAN	Communication Protocol	Protocol in which every device is identified by a unique IPv6 address [48].
Radio-Frequency Identification (RFID)	Technology	Characterized by a variety of standards, consists of a reader device and a small radio-frequency (from 3 to 30 GHz) transponder called RF tag. Main feature of RFID is the necessity of programming static information into the tag; since static nature of programmed data, possible application are restricted.
Bluetooth Low Energy (BLE)	Communication protocol	It aims at minimize power consumption in low data rate application in power constrained IoT application [234].
Transfer Control Protocol (TCP)	Communication protocol	It aims at minimize power consumption in low data rate application in power constrained IoT application [234].

Table 3.10 Semantic-related adopted technologies

Technology	**Functionality**	**Description**
BIM to IFC Conversion	Conversion	IFC used as an exchange format to allow reusing of BIM data.
BIM to Resource Description Framework (RDF)	Conversion	RDF used for semantic query via SPARQL towards converted BIM data.
Ontology Web Language (OWL)	Knowledge formalization	Semantic Web language designed to represent ontologies over the web.
SPARQL	Query Language	Language used to query data in RDF format.
D2RQ	Platform	Solution to map and expose SQL databases as RDF/OWL ontologies [235]
Protege	Platform	Open-source service and framework to build ontology on the Web, fully supporting OWL2 specification
Semantic Web Rule Language	Language	
IfcOpenShell	Visualization	Open-source library to work with IFC files
Apache JENA	Development framework	Open-source framework for Semantic Web and Linked data-oriented application development
IFCtoRDF	Conversion	Development components written in JAVA to convert from IFC to RDF graphs.
Smart Applications REFerence (SAREF)	Knowledge formalization and sharing	An official ontology model for smart applications domains.
IFC Splitter	Conversion	Library for splitting IFC file in smaller parts.

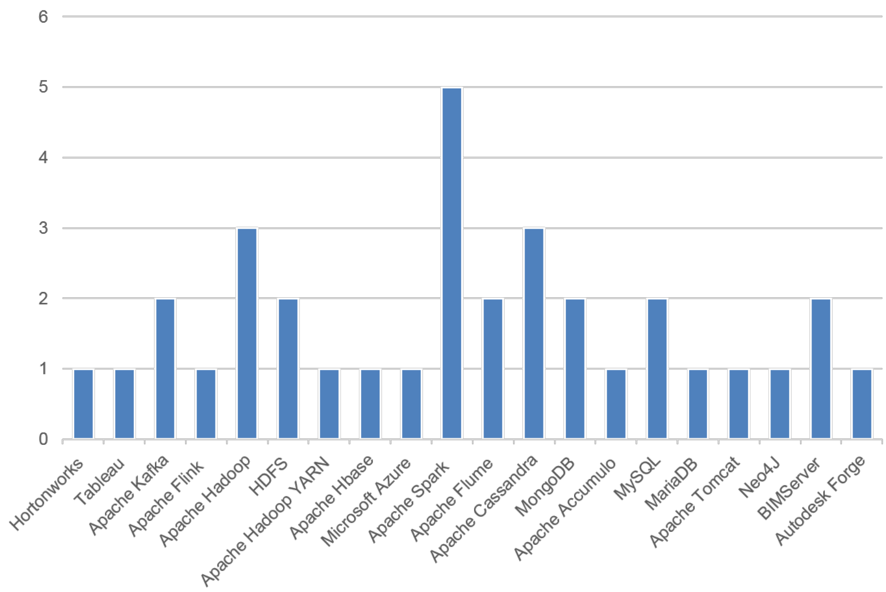


Figure 3.10 BD-related technologies adoption.

In Table 3.8 the specific BD-related technologies adopted in the considered papers are reported by focusing on BD architectures, BD technologies and widespread standard cloud technologies. Fig. 3.10 enlightens that Apache Spark, Apache Cassandra and Apache Hadoop are the most mentioned technologies. In particular, the Apache Hadoop environment remains one standard and practically adopted tool because of its prior release. Relation databases such as MySQL technologies have valuable applications.

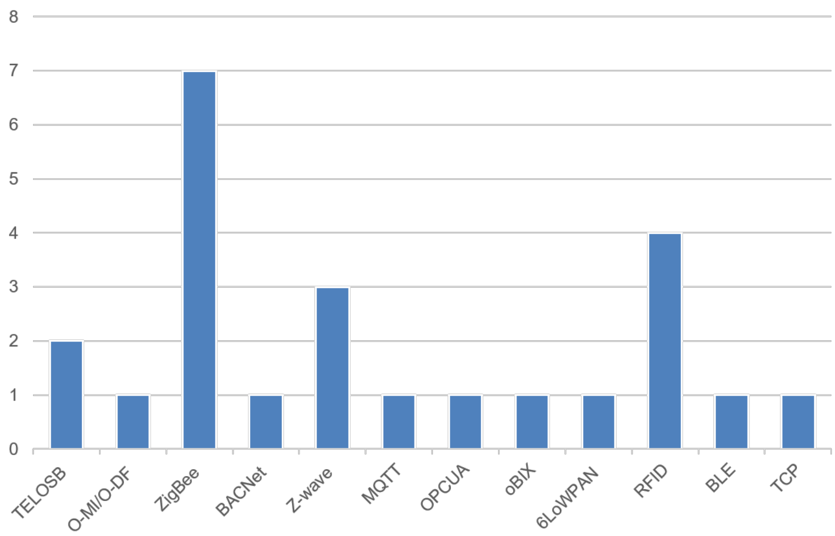


Figure 3.11 IoT-related technologies adoption.

Table 3.9 reports the specific IoT-related technologies adopted in the considered papers by referring to communication protocols and hardware devices. Fig. 3.11 shows that ZigBee is the most used technology because of its double nature of hardware device integrated with specifically implemented communication protocol. RFID and Z-wave are also widespread.

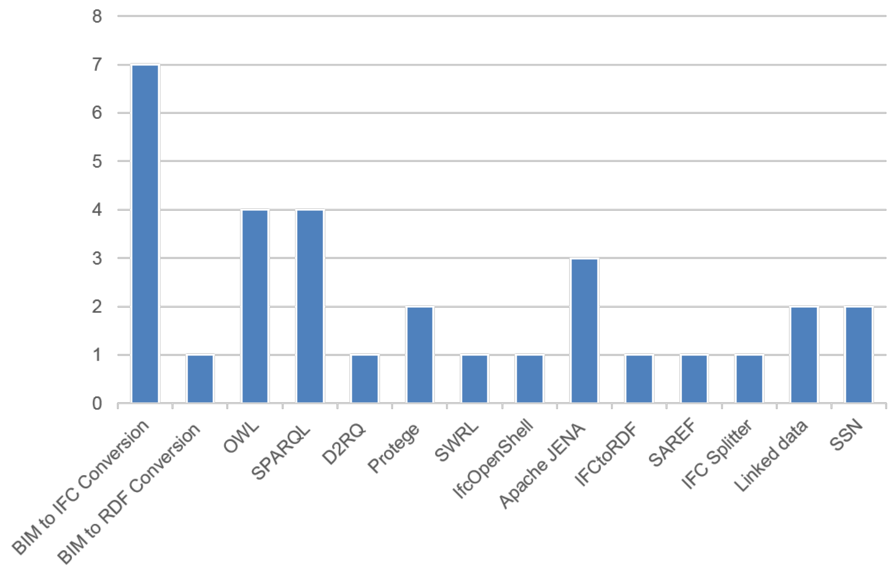


Figure 3.12 Semantic-related technologies adoption.

In Table 3.10 the specific ST-related technologies adopted in the reviewed papers are reported. More precisely, the considered ST applications deal with: i) the conversion issues from BIM proprietary format to a common IFC interoperable format; ii) the cloud-exploitation of converted format; iii) the semantic web technologies to deal with converted data; iv) the ontology-based reasoning basing on the converted format and semantic web technologies; v) the semantic enrichment of IoT data from sensors. In addition, Fig. 3.12 highlights that the use of conversion tools from BIM to IFC format is the most widespread application, but also ontology-based reasoning has numerous applications due to OWL usage.

The distribution of the reviewed works in the building life-cycle is also an important aspect to be investigated. To this aim Fig. 3.13 shows the distribution of the considered papers in the different life cycle domains reported in Fig. 3.3. The analysis points out that about half of the reviewed works focus on the operation/maintenance stage. This result was expected since the most investigated topics in IBs-related literature are Energy Management, Building Automation Systems, etc. as it is highlighted in the review analysis performed in 3.2.

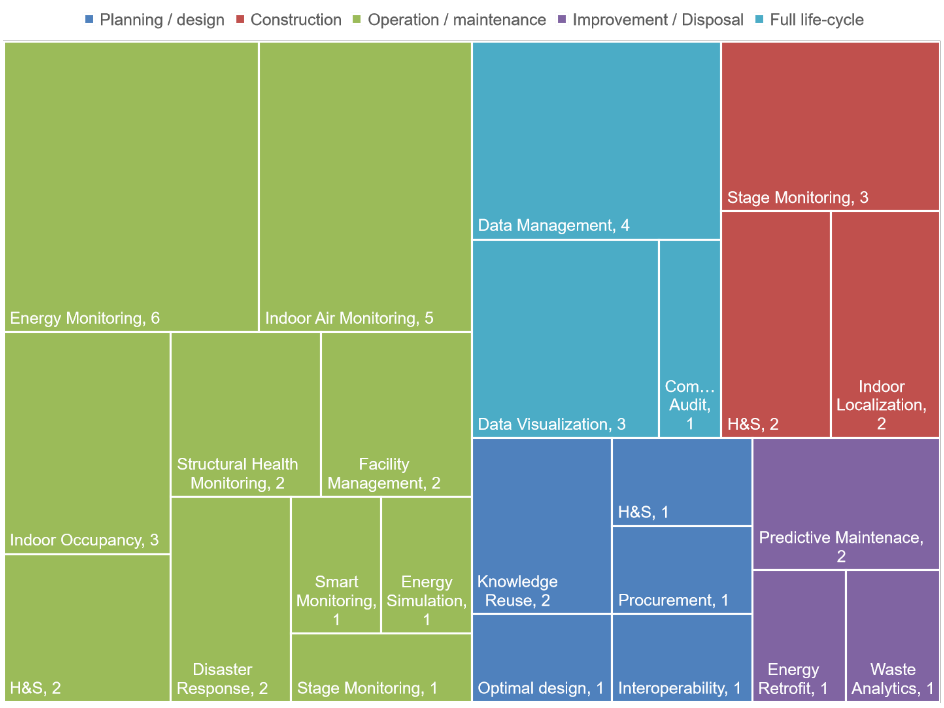


Figure 3.13 Life cycle classification of applications.

3.5 Conclusions and future works

This chapter reviews the ICT tools and strategies presented in architecture, engineering and construction literature and implemented in the IBs, by considering the specific applications in the different building life cycle phases. The review analysis is performed by using an original framework that consists of a hierarchical two-layer structure, of which the lowest layer, named IB ICT Layer, contains one construction-specific sub-layer and one ICT generic sub-layer. The components of the ICT generic sub-layer are identified by a procedure supported by a technique based on natural language processing.

The defined methodology can be applied for a review analysis in different research contexts where there is a huge number of aspects and documents to be considered. Indeed, the specification of the hierarchical framework helps to single out and rank the aspects to be analysed in the review process. Moreover, the automatic procedure for exploring the papers' contents allows objectively structuring the framework and does not need any prior assumptions. The proposed approach should be supported by critical experts' supervision to guide the obtained research outcomes. However, the analysis performed in this work has been useful to determine the most applied ICT tools in the AEC field and the technologies that are not adequately exploited and need future consideration.

In particular, two main conclusions can be pointed out. First, the authors in the considered literature develop their innovative results and integrate new findings in the BIM environment. This common approach is a limitation for wide knowledge management and reuse and may hinder or slow the development of new ICT tools for construction. Indeed, focusing on the BIM implementation of the technical results may prevent the evolution of more innovative environments such as the digital twin. Such drawbacks could be overcome by fostering the interoperability of the software currently employed for BIM systems.

Second, a roadmap for a large application of the analyzed technologies in the construction process is still far. Indeed, the solutions presented in the literature deal with very specific construction-related problems and do not propose general outcomes for wider purposes.

Despite the evidence of a large amount of data generated from the construction industry during the entire building life cycle, it is possible to conclude that there are not yet consistent applications in this field that can effectively represent a general intelligent system.

Chapter 4

Automated Location of Steel Truss Bridge Damage Using Machine Learning and Raw Strain Sensor Data

Partially published in *Fabio Parisi, Agostino Marcello Mangini, Maria Pia Fanti, & José M. Adam. (2022). Automated location of steel truss bridge damage using machine learning and raw strain sensor data. Automation in Construction, 138, 104249.*

4.1 Introduction

Many safety concerns in major transport infrastructure management are due to ageing and degradation [236]. The deterioration of infrastructure systems contributes to over 3% of the Gross Domestic Product of industrialized countries [237]. These issues arise especially when dealing with steel truss railway bridges, most of which in Europe are more than 50 years old [238, 239] and were built before designs and guidelines were standardised [240]. Given their number, a re-building strategy would be extremely costly in terms of resources and time [241]. Structural Health Monitoring (SHM) is considered valuable support that needs to be further exploited to face these critical issues. Some serious recent disasters in major infrastructure management, such as the collapse of the I-35 bridge over the Mississippi River in

2007 and the Morandi bridge collapse in Genova in August 2018, show that an efficient structural monitoring strategy is crucial.

Recently, Machine Learning (ML) tools have emerged as effective approaches for SHM. ML algorithms build models based on sample data, known as training data, to make predictions or decisions. Thanks to the considerable computational power available in cloud services and the Information and Communication Technologies enhancement, a continuous data flow is generated by monitored structures, collecting and sending data analysed in real-time according to the Internet of Things approach. Many attempts have been made to extract crucial information about structural conditions from big data generated by sensors on infrastructures, letting damages location and assessment of structural systems become a central topic in SHM [242].

In [243] the authors propose a Convolutional Neural Network (CNN) classifier to predict damage location labels, detecting structural damages from numerically simulated low-level waveform signals. The work [244] describes a CNN followed by a Long Short-Term Memory (LSTM) for classifying, into different structural damage classes induced, raw vibrational data collected from a three-story frame structure. In [245] the authors deal with damage detection and location of offshore wind turbine blades by training a LSTM network on simulated vibrational data of different damage scenarios. Four different architectures trained on raw vibrational data, such as Multi Layer Perceptron, LSTM, one- and two-dimensional CNNs are studied in [246]. The data are collected both from an experimental set-up and finite element (FE) simulations while uncertainties are taken into account by Monte Carlo simulations. In [247] the authors propose a Neuro-Fuzzy classifier, based on statistical features extracted from vibrational signals, for damage states. An autoencoder that maps from vibrational features (such as modal forms and frequencies) to structural damages is developed in [248]; the data are collected from an experimental lab set-up and FE analysis. In [249] the authors use frequencies and modal shapes to train a Deep Belief Network built with Restricted Boltzmann Machine blocks to detect damages localisation. A combination of the Hilbert-Huang transform with an optimized CNN is used in [250] to perform a fault classification task on time series. In [251] the authors train a sparse autoencoder to map pre-processed vibrational features to structural stiffness reduced; the data are collected from an experimental laboratory set-up. In [252], a modified Principal Component Analysis involving autoencoders is developed and its performance in damage detection is tested on Z-24 benchmark data. The work [253] studies the damage detection issue by training a CNN-LSTM network on data obtained by FE and simulations, while in [254] a CNN classifier operates on data generated from an updated FE model. In [255] the authors compare three different models (Principal Component Analysis, Fully-Connected Autoencoder and Convolutional Autoencoder) by using real data for anomaly detection in bridge behaviour. A CNN application to the structural dynamics response estimation is proposed in [256] to predict different signals measured in a full-scale framed structure. In [257] the authors employ a support vector machine model that first classifies the state of a structure and then evaluates damages severity. Data are simulated with a procedure that creates anomalies by removing portions of the solid structure. In [258] a novel anomaly detection method based on adaptive Mahalanobis-squared distance and one-class k-Nearest Neighbours (kNN) for SHM is studied under varying environmental conditions.

Several of the above-cited works deal with damage detection and location problems in the form of classification tasks [243–246]. Preliminary signal pre-processing approaches to extract damage sensitive features are widely used in ML models. Most of the authors base their investigations on accelerometer signals from which they extract frequency and damage-sensitive modal features [246, 245, 247, 249, 248]. However, there are still limitations for applying these systems to real-life structural monitoring because of different issues: i) the need for a preliminary consistent pre-processing phase for damage-sensitive feature extraction; ii) the limited accuracy of the procedures to detect frequencies and modal forms [259]; iii) the poor damage representation of the features extracted [243].

This chapter proposes a new method for detecting damages in steel truss railway bridges by using ML tools to classify raw strain multivariate time series data. In a future digital twin approach, the method is suitable for real-time monitoring of infrastructures.

The method consists of several phases. First, a set of damage scenarios is selected. Second, a series of structural analyses are performed by an FE software driven by a dedicated routine that applies loads and damages to the FE model. Then the raw strain signals are collected and subjected to a feature selection phase: a k-nearest neighbour model highlights the most informative portions of the data. Successively, the data selected are used to train a CNN for locating damage and assessing its severity. The method and the tool are validated by testing the classifier accuracy on test data.

The approach proposed is applied to a real case scenario of the Quisi bridge in Valencia (Spain): it is a riveted steel truss railway bridge subjected to moving loads monitored in a testing phase with strain sensors.

The chapter is structured as follows. Section 4.2 introduces the proposed methodology and the ML tools used; Section 4.3 describes the case study and presents the outputs and the results of the research; Section 4.4 draws the conclusions.

4.2 Methods and Materials

This section introduces the methodology adopted and the ML tools used, highlighting their application in each phase. The overall method is shown in Fig. 4.1 and specified as follows: i) Fault Analysis, ii) Control Points Location, iii) Data Generation, iv) Data Collection, v) Feature Selection, vi) Damage Location and Damage Severity Assessment.

4.2.1 Fault Analysis: selecting damage scenarios

In line with the existing literature [253, 248, 251], a set of different damages to be investigated is identified (phase (1) in Fig. 4.1, Faults Analysis). To this aim, the set of structural elements considered $\boldsymbol{S} = \{s_1, ..., s_s, ..., s_{n_s}\}$ is first determined, and we call *damage scenario* the generic element $s_s \in \boldsymbol{S}$ with $s = 1, ..., n_s$. Then, for each s_s, different *damage levels* $l \in \boldsymbol{L} = \{0, ..., l, ..., (n_l - 1)\}$ are investigated, each $l \in \boldsymbol{L}$ representing the severity of a selected damage scenario. Now, the set of *damage conditions* $\boldsymbol{F} = \{\, (s_s, l) \mid s_s \in S, l \in L \,\}$ is defined. Moreover, for the sake of notation simplicity, a label y_j for $j = 1, ..., n_F$ with $n_F = n_s \cdot n_d$ is associated to each couple (s_s, l) specifying: i) the damage location (related to damage scenarios s_s) and ii) the damage severity (related to damage levels l).

4.2.2 Location of Control Points

This phase specifies the locations for the monitoring sensors to measure the deformation in the considered bridge structural elements (phase (2) in Fig. 4.1, Control Points Location and in red in FE Model). The set of control points $\boldsymbol{P} = \{p_1, ..., p_n, ..., p_{n_{cp}}\}$

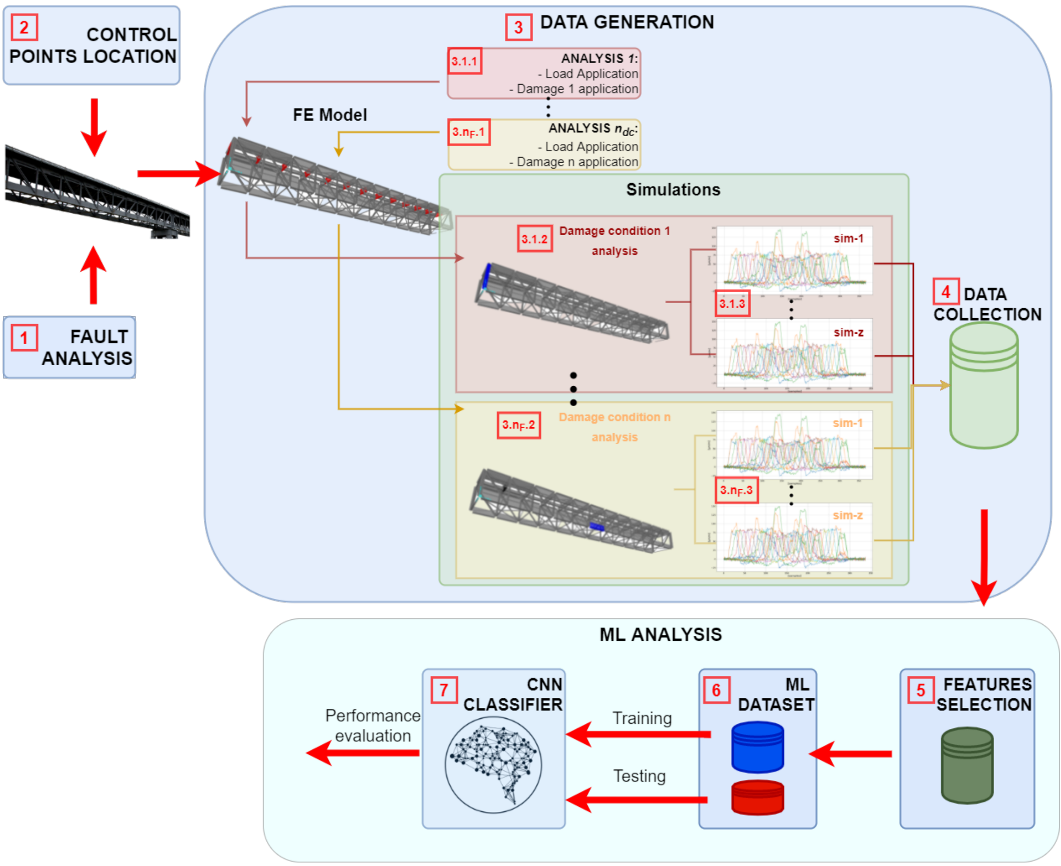


Figure 4.1 Research method

represents the selected locations, where n_{cp} is the total number of control points, while the monitoring collects the strain signals at each point $p_n \in \boldsymbol{P}$ where sensors are placed. Note that the control points location depends on the studied structure. If the real structure is already monitored by strain sensors, then the control points location corresponds to the strain sensors position. If there is no monitoring system on the real structure, it is necessary to provide an optimized procedure for determining the control points location.

4.2.3 Data Generation

Once the damage conditions $\boldsymbol{F}$ and the control points $\boldsymbol{P}$ are determined, a procedure generates the data (phase (3) in Fig. 4.1, Data Generation). Using a FE software, each damage condition and random weights and speeds of the moving loads are applied to the FE model (phase ($3.n_F.1$) in Fig. 4.1). Hence, z different simulations for each damage condition $(s_s, l) \in \boldsymbol{F}$ (phase (3.n_F.3) in Fig. 4.1) are performed with a total number of $n_{sim} = n_F \cdot z$.

The strain values in the control points $\boldsymbol{P}$ are saved (phase (3.n_F.3) in Fig. 4.1) as the outputs of the simulations (phase (3.n_F.2) in Fig. 4.1), so that a monodimensional time series [260] $\boldsymbol{x} = (x_1, ..., x_t, ..., x_T)$ of strain values is collected for each analysis in each p_n. Since there are n_{cp} control points, for each simulation a multivariate time series [261] $\boldsymbol{X_m} = [\boldsymbol{x_1}, ..., \boldsymbol{x_n}, ..., \boldsymbol{x_{n_{cp}}}]'$ is collected (phase (3.n_F.3) in Fig. 4.1).

4.2.4 Data Collection

In the proposed methodology, the damage location is set as a classification problem, hence the related dataset requires data and class labels. The dataset is generated by running the n_{sim} simulations (phase (4) in Fig. 4.1, Data Collection): for each damage condition $(s_s, l) \in \boldsymbol{F}$, the z simulations are performed and the resulting multivariate strain signal time series generated in $\boldsymbol{P}$ are labelled by the corresponding label y_j. By running the n_{sim} simulations, a set of multivariate time series $\bar{\boldsymbol{X}} = \{\boldsymbol{X}_{\boldsymbol{1}}^{y_1}, ..., \boldsymbol{X}_{\boldsymbol{z}}^{y_1}, ..., \boldsymbol{X}_{\boldsymbol{1}}^{y_j}, ..., \boldsymbol{X}_{\boldsymbol{z}}^{y_j}, ..., \boldsymbol{X}_{\boldsymbol{1}}^{y_{n_F}}, ..., \boldsymbol{X}_{\boldsymbol{z}}^{y_{n_F}}\}$ is obtained so that the dataset of multivariate strain sensors time series and labels is denoted by $\boldsymbol{D} = \{(\boldsymbol{X}_{\boldsymbol{i}}^{y_j}, y_j)\}$ with $i = 1, ..., z$ and $j = 1, ..., n_F$.

4.2.5 Feature Selection and ML Dataset

Feature selection is a technique that refers to the general process of detecting the relevant features in the dataset and discarding the irrelevant ones [262]. It is closely related to the dataset knowledge domain and is based on procedures that measure the sensitivity of an ML model performance (e.g. accuracy) to data modifications.

A *distance-based criterion* is introduced in this thesis to perform feature selection (phase (5) in Fig. 4.1, Feature Selection). Both control points $\boldsymbol{P}$ and damage scenarios $\boldsymbol{S}$ are geometrically localized on the structural system so that the $\boldsymbol{P}$ distance-based sensitivity to damage scenarios $\boldsymbol{S}$ is investigated to answer the question: *Is the information collected in a p_n useful for each s_s damage scenario classification?* This sensitivity is studied by measuring the performance (i.e., the accuracy) of a ML model to modifications of the dataset. In particular, the investigation identifies a subset $\boldsymbol{P_s(r)} \subseteq \boldsymbol{P}$ to train a ML classifier on each damage scenario s_s, where $\boldsymbol{P_s(r)}$

collects the r control points that are the r closest points to the damage scenarios s_s, with $r = 1,...,n_{cp}$. More precisely, being $\boldsymbol{X}_{\boldsymbol{i}}^{y_j}$ the multivariate time series obtained by the i-th simulation corresponding to the damage condition y_j (and thus to a damage scenario s_s), the feature selection phase allows considering only the most informative portion $\boldsymbol{X}_{i,s}^{y_j}$ whose components are selected in relation to the $\boldsymbol{P}_s$ subset. Thus, the resulting dataset is $\boldsymbol{D_s} = \{(\boldsymbol{X}_{i,s}^{y_j}, y_j)\}$ with $i = 1,...,z$ and $j = 1,...,n_F$.

The ML model used for this phase is a k-nearest neighbours (kNN) classifier featured with the Dynamical Time Warping (DTW) [263] as a metric. This algorithm is widely used in time series classification problems [264–266]. For each possible cardinality $r = 1,...,n_{cp}$ of $\boldsymbol{P}_s$, a kNN model is fitted on the basis of the $\boldsymbol{D_s}$ training data, and we denote by $\boldsymbol{M} = \{m_1,...,m_r,...,m_{n_{cp}}\}$ the set of the obtained fitted models. The accuracy of m_r is evaluated on the $\boldsymbol{D_s}$ test set and the model with the best accuracy identifies the optimum r to be considered in the CNN training and thus the most informative portion of the dataset.

4.2.6 ML Dataset and CNN Classifier: Damage Severity Assessment and Damage Detection and Location

The dataset $\boldsymbol{D_s}$ is split into two parts: one for training the classifier and one to test its performance in classification (phase (6) in Fig. 4.1, ML Dataset). The usual split of 70% for the training and 30% for the test was used [267, 268]. A CNN is used as the ML model to classify the multivariate strain signals time series (phase (7) in Fig. 4.1, CNN Classifier) and is trained in two distinct tasks:

- Damage Location: the labels in the dataset are assigned only considering the damage scenarios $\boldsymbol{P}$ as label class;
- Damage Severity Assessment: the labels in the dataset are associated with the couples belonging to the set $\boldsymbol{F}$ so that damage levels are also considered.

After successful training, the CNN represents the ML tool that predicts damage location by using the multivariate strain signal time series as input. Its performance is evaluated on the test set, a part of the data collected that have not been provided to the model during the training phase. The model takes the test set as input and predicts a class $\hat{y}_j$ for each of the $\boldsymbol{X}_{i,s}^{y_j}$ in the test set and its performance is based on its capacity to predict the class $\hat{y}_j$ that matches the real class y_j. The confusion matrices (CMs) [269] are used to measure this performance: for each true class in test data, the CM reports the percentage of times that the model predicts a label. In addition, the accuracy score [270] is employed as a performance measure.

4.2.7 The ML Tools used

This section describes the ML tools adopted in the procedure and their main theoretical aspects.

The nearest neighbours algorithm predicts the label of an unlabelled instance with a predefined number of closest labelled instances. The number of labelled instances is a user-defined constant k. The distance can be any metric measure, such as standard Euclidean distance. This algorithm is a type of non-generalizing learning: it does not attempt to construct a general internal model, but simply stores and "remembers" instances of the training data. Classification is computed from a simple majority vote of the k-nearest neighbours of each point [271]. The optimal choice of the value k is highly data-dependent: in general a larger k suppresses the effects of noise, helps the generalization but makes the classification boundaries less distinct.

The DTW distance between two time series is computed by first finding the best alignment between them: for each point in the time series, a cost matrix that represents the cost of aligning the two points from the respective time series is constructed. An alignment between the two time series is represented by a warping path in the cost matrix. The best alignment is then given by a warping path through the cost matrix that minimizes the total cost of aligning its points, and the corresponding minimum total cost is termed as the DTW distance. In this methodology, the algorithm 1NN-DTW was used for the feature selection phase since it is recognized as very effective for its performance [272, 273]. A recent implementation of the DTW applied to time series classification is available in [274].

CNNs are analogous to traditional artificial neural networks: they are composed of subsequent layers whose neurons parameters are self-optimized during the training process. They give good performance in applications with multi-dimensional input data, like images or videos, and their power in such applications comes from implementing the convolutional layer as the base layer: it focuses on local portions of the input data enabling the network to speed up the computations.

In our problem settings, the CNN was applied on time series classification as a feature extractor with a multivariate time series as input and output a probability distribution of possible classes y_j in the dataset. In this chapter, an architecture proposed in [266] is implemented, already used for time series classification and as a baseline in many studies, such as [275].

Fig. 4.2 shows the CNN architecture used. Each basic block is a convolutional layer followed by a batch normalization layer [276] and a Rectified Linear Unit (ReLU) activation layer. Convolution is fulfilled by three one dimensional kernels with sizes $\{3,3,3\}$.

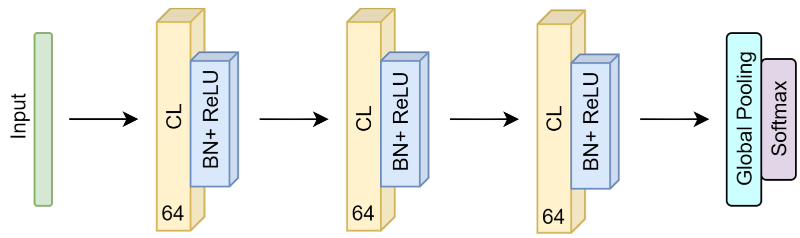


Figure 4.2 CNN architecture [266]

The whole network is built by stacking three convolution blocks with the filter numerosity $\{64,64,64\}$ in each block. Every pooling operation is excluded, as in the ResNet [277], to prevent overfitting. Batch normalization is applied to speed up the convergence and to improve generalization. After the convolution blocks, the features are fed into a global average pooling layer [278].

Tensorflow framework [279] with its Application Program Interface (API) in Keras [280] were used for the CNN training and validation.

4.3 The Case Study

In this section, the methodology introduced in Sec. 4.2 is applied and specified in a real case scenario. All the phases are reported as well as the resulting performances in both damage location and damage severity assessment.

4.3.1 The Quisi bridge

The Quisi Bridge (Fig. 4.3) in Valencia is part of the Spanish national railway network, connecting the towns of Alicante and Denia. It is a steel Pratt truss railway bridge with riveted connections. The structure is approximately 170 m long and is composed of 6 spans with lengths varying between 21 and 42 m on five steel truss columns of different heights. A description of all the geometrical and mechanical characteristics can be found in [241].

Figure 4.3 Quisi bridge, Benissa, Valencia Region

Since its lateral end spans are isostatics, only the first span was considered to test the method without any loss of generality: the portion of the infrastructure used is shown in Fig. 4.4 with a view from the FE model used in the procedure. FRAME type elements were used to model the trusses, while SHELL elements were used to model four stiffening plates in the initial and end portion of the span (in black in Fig. 4.4). The boundary conditions applied reproduced the real constraints of the first span: it has a fixed support on the right external node ends and a mobile one on the abutment on the left. All the boundaries conditions allow rotations. Elastic linear behaviour was considered for the steel material with an elastic modulus of $210GPa$ and density equal to $78.5kN/m^3$

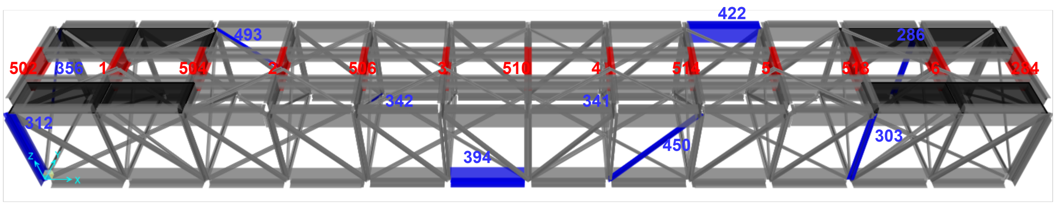


Figure 4.4 Control points location $\boldsymbol{P}$ (in red) and damage scenarios $\boldsymbol{S}$ (in blue)

4.3.2 Method

Selection of damages scenarios and location of Control Points

A set of $n_s = 10$ bridge structural elements was randomly selected to ensure generality for the investigation so that the whole span of the bridge was subjected to damages. Close elements also with different structural hierarchy were considered to study the method sensitivity. The set of the elements selected $\boldsymbol{S} = \{286, 356, 342, 450, 493, 341, 312, 303, 394, 422\}$ is shown in blue in Fig. 4.4, where s_s is the element name from the FE model. The faults of these elements were the damage scenarios investigated and three damage levels $\boldsymbol{L} = \{0, 1, 2\}$ were defined. A reduced cross-sectional area A_s was considered for each element s_s to simulate the damage [281, 282]. In particular, the area A_s was multiplied by $0.66, 0.33, 0$ for the corresponding level $l = 0, 1, 2$, respectively.

The set of all the damage conditions was $\boldsymbol{F} = \{(286, 0), ..., (286, 2), ..., (312, 2), ..., (422, 2)\}$ and the total number of damage conditions was $n_F = n_s \cdot n_l = 30$.

The set of the control points $\boldsymbol{P} = \{502, 1, 504, 2, 508, 3, 510, 4, 514, 5, 518, 6, 284\}$ at which the strain values monitored the damage is show in red in Fig. 4.4, where p_n is the name obtained by the FE model.

Data Generation: train load modelling

In order to perform the simulations, the train weights w_t and speeds v_t [283] were selected at random. In particular, the train speed v_t was sampled from a normal distribution $\mathcal{N}(v_{mean}, \sigma_v)$ with $v_{mean} = 8.33 m/s$ and $\sigma_v = 1$ [284]. The train weights w_t were those of a 2500 Series diesel locomotive. The total weight of an empty train is $55.8tons$, distributed in four bogies and two axles per bogie with a total length of $34.79m$. With $l_{w_{full}} = 70tons$ the maximum possible weight of a fully loaded train [285], the train loads w_t at each simulation were sampled from a normal distribution $\mathcal{N}(w_{mean}, \sigma_w)$ with $w_{mean} = 62tons$ and $\sigma_w = 5$ [286]. The computed load was uniformly distributed over the axles.

Data Generation: simulations

Strain signal data at control points $\boldsymbol{P}$ were generated by analyses in SAP2000 software, used in research applications and commercial activities. It exposes some Application Program Interfaces that enable its exploitation through code and was chosen because of the availability of an already calibrated FE model [287, 241]. The simulation campaign was implemented by Python programming language [288] that is widely used in the ML field.

In Fig. 4.5 the activity diagram of the procedure implemented is shown. The user specifies the damage conditions $\boldsymbol{F}$, the train model (w_t and v_t) to use in the analysis and the FE model file to the Configuration Handler, and then starts the SAP2000 Manager by setting the total number of simulations $n_{sim} = n_F \cdot z = 6000$ with $z = 200$. The SAP2000 Manager first checks if any instance of SAP2000 software is already running locally, and it starts one if not present. It then checks if the right FE Model provided by the user is loaded in the SAP2000 instance, and corrects it if necessary. The SAP2000 Manager then obtains the user-identified train model (w_t and v_t) and the damage condition y_j by the Configuration Handler, computes random loads for w_t and v_t, communicates the loads and the damages to apply to the model to SAP2000 FEM that finally starts the analysis. The results are stored locally in files that refer to the damage conditions applied to the FE model. The procedure is repeated until the last simulation for the final damage condition in $\boldsymbol{F}$ is considered.

Direct integration time-history analyses [289] were performed for the n_F selected damage conditions. This type of analysis was selected because it enables: i) considering the dynamical effects induced by moving loads [290], ii) obtaining the time-dependent strains variations due to passing trains.

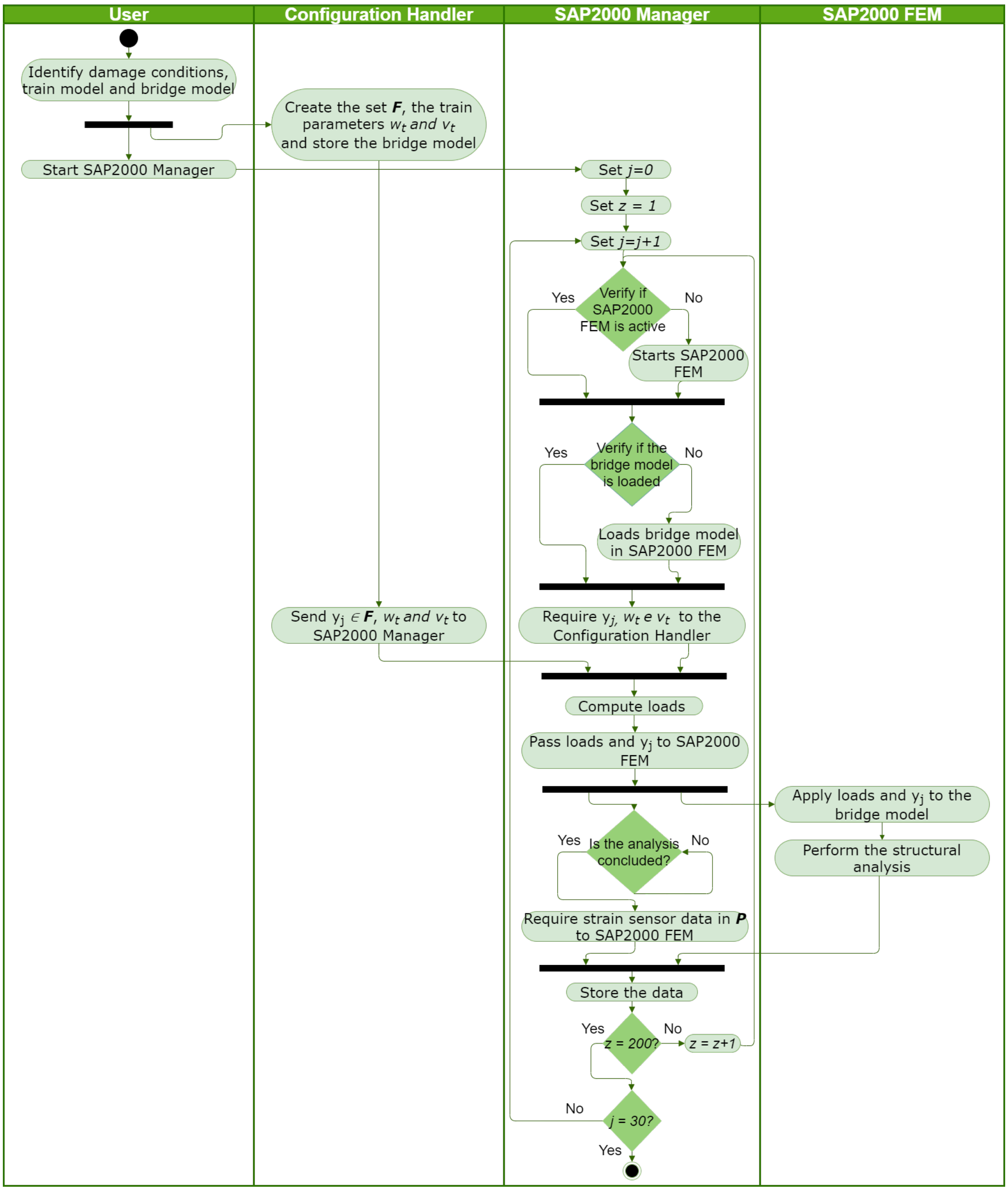
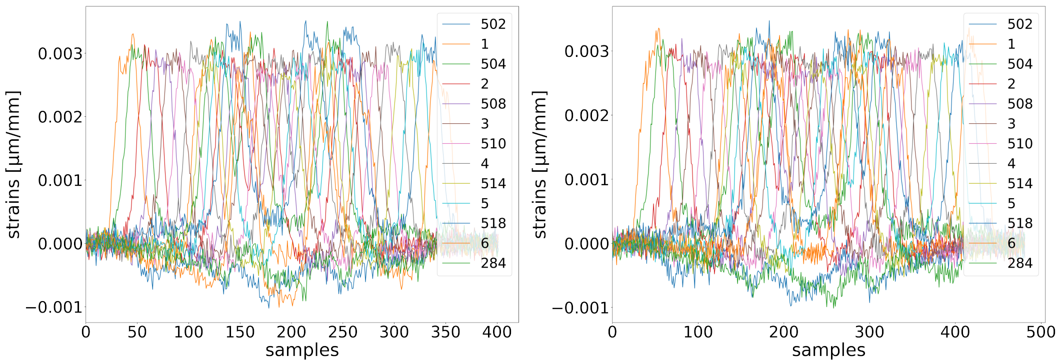


Figure 4.5 Simulations Activity Diagram

Data Collection

A single analysis consisted of one train crossing the bridge. Fig. 4.6 gives two examples of the strain signals of different simulated damage conditions: Fig. 4.6a shows the signals generated for damage condition $(286, 2)$, while Fig. 4.6b refers to damage condition $(341,1)$. The figures give thirteen time series obtained in each analysis from control points p_n in $\boldsymbol{P}$ (in legends, and in red in Fig. 4.4).

With n_{sim} simulations the dataset is generated as a collection of pairs $\{(\boldsymbol{X}_{\boldsymbol{i}}^{y_j}, y_j)\}$ with $i = 1,...,z$ and $j = 1,...,n_F$, where: i) $\boldsymbol{X}_{\boldsymbol{i}}^{y_j}$ is the multivariate strain signals time series collected in $\boldsymbol{P}$ related to the damage condition y_j (e.g. the signals in Fig. 4.6a); ii) y_j is the related label from the damage conditions $\boldsymbol{F}$ (e.g. the label $y_j = (286,2)$).



(a) Damage condition (286,2)

(b) Damage condition (341,1)

Figure 4.6 Two examples of acquisition in all $\boldsymbol{P}$ (in legend) for two different damage conditions: thirteen signals are collected together for each simulation

Feature selection

The feature selection phase aimed at identifying the optimal cardinality r of P_s that maximizes the accuracy of the ML model used and thus at detecting the most informative part of the dataset (Sec. 4.2.5).

To assess the crucial role of this phase, the 1NN-DTW model chosen was fitted with the complete training dataset without feature selection, i.e., $\boldsymbol{X}_{\boldsymbol{i}}^{y_j}$. Its classification performance was then tested and the results are shown in the CM [269] in Fig. 4.7.

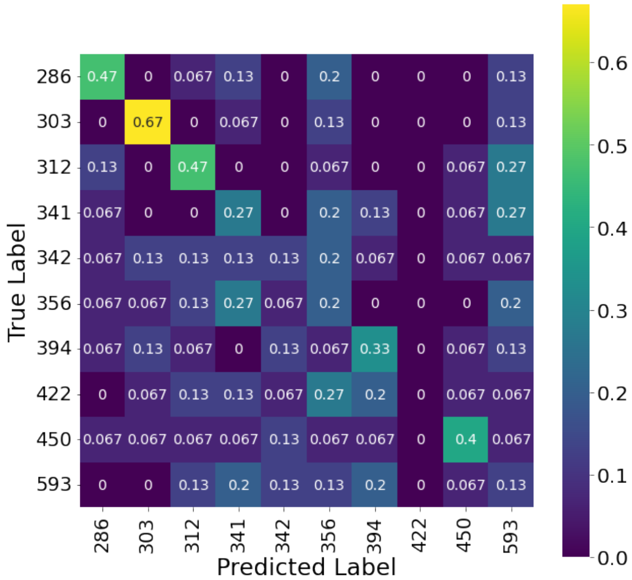
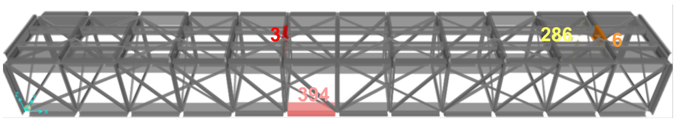


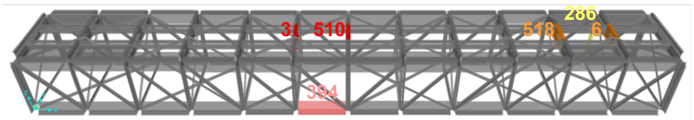
Figure 4.7 1NN-DTW CM with all available strain signals for damage location

A scattered CM with many elements far from the diagonal shows poor model classification performance: the classifier often misclassifies the time series and the values reported show the percentage of times of these events. The results highlight that the classifier was limited in classifying the damage scenarios when the signals from each p_n were simultaneously used, showing that was necessary to improve the procedure as explained in Sec. 4.2.5.

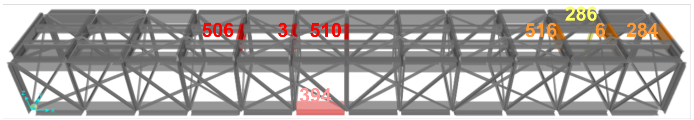
The idea proposed in this study is shown in Fig. 4.8 with an example in which only $s_9 = 394$ (pink) and $s_1 = 286$ (yellow) were considered: Fig. 4.8a shows $r = 1$ case in which only the signal from $p_6 = 3$ (in red) was used to train the classifier for all damages scenario related to $s_9 = 394$ (thus all damage conditions related to $s_9 = 394$); for all damages scenario related to $s_1 = 286$ instead, only the signal from $p_{12} = 6$ (orange) was used to train the same classifier. In Fig. 4.8b the $r = 2$ case is shown, where $p_6 = 3$ and $p_7 = 510$ signals were considered for $s_9 = 394$ and $p_{11} = 518$ and $p_{12} = 6$ signals were considered for $s_1 = 286$. Fig. 4.8c and Fig. 4.8d show respectively $r = 3$ and $r = 4$ cases. This analysis was performed for each r.



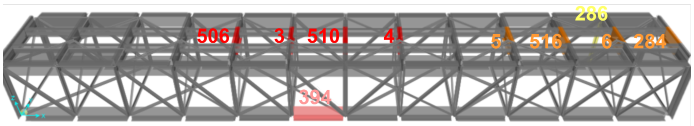
(a) $r = 1$ case: $P_s = \{3\}$ for $s_9 = 394$ and $P_s = \{6\}$ for $s_1 = 286$



(b) $r = 2$ case: $P_s = \{3, 510\}$ for $s_9 = 394$ and $P_s = \{6, 518\}$ for $s_1 = 286$

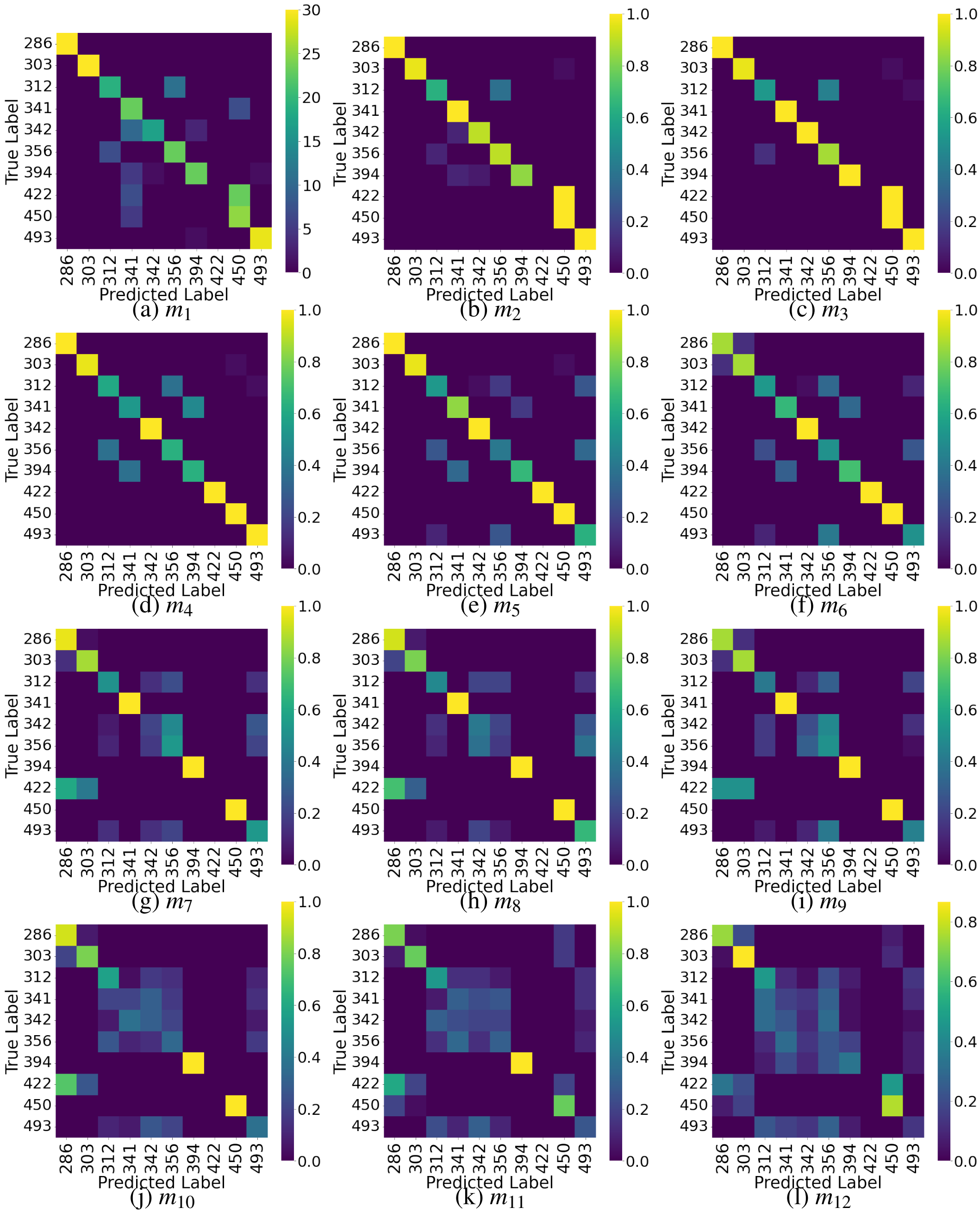


(c) $r = 3$ case: $P_s = \{506, 3, 510\}$ for $s_9 = 394$ and $P_s = \{6, 518, 284\}$ for $s_1 = 286$



(d) $r = 4$ case: $P_s = \{506, 3, 510, 4\}$ for $s_9 = 394$ and $P_s = \{5, 6, 518, 284\}$ for $s_1 = 286$

Figure 4.8 Cardinality r of $\boldsymbol{P_s}$ for damage scenarios $s_9 = 394$ and $s_1 = 286$



(a) m_1 (b) m_2 (c) m_3 (d) m_4 (e) m_5 (f) m_6 (g) m_7 (h) m_8 (i) m_9 (j) m_{10} (k) m_{11} (l) m_{12}

Figure 4.9 CMs of 1NN-DTW fitted models for varying r: the accuracy of the models varies depending on r values

A number of $n_p = 13$ 1NN-DTW classifiers were fitted to training data, each one related to a different r value: the subsequent set of fitted model is thus $\boldsymbol{M} =$

$\{m_1, \ldots, m_{13}\}$. Their performance was then investigated by testing their classification predictions: Fig. 4.9 shows their CMs for predictions on test data.

The performances are resumed in Tab. 4.1 and Fig. 4.10 where the testing accuracy (i.e. the percentage of exact predictions [270]) is reported. The best performances were reached by m_3 and m_4. This is also evident in Fig. 4.9c and Fig. 4.9d where the CMs referred to m_3 and m_4 are the least scattered. The performance deteriorated for classifiers with: i) $r < 3$ due to insufficient information; ii) $r > 4$ due to more non-informative data that spoiled the performance.

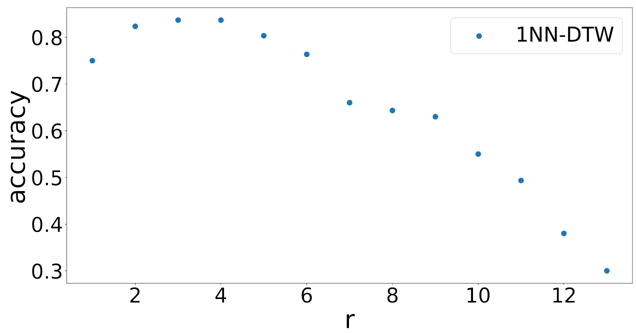


Figure 4.10 1NN-DTW testing accuracy in damage location

Table 4.1 1NN-DTW accuracy in damage location

r	1	2	3	4	5	6	7	8	9	10	11	12	13
Accuracy	0.75	0.82	0.84	0.84	0.80	0.76	0.66	0.64	0.63	0.55	0.49	0.38	0.31

The result was finding the best m_3 and m_4 1NN-DTW classifiers that led to considering only their related P_s cardinalities $r = 3$ and $r = 4$ in CNN classifier training. The reduced dataset $\boldsymbol{D_s}$ was determined and split in training and test set.

CNN models training for assessing and locating damage

The CNN selected to perform time series classification was trained in this phase to locate damage and assess its severity on the test set (see Sec. 4.2.6). Since the two values $r = 3$ and $r = 4$ were found in the previous phase, two CNN models were trained to locate damage and assess its severity: four CNN models were trained in total (see Tab. 4.2).

Table 4.2 CNNs abbreviations

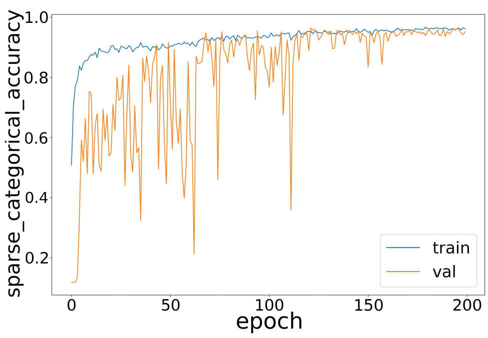
r	Damage Location (DL)	Damage Severity Assessment (DA)
$r = 3$	$CNN_{3,DL}$	$CNN_{3,DA}$
$r = 4$	$CNN_{4,DL}$	$CNN_{4,DA}$

The architecture used and the hyper-parameters in the training phase were obtained by the authors in [266] and [275] and are reported in Tab. 5.1.

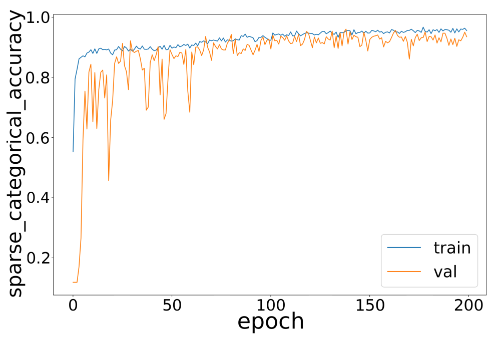
Table 4.3 Hyperparameters for CNNs training [266][275]

Hyperparameter	Specification
Epochs	500
Batch size	16
Optimizer	Adam [291]
Learning rate	0.001
Loss function	Cross-entropy

Fig. 4.11 shows the training and validation accuracy obtained for $CNN_{3,DL}$ and $CNN_{4,DL}$, while Fig. 4.12 refers to $CNN_{3,DA}$ and $CNN_{4,DA}$. The evidence of the training curves is the lower accuracy reached by models in Damage Severity Assessment ($CNN_{3,DA}$ and $CNN_{4,DA}$) in comparison with the Damage Location ($CNN_{3,DL}$ and $CNN_{4,DL}$).

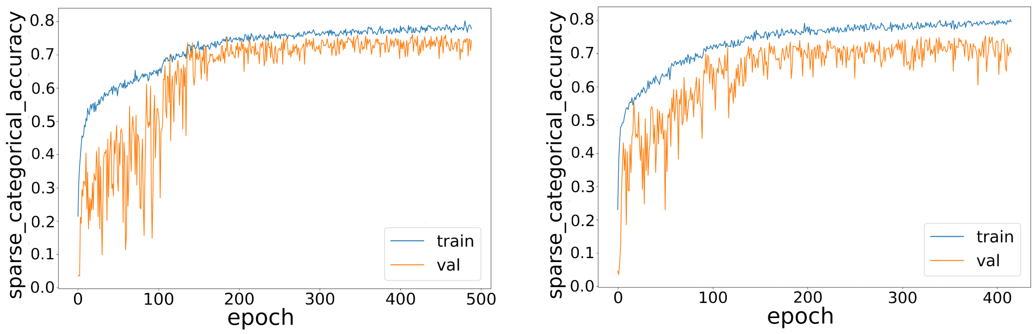


(a) $CNN_{3,DL}$ accuracy



(b) $CNN_{4,DL}$ accuracy

Figure 4.11 CNNs training and validation accuracy in Damage Location



(a) $CNN_{3,DA}$ accuracy (b) $CNN_{4,DA}$ accuracy

Figure 4.12 CNNs training and validation accuracy in Damage Severity Assessment

4.3.3 Results: Damage Location and Damage Severity Assessment test

In this section, the trained CNNs used the test set as input to predict damage location and severity. The CNNs were compared with the 1NN-DTW in damage location and severity assessment to evaluate their performance and it was found that they normally perform better than the 1NN-DTW.

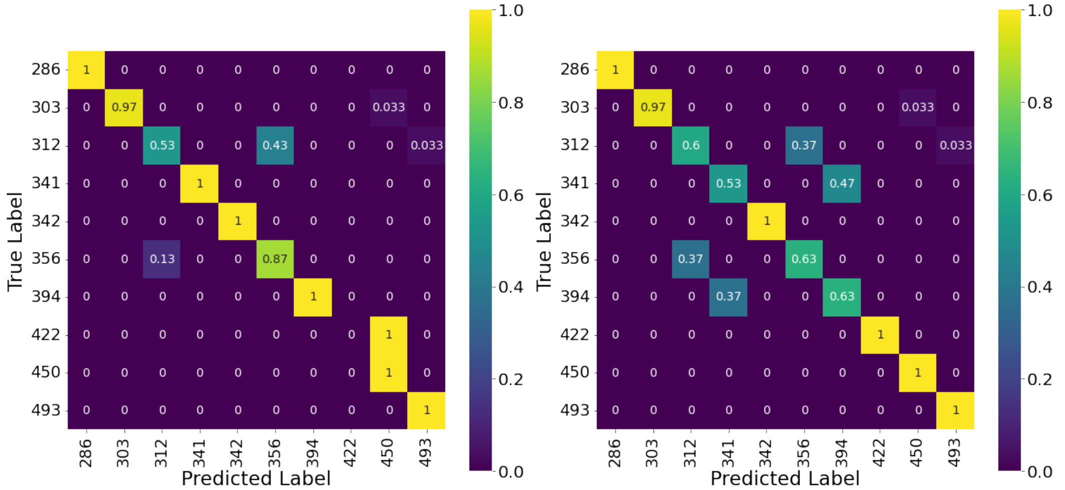
Table 4.4 CNNs and 1NN-DTW models accuracy resume

	Damage Location (DL)		**Damage Severity Assessment (DA)**	
r	**CNN**	**1NN-DTW**	**CNN**	**1NN-DTW**
$r = 3$	$CNN_{3,DL} : 93\%$	$m_3 : 84\%$	$CNN_{3,DA} : 73\%$	$m_{3,DA} : 56\%$
$r = 4$	$CNN_{4,DL} : 91\%$	$m_4 : 84\%$	$CNN_{4,DA} : 75\%$	$m_{4,D4} : 55\%$

Damage Location

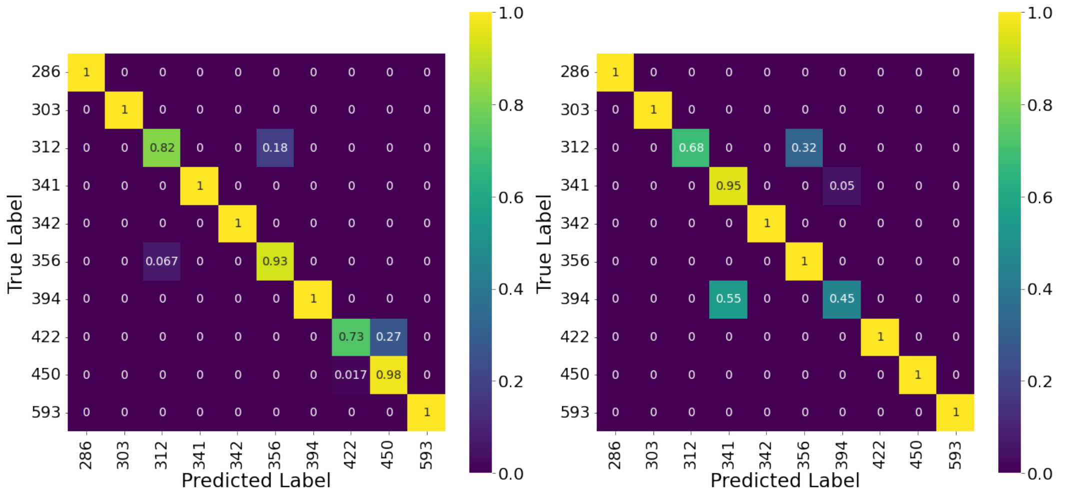
In Damage Location, the trained CNNs took in input the test multivariate strain sensor time series and predicted a $\hat{y}_j \in \boldsymbol{S}$. Tab. 4.4 reports the models overall accuracy in prediction: despite showing good performance (84% accuracy), m_3 and m_4 performed worse than the CNNs and $CNN_{3,DL}$ resulted the most accurate.

Fig. 4.14a and Fig. 4.14b show the $CNN_{3,DL}$ and $CNN_{4,DL}$ CMs obtained by classifying the test data, while Fig. 4.13a and Fig. 4.13b refer to m_3 and m_4.



(a) CM for m_3 (b) CM for m_4

Figure 4.13 1NN-DTW testing performance in damage location



(a) CM for $CNN_{3,DL}$ (b) CM for $CNN_{4,DL}$

Figure 4.14 CNNs testing performance in damage location

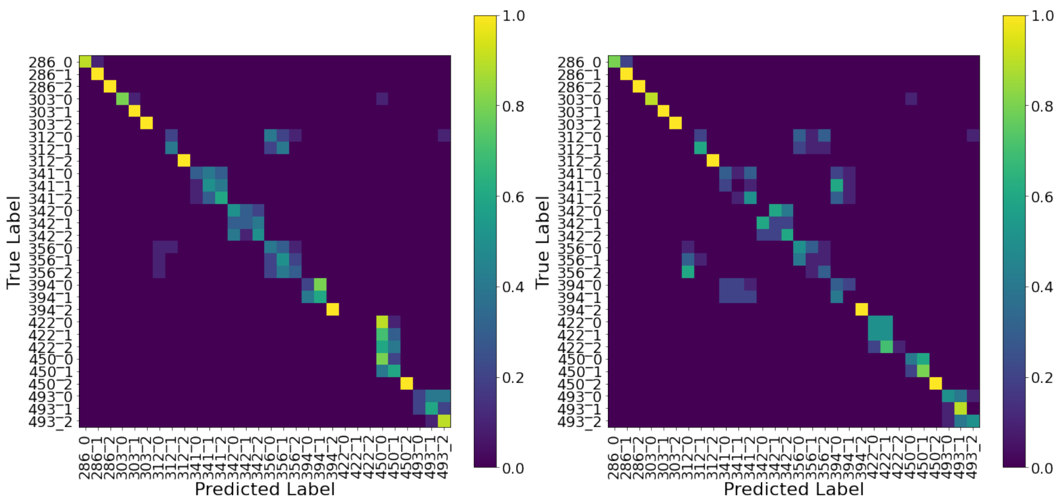
In particular, m_3 predictions showed less dispersion than m_4 with respect to the diagonal, but there was a noticeable misclassification of $s_{10} = 422$ in $s_4 = 450$. Moreover, m_4 manifested difficulties in classifying $s_6 = 341$ and $s_9 = 394$, while both classifiers also misclassified $s_7 = 312$ in $s_2 = 356$.

The CNNs outperformed m_3 and m_4. $CNN_{3,DL}$ and $CNN_{4,DL}$ shared similar difficulties with m_3 and m_4 respectively, but the misclassification severity was reduced; in particular, $CNN_{3,DL}$ misclassified $s_{10} = 422$ in $s_4 = 450$ like m_3, while $CNN_{4,DL}$ misclassified $s_6 = 341$ in $s_9 = 394$ like m_4. The CNNs accuracy confirmed their utility in damage location.

Damage Severity Assessment

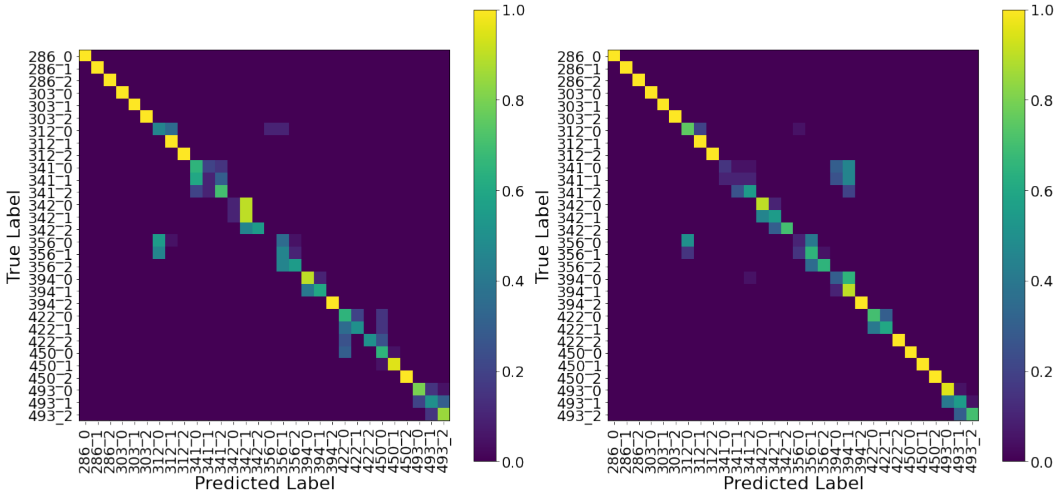
The trained CNNs took in input the test multivariate strain sensor time series and predicted a $\hat{y}_j \in \boldsymbol{d_c}$. The damage severity assessment is more complex than damage location because different l damage levels of the same s_s element are closer in terms of similarities than two distinct s_s. This complexity is shown in the following results.

The overall results are reported in Tab. 4.4, in which 1NN-DTW limitations are highlighted by the low accuracy in discriminating between different damage levels: $m_{3,DA}$ accuracy is about 56%, while $m_{4,DA}$ is about 55%. CNNs accuracy is instead acceptable, even if lower than damage localization.



(a) CM for $m_{3,DA}$ (b) CM for $m_{4,DA}$

Figure 4.15 1NN-DTW testing performance in damage severity assessment



(a) CM for $CNN_{3,DA}$ (b) CM for $CNN_{4,DA}$

Figure 4.16 CNNs testing performance in damage severity assessment

Fig. 4.15 and Fig. 4.16 show respectively the 1NN-DTW and CNNs models CMs. Both $m_{3,DA}$ and $m_{4,DA}$ manifested similar difficulties respectively to m_3 and m_4 as in Sec. 4.4, and the majority of the mis-classifications belongs to the same damage scenario s_s. $CNN_{3,DA}$ and $CNN_{4,DA}$ also manifested the same general behaviour concerning $CNN_{3,DL}$ and $CNN_{4,DL}$ as in Sec. 4.4, with the majority of the misclassifications belonging to the same s_s, but they performed better than 1NN-DTW models in detecting different damage levels.

4.4 Conclusions

This chapter describes a method for damage location and severity assessment of railway steel truss bridges by raw strain sensor signals, through a CNN classifier that operates with multivariate strain signals time series as input. More precisely, different damage scenarios were simulated with FE simulations and strain data were generated. The CNN was trained on the generated data and performed the classification: it assigned multivariate strain time series to damage classes.

A real case study was considered to apply the method: the Quisi bridge, a riveted railway steel bridge located in the Valencia Region in Spain. The method uses SAP2000 and an external application that manages simulations to collect the data.

The phases that compose the method are: i) Faults Analysis, ii) Control Points Location, iii) Data Generation iv) Data Collection, v) Feature Selection, vi) ML Dataset, vii) Damage location and severity assessment. A 1NN-DTW algorithm was used in the feature selection phase to select the most informative portion of the dataset, while the CNN classifier was trained on the resulting data.

The main characteristics of the study are the raw strain sensors signals exploitation, without any prior feature extraction pre-processing phase, and a physical-based feature selection procedure to select the most informative portion of the dataset generated. Differently from other approaches, the method presented avoids critical issues on applications to real case scenarios implied by the explicit damage-sensitive frequency-domain feature extraction. The trained CNN classifier resulting from the method achieves high accuracy in damage location and shows good results in damage severity assessment.

In future research, the method will be improved by using ML models that exploit an explicit physical and geometrical description of the system.

Chapter 5

A new concept for large additive manufacturing in construction: Tower crane-based 3D printing controlled by deep reinforcement learning

Accepted and partially published in *Parisi, F., Sangiorgio, V., Parisi, N., Mangini, A. M., Fanti, M. P., & Adam, J. M. (2022). A new concept for large additive manufacturing in construction: Tower crane-based 3D printing controlled by deep reinforcement learning. Construction Innovation. DOI:10.1108/CI-10-2022-0278*

5.1 Introduction

The construction sector tends to fall behind other sectors in adopting technological innovation [292, 5]. Studies carried out over past ten years pointed out that much of the innovation in the construction industry goes unnoticed and is not visible to traditional metrics and measurements [293]. In the last decade, the unprecedented development and diffusion of novel systems in the building sector have included the advent of 3D printing and additive manufacturing technologies [294]. Several companies have developed 3D construction printing systems and are investing in applied research, while the positive trend toward original research articles and reviews shows the considerable interest and potential of this revolutionary construction process [295].

Additive manufacturing systems (or 3D printers) are classified into seven categories according to the ISO/ASTM 52900 [93]: i) binder jetting, ii) directed energy deposition, iii) material extrusion, iv) material jetting, v) powder bed fusion, vi) sheet lamination and vii) vat photopolymerization. Of these seven, the most popular additive manufacturing category in construction is extrusion-based 3D printing, in which a viscous material (e.g. cementitious material, clay or raw earth) is deposited in layers as a continuous filament from a nozzle [96]. Concrete is the printing material of greatest interest to companies and researchers (extrusion-based 3D concrete printing) and has been widely studied in recent research projects [98]. The focus of additive manufacturing and prototyping in the construction field is on cement and concrete because of their broader use and lower costs [99, 100]. Even if extrusion-based 3D concrete printing is the most frequently used method in the building sector [295, 296], there are still no "better" or "more widely used" systems to make printing machinery. The printing extruder is typically positioned on a gantry or robotic arm according to the required precision and building dimensions. Although the system is being improved thanks to global interest, certain limitations prevent its massive diffusion. The actual dimensions and performance of 3D printed buildings are very different from the structures achieved with traditional techniques [297, 298]. One of the most important limitations is the max dimension of the build volume. The current machine systems reach heights of about ten meters with typically no more than two floors. Moreover, the large size of the gantry system or robotic arm would make the machinery system repositioning from one construction site to another difficult, implying the impossibility of printing components directly on different floors unless the printer is moved from floor to floor.

In the traditional construction industry, tower cranes, which have fewer independent actuators than the degrees of freedom of the system, are used to construct high-rise buildings, move heavy objects and cast concrete on higher floors [299]. Compared with fully actuated systems, under-actuated systems have advantages in energy saving, cost reduction, weight reduction and system flexibility [300], while being more difficult to control due to the lack of control inputs [301]. The related literature indicates that these machines are the most widely used systems for high-rise buildings. The use of tower cranes becomes much more important in large-scale projects (especially for high-rise buildings) [302], so that recent research interest has focused on integrating modern methods such as control systems [303, 92, 304] and monitoring [305] in tower cranes. A recent review [306] emphasizes that Reinforcement Learning (RL) will play a leading role in improving the applicability and effectiveness of these machines [307]. Of the 129 papers cited in the literature review [306], only six papers were found dedicated to AI control.

This chapter proposes a new additive manufacturing system including an AI-controlled TC-based 3D Printing as the first step in developing 3D printing for high-rise buildings. It combines one of the most important machines used for constructing high-rise buildings and 3D printing through an "aero-pendulum extruder". The extruder is based on recent studies that showed the effectiveness of aero-pendulum control systems, consisting of a pendulum arm with a motorized propeller at its free end [308]. This ambitious research was carried out in three stages: firstly, the aero-pendulum extruder (hooked up to a crane cable) was proposed to correct the extruder toolpath during the printing process. Secondly, a Deep Reinforcement Learning agent was trained to control the crane and the extruder toolpath to achieve an effective printing of large components. Thirdly, according to other works in the literature [309–313], the proposed system was then validated by simulating the control system dynamics. This approach overcomes one of the main drawbacks of current large 3D printing systems, i.e. the extrusion of large components on high floors in multi-story buildings.

The chapter aims to introduce this potential new technology, supported by a feasibility study. This study investigates high-level system control to verify if the accuracy reached in counteracting the swing effect, even when subjected to external uncertainties, is acceptable for applications in the construction industry.

The novelty of the proposed approach is threefold: i) a tower crane system is used for the first time for 3D printing in combination with an aero-pendulum extruder; ii) the novel concept represents an advance on the current systems for high-rise constructions; iii) an AI-based control system is included to control both the Tower-Crane and the aero-pendulum extruder.

The rest of the chapter is structured as follows. Section 5.2 contains a review of the literature in the field of large 3D construction printing. Section 5.3 describes the technological and methodological approach, Section 5.4 gives the validation results and performances and Section 5.5 contains our conclusions.

5.2 Literature review

5.2.1 Large 3D construction printing

The growing interest in extrusion-based 3D concrete printing in architecture, engineering and the construction (AEC) industry is principally due to its lower costs, reduced waste and simple supply chain [314]. According to the classification in [315], the possible use of additive manufacturing in AEC includes 3D printing elements, prefabricated 3D printing formworks, and monolithic 3D printing on-site. While the first two applications are usable both on-site and in laboratories, the third must necessarily be carried out on-site; thus, large and precise 3D printers are required to create large structures both in laboratories and in situ (even on floors in elevation). Currently, there are four systems used to achieve large extrusion-based 3D concrete printing (Fig.5.1):

- The **gantry system** is based on a frame structure to support the printer extruder and its actuator which control the movements in any direction along the Cartesian coordinates X, Y and Z [316]. [317] or [318] represent some of the companies applying this system for two-story buildings;
- The **cable-suspended** solution arose from the need to obtain large 3D concrete printing easy to transport, dismantle and reassemble [319]. The cable-suspended printer system is composed of an extruder attached to an external frame by multiple cables. Different types of the frame can be used to make the printer easily reconfigurable and transportable [320]. Different applications using cable-suspended 3D have been developed by the WASP company [321] to construct single-story buildings;
- The **robotic arm** is a solution in terms of print quality and freeform geometries generation and has been used to obtain complex shapes [322] and geometries with non-planar layers to the printing plane [323]. Despite its numerous advantages, it has high machine costs and difficulty in reaching large printers, so only a few companies and research groups have applied the system to single-story buildings [106]. A robotic arm coupled to a modified truck was used in a recent attempt to convert a commonly used construction system (a truck-mounted concrete pump) into a 3D printer [296]. This novel concept, named

CONPrint3D, is still under development and aims to reach a more efficient and economical advanced construction process that is less resource-consuming and acceptable to industry practitioners. Recent studies have developed control systems to reduce the oscillation amplitudes by up to 95% and expand the extruder toolpath [105].

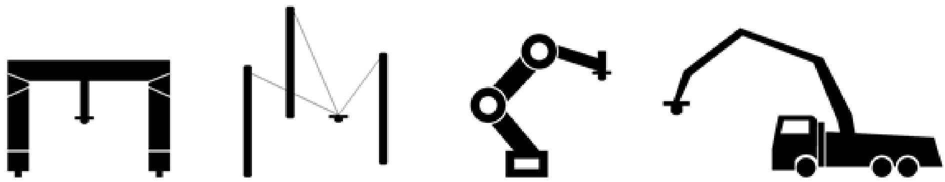


Figure 5.1 Different systems used to obtain large extrusion-based 3D concrete printing machines. a) Gantry, b) cable-suspended, c) robotic arm, d) robotic arm coupled to a modified truck.

A literature review of large 3D construction printings emphasizes the direction of recent investigations and the companies' interest in even larger systems, while the aim is to adapt the existing large construction machines to meet the needs of both industry and practitioners. This idea is in line with the bibliographical review in [296] which came to the following conclusion, "The development of new printing systems for large-scale buildings as well as new composite materials is essential to provide versatile and viable applications for 3D construction printing in the future." According to [105], the current large construction machines (such as tower cranes, mobile excavators or loaders) are not designed for the precision required in concrete printing, and their improvement with modifications and modern control systems to meet the required accuracy is needed.

5.2.2 Artificial intelligence in the control for 3D printing and tower-crane handling

AI is designed to deal with ill-defined complex problems intentionally, intelligently and adaptively and can be very effective in AEC to learn inputs such as human perceptions, representing knowledge, reasoning, problem-solving and planning [324]. In synergy with additive manufacturing, it can be used to improve different aspects of 3D printing: i) material tuning, ii) process optimization, iii) on-site monitoring, iv) cloud service, and v) cybersecurity. Some widespread AI applications in additive manufacturing, such as autonomous anomaly detection [325–328] or 3d-printed parts inspection [329–332], are based on its strong capability to deal with high-dimensional data such as images or videos.

DRL implements the control task by the AI (precisely Deep Learning) capability to manage images and videos. Many successful applications of this potential are available in autonomous vehicles control [333, 334] and robotics-related [335, 336] literature. There are also applications in the additive manufacturing literature using DRL controllers driven by real-time high-dimensional data: in [337] authors use DRL to learn and control an high-sensitive to parameters process in Robotic Wire Arc Additive Manufacturing; in [338] authors employ DRL in the field of Laser Powder Bed Fusion additive manufacturing technology for dynamically altering process parameters to avoid phenomena that lead to defect occurrences; [339] investigates the sensor-adaptive 3D printing with a robotic agent by implementing DRL. While few applications can be found to improve 3D printing control systems for the construction industry, a recent review [340] pointed out that AI systems have been developed in a wide spectrum of applications, ranging from the design of 3D printing, process optimization and in situ monitoring. The reason for this lack of applications is that there are no publications in the literature to convert complex handling systems (such as under-actuated machines) into additive manufacturing systems.

The tower crane control is a topic already deeply investigated in the academic literature, and many different advanced control approaches have been applied [309, 341, 310, 92, 342, 311, 312, 343], but there are no applications in which the control is intended for additive manufacturing applications. Some AI applications can be used in construction to support tower-crane 3D printing. Most research studies have been conducted to support decision-making on crane selection, crane layout and increasing safety in lift path planning. For example, Artificial Neural Network (ANN) systems are used in [344] to support crane selection, in [345] for the optimization of transport time and related costs, and in [346] to study safety aspects and structural monitoring. Some works can also be found in the field of ANN-based control for tower-crane handling. [309] proposes a hybrid evolutionary algorithm using a recurrent neural network to control a 3D tower crane, while [347] uses an additional neural network-based friction compensator to systematically

control system complexity. The latest studies in the field investigated the use of an ANN-based system to control the payload swing of a tower crane [348] and track a double-pendulum tower crane with non-ideal inputs [343]. There is still no application in the literature of DRL for tower crane control.
To sum up, even though the potential of AI-based control systems has been demonstrated, no application is at present available to improve 3D printing control or to convert current construction systems into large 3D printers.

5.3 Methods and material

5.3.1 Tower-crane based 3D printing controlled by AI

Most of the current 3D printing systems used in AEC do not comply with the requirement of on-site, large-scale multi-story building systems [105]. The most widely used 3D printing systems cannot construct higher than two stories and have to be raised to build the second story. In addition, as increasing the size of the printer involves higher costs and complex transport problems, the 3D components are printed off-site (prefabricated 3D printing)[105, 295]. Therefore, the present study proposes the new TC 3D printing concept, a building system as the first step towards achieving a multi-story construction process based on additive manufacturing, to reduce time, costs and resources.
The new concept is presented in Fig.5.2 in which the large curved wall marked in red is a challenging geometry (extremely common in architecture) to be achieved by using the proposed tower crane 3D printing. The concept proposed is based on two synergistic improvements of the classical tower crane to transform it into a large additive manufacturing machine. The first improvement is the use of an aero-pendulum extruder mounted on the crane cable, on the basis of studies carried out at the University of Arizona (Dep. of Aerospace and Mechanical Engineering) [349–351, 308]. While the geometry to build is obtained by actuating the trolley and the jib, the controlled propellers of the aero-pendulum extruder counteract the swing effect induced by the movement during the extrusion and keep the extruder aligned with the crane trolley, and the cable perpendicular to the crane jib. The second improvement deals with the control of the whole machine to achieve the needed accuracy: a DRL controlling agent is proposed to control the tower crane

actuation and the aero-pendulum extruder propellers.

The concept proposed differs from other approaches in that it is the first time

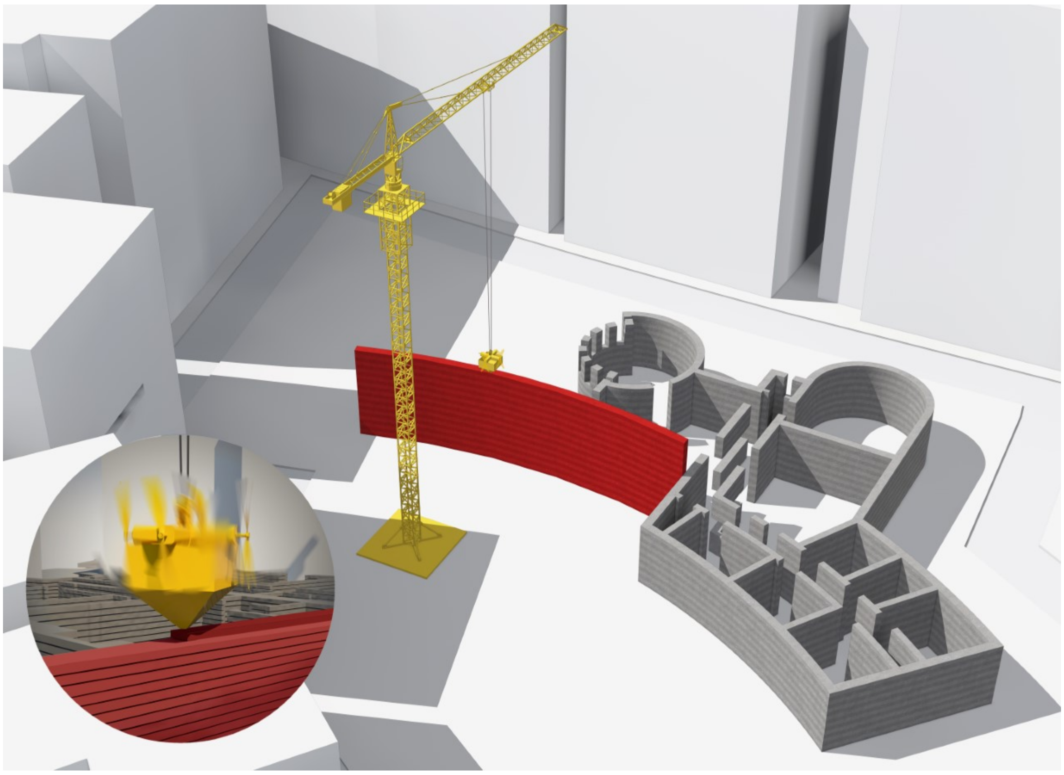


Figure 5.2 TC-based 3D Printing system concept and aero-pendulum extruder.

a commonly used tower crane system is equipped with a custom extruder and is controlled with an AI-based control system. New concepts that have not yet been tested propose the upgrading of existing construction machinery with the goal of economic sustainability and early deployment in construction. For example, the system proposed in [105] consists of a modified truck equipped with a robotic arm and a concrete pump. In the present study, a modern AI-based control system was developed, trained, tested and validated to obtain an effective extruder path. The following sections describe the control problem of the tower crane equipped with the aero-pendulum extruder with DRL.

5.3.2 DRL control framework for the tower crane and extruder swing effect

This section describes the DRL tower crane control framework to transform it into an extrusion-based 3D printing system. The core of the approach is based on an intelligent DRL agent that dynamically activates the tower's degrees of freedom to minimize the extruder swing effect while maximising printing speed (Fig.5.3). The aero-pendulum is kept aligned with the crane trolley and the crane cable remains perpendicular to the jib. The AI-based control system was modelled by defining: i) the environment and its states, ii) the possible actions that the agent can execute, iii) the reward function and iv) the agent modelling with its learning algorithm.

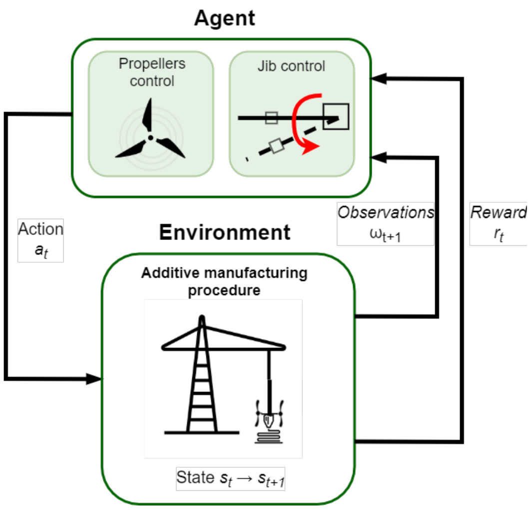


Figure 5.3 DRL framework specification of the problem.

System model

The system consists of the tower crane structure from which the extruder is suspended. The jib rotates around the tower axis while the trolley moves along the jib (Fig.5.4). The trolley position at time t is described by a vector of polar coordinates $\mathbf{c}_t = [\rho_t, \theta_t]^T$, where ρ_t is the linear coordinate along the jib and θ_t is the angle around the tower axis at time t (Fig.5.5).

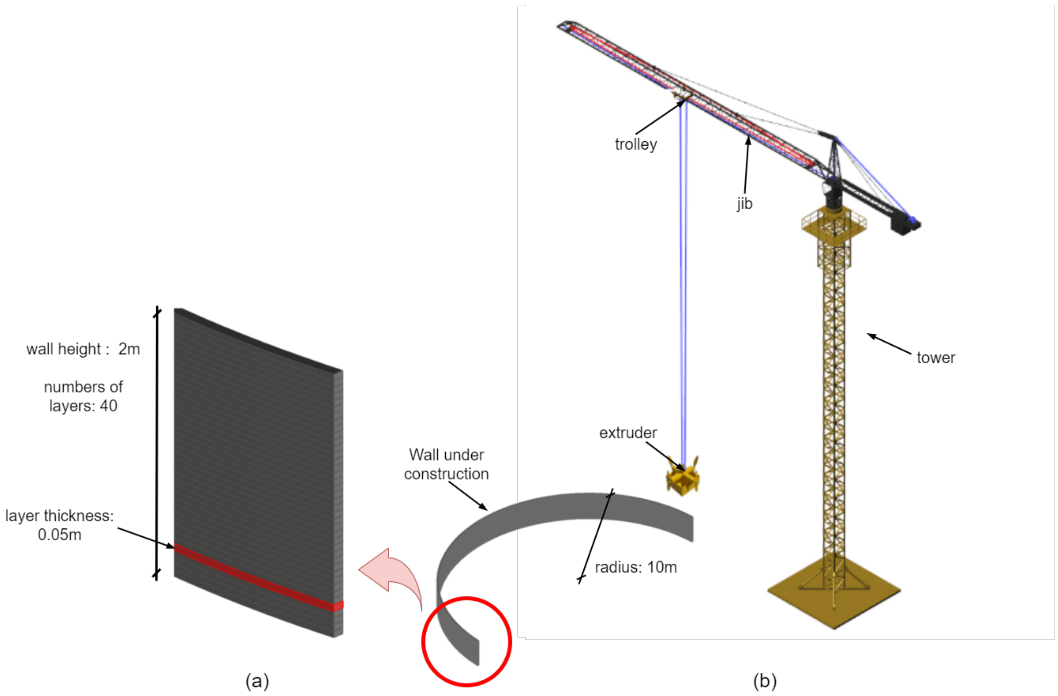


Figure 5.4 Tower-crane 3D printing system: a) wall geometry detail: height, number of layers and layer thickness; b) manufacturing system general view.

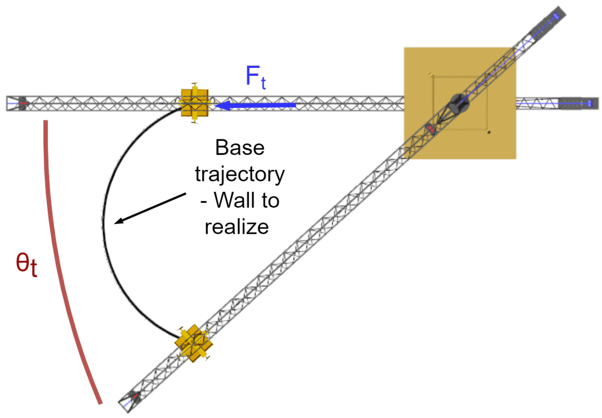


Figure 5.5 System configuration: trajectory, jib actuation θ_t and propeller thrust force F_t.

The trolley is confined to the trajectory, so that $\rho_t = f(\theta_t)$, where θ_t is the only actuated trolley degree of freedom. In related literature [309, 341, 310**?** , 342, 303, 304, 313], the tower crane's deformability is typically not considered even if loads are heavy. In the presented application, the influence of structural deformations is negligible since there is not a heavy load. The extruder has to follow a semi-circular trajectory to build the required object: a $2m$ high curved wall of radius $r = 10m$, made up of $40 \times 5cm$ layers. This shape was chosen since curved trajectories are the most complex for the proposed Tower-Crane based 3D Printer because of the variation of the direction of acceleration (Fig.5.4, Fig.5.5). While the trolley is directly actuated, it induces a swing effect on the suspended extruder, which is stabilized by the thrust force generated by the propellers. The swing effect is investigated only in the direction perpendicular to the trajectory, so that a single thrust force F_t was considered to act on the extruder (Fig.5.5).

Environment

The environment represents the system with which the agent interacts, applying actions and observing states. The tower crane structure was modelled together with the suspended extruder on Simscape Multibody software [352] and by appropriately modifying the related model in [353]. The tower crane considered has a working volume defined by a radius of $50m$ (jib length) and a height of $45m$ (tower height). The original Simscape Multibody model included pulleys, cables and belts to control the trolley's movements along the jib and to lift the suspended extruder by specifying the whole range of kinematics. In Fig.5.6 (upper left, with no coloured boxes) represents the existing tower crane model and its relative components:

- tower, jib, trolley and extruder, as shown in Fig.5.4 and Fig.5.5;
- trolley pulleys, together with the revolute trolley drum and prismatic trolley are responsible for the trolley's movements along the jib;
- the hoist pulleys and revolute hoist drum are responsible for raising the extruder.

Other components were included to configure the DRL problem to model the proposed TC-based 3D Printer, represented by colored boxes in Fig.5.6:

- an *aero-pendulum extruder* substitutes the suspended load and a block is included to collect and convert the extruder coordinates (yellow box);

- the trolley is constrained on the trajectory and its position is θ_t, the actuated degree of freedom (green box);
- a specific component represents the actions of the agent on the environment and, in particular, the actuations of the proposed system. The jib revolution around the tower is actuated by specifying the angle θ_t , while the thrust force F_t acts directly on the hanging extruder (blue box);
- a state component collects the fundamental information from the system (such as extruder and trolley coordinates, red box).

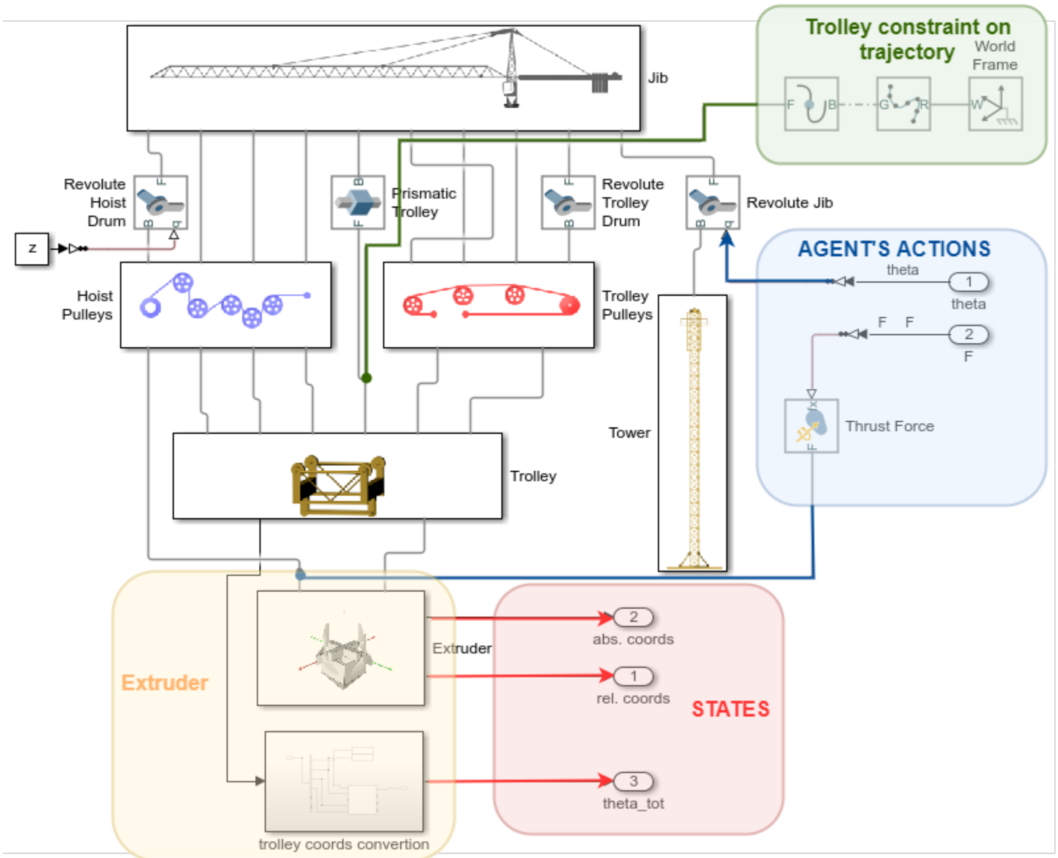


Figure 5.6 Simscape Multibody model of the tower crane (DRL problem environment) adapted from [353].

Action space

The action space is of basic importance since it allows the intelligent agent to control the degrees of freedom actuated. In this set up, the agent can act on the polar coordinates of the trolley to determine the thrust force on the swinging extruder. As the action space is continuous, the agent can select all the values between the actions boundaries. In each time step the actions are identified by the vector $\boldsymbol{a}_t = [\theta_{a,t}, F_t]^T$, where $\theta_{a,t}$ is the increment of the agent angular actuation of the jib at time t, and F_t is the thrust force applied by the agent to compensate the extruder swing at time t. $\theta_{a,t}$ being an increment, the angular coordinate of the jib at each time step is $\theta_t = \sum_{t=0}^{t} \theta_{a,t}$. The boundaries to the actions value are imposed depending on the system investigated. Then the action space is the set defined in Eq.5.1:

$$\mathscr{A} = \{\boldsymbol{a}_t = [\theta_{a,t}, F_t]^T | F_t \in [-300N, 300N], \theta_{a,t} \in [0.005, 0.2]\} \tag{5.1}$$

More precisely, the thrust force action space represents the feasible thrust obtainable with the propellers momentum theory [354] and $\theta_{a,t}$ is selected so that the system is never stopped and can print at an angular speed of up to $2deg/s$ limit.

State space

The agent observations represent the information on the environmental states available to the agent in each time step t. The observations are identified by the vector $\boldsymbol{\omega_t} = [p_t, \dot{p}_t, \ddot{p}_t, \theta_{a,t}, F_t, \theta_t, x_{tr,t}, y_{tr,t}, \dot{x}_{tr,t}, \dot{y}_{tr,t}, \ddot{x}_{tr,t}, \ddot{y}_{tr,t}]^T$, where all the values refer to time step t:

- $p_t, \dot{p}_t, \ddot{p}_t$ are respectively the relative positions, speeds and accelerations between the extruder and the trolley in the direction perpendicular to the trajectory;
- $\theta_{a,t}$ is the agent angular actuation;
- F_t is the thrust force applied by the agent to compensate the extruder swing;
- θ_t is the trolley angular coordinate;
- $x_{tr,t}, y_{tr,t}, \dot{x}_{tr,t}, \dot{y}_{tr,t}, \ddot{x}_{tr,t}, \ddot{y}_{tr,t}$ are respectively the trolley absolute coordinates, speeds and accelerations in x and y directions in the global reference system.

Reward

At each time step, the agent executes its actions and receives a reward representing the effects of the actions on the environment. The reward can be considered the feedback from the environment and measures the success or failure of the agent's actions. In the proposed environment, the agent collects a high (and positive) reward if the extruder closely follows the imposed trajectory as fast as possible, so that the agent needs to reduce the swing effect while moving faster. In order to obtain this result it is necessary to select the right reward function R. In the considered system, the reward r_t provided to the agent at time step t is the following:

$$r_t = \theta_{a,t-1} \cdot r_{p,t} = \theta_{a,t-1} \cdot \frac{25}{1+10^{8p_t}} \tag{5.2}$$

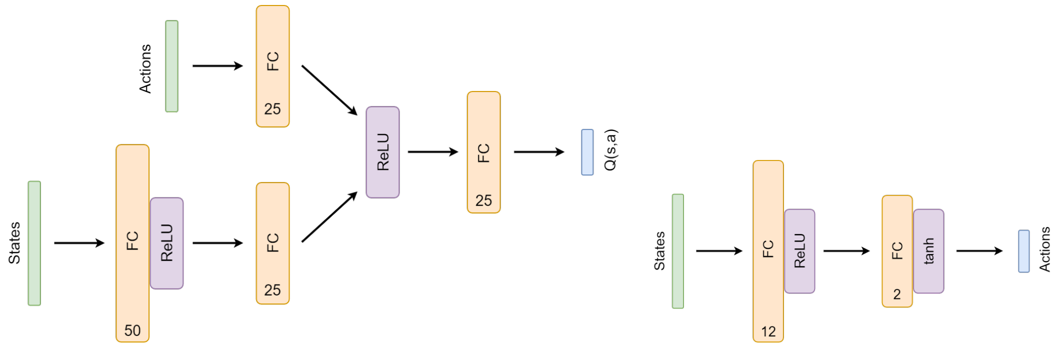
where $\theta_{a,t-1}$ is the angular actuation of the agent in the previous time step. The proposed reward function is justified by two objects:

- $r_{p,t} = \frac{25}{1+10^{8p_t}}$ is the reward component that depends on the desired trajectory in terms of position. The better the extruder follows the trolley the bigger the agent's reward. In order to behave correctly, the extruder has to minimize its distance from the moving trolley and the agent gains a greater reward if it maintains the extruder close to the desired trajectory.

- $\theta_{a,t-1}$ is the reward component that considers the angular jib actuation in the previous time step. This component encourages the agent to go faster in following the trajectory.

Agent modelling and learning algorithm

Of the families of RL algorithms, we used the policy gradient method, which optimizes the performance of the expected cumulative reward by finding a good parametrized neural network policy. The chosen algorithm is the Twin-Delayed Deep Deterministic Policy Gradient (TD3) [355, 356], an RL method suitable for models characterized by continuous action spaces [357]. The TD3 is an actor-critic architecture that consists of two parts: an actor and a critic. The actor refers to the policy and the critic estimates a value function such as the Q-value function.



(a) Critic Neural Network architecture. (b) Actor Neural Network architecture.

Figure 5.7 Actor-Critic architectures.

Both the critic and the actor are represented by neural networks [358]. The critic network in Fig.5.7a processes both the environment states (observations) and agent's actions as input and computes the expectation of the long-term reward $Q(s,a)$. It is composed of fully-connected layers (FC) with ReLU activation functions, and its output is used to update the policy. The actor network in Fig.5.7b processes the environment states and outputs the actions that maximize the long-term reward. It is composed of a single path of subsequent FC layers, while the output layer is featured with a Tanh activation function [359]. An extensive description of the learning algorithm used is given in [360].

5.4 Results and validation

5.4.1 Training and simulation

The training phase aims at training both the actor and the critic networks to make the agent behave as desired. The agent's iterative interaction with the environment, as schematized in Fig.5.3, thus updates the neural network weights and biases to match the correct behavior. The iterative interaction is performed through simulations in the software environment, with discrete time steps $t = 0.1s$, while the total simulation time is $T = 60s$. The agent acts on the environment by applying the actions specified in each time step, gets the reward and the observations on the environment state, and updates the actor and critic parameters. Tab. 5.1 shows the network parameters used in the training phase: the Adam algorithm [291] was used to minimize the loss with learning rate $\mu_a = 0.0001$ for the actor and $\mu_c = 0.001$ for the critic; the experience buffer length was set to 10^6 and the discount factor to $\gamma = 0.99$.

Table 5.1 Parameter in the RL networks

Parameter	**Values**
Minibatch size size	512
Experience Buffer Length	$1 \cdot 10^6$
Optimizer	Adam [291]
Actor Learning rate	0.0001
Critic Learning rate	0.001
Discount Factor	0.99

Fig.5.8 provides the plot of the total accumulated rewards during the training phase. The cumulative reward of each episode is shown in light blue, while the cumulative average reward of the whole training phase is highlighted in red. It can be seen that the agent needed roughly 5000 simulation episodes to explore the action space, before starting to consistently gain growing accumulated rewards. After 5000 episodes, the agent gradually improved its behavior, reaching its best performance in the final part of the training in which it stabilized around an average cumulative reward of approximately 750. After training, the agent was ready for testing in the 3D printing procedure, i.e., a test of its ability to follow the trajectory in comparison with the non-controlled configuration.

5.4.2 Testing and validation

The agent's performance was compared with the non-controlled configuration by simulating the printing process of the full-scale testing geometry and the accuracy achieved was compared with permissible tolerance allowed by the Eurocode 6 EN 1996-2:2006 [361].

The test considered external disturbances, modelled as forces acting on the extruder during the whole printing process. The disturbances $d(t)$ to the system are modelled by the following function: $d(t) = A \cdot sin(f \cdot t + \phi) + b$, where A, f, ϕ and b are respectively the disturbance amplitude, frequency, phase and bias sampled from uniform distributions, respectively, in the open intervals $(-200, 200)N$,

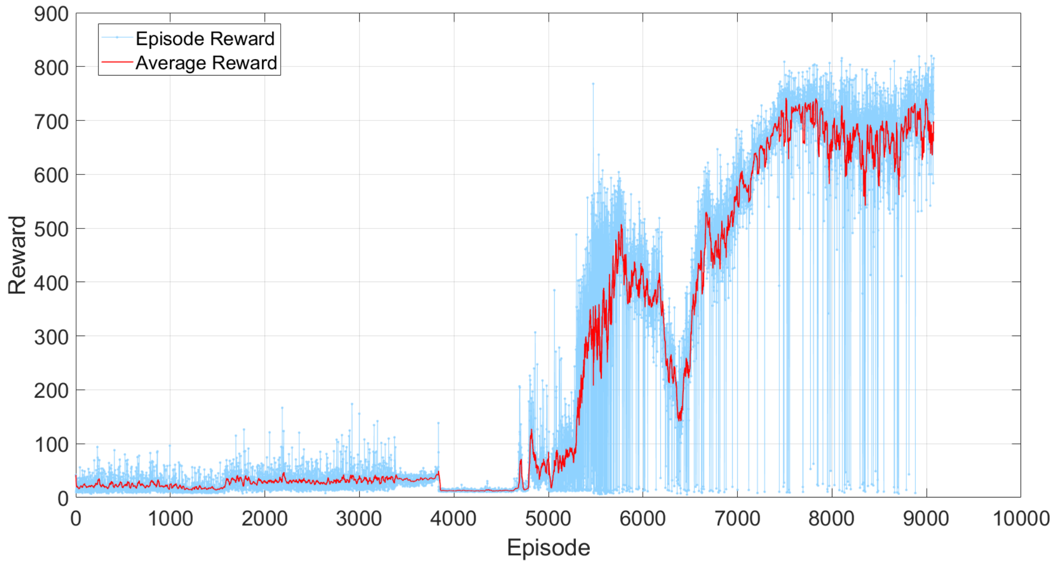


Figure 5.8 Training phase: episode reward and average reward of the agent.

$(6.28, 62.8) rad/s$, $(0, 0.35) rad$ and $(0, 30) N$.

Both the uncontrolled and controlled systems were simulated applying a different disturbance function in each layer and the global coordinates of the extruder were collected, after which a trajectory was obtained for each printed layer for both configurations.

Fig.5.9 depicts the plan of the geometries printed in both system configurations. The trajectories of the 40 layers of the 2m high curved wall are overlapped and their envelopes were obtained to emphazise the minimum and maximum distances reached from the base trajectory. Fig.5.9 shows the following curves in more detail: i) the black dotted curve represents the target trajectory, i.e. the ideal trajectory required to print the planned wall; ii) the red continuous curves show the envelope obtained in the non-controlled configuration with the maximum deviations of the extruder from the target trajectory by showing the poor performance obtained with no control; iii) the blue continuous curves represent the envelope of the controlled trajectories, which are extremely close to the ideal target trajectory. The uncontrolled trajectory was obtained by requiring the extruder to realize a single layer in $T = 60s$ at a constant angular speed of $\dot{\theta} = 0.72 deg/s$. The resulting swing effect of the uncontrolled extruder compromises the geometry, highlighting that the full-scale 3D printing can not correctly work without a suitable control. On the other hand, the RL controlled configuration shows great potential: in Fig.5.9 the target trajectory and the controlled trajectory are effectively overlapping, with very narrow envelope,

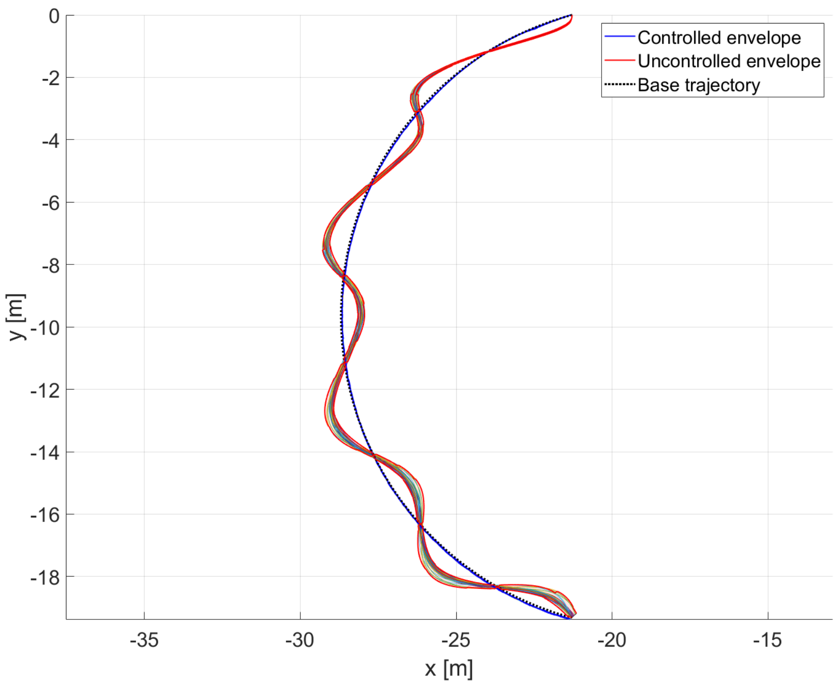


Figure 5.9 Trajectoriy envelopes in controlled and un-controlled configurations.

showing that the layers are aligned with each other in height (fundamental principle for effective printing) and the RL agent's ability to consistently react to varying external conditions while performing accurately.

Fig.5.10 depicts the trajectories of the whole geometry printed in both configurations in a three-dimensional visualization (with and without control). The layer trajectories are represented and colored according to the absolute error value measured in meters. Fig.5.10a shows the not correct behaviour of the non-controlled system: the geometry of the printed element exhibits an absolute error that reaches a value of 0.99 m in relation to the base geometry (black dashed curve). Fig.5.10b shows instead graphically the good performance of the RL-controlled approach, reporting an absolute error always less than 0.1 meters.

The accuracy of the proposed system was further analyzed by investigating the absolute error of the printed geometry in relation to the base geometry. Fig.5.11 gives the numerical information contained in Fig.5.10, representing the absolute error envelopes in both configurations. This additional investigation emphasizes the envelope of the maximum and minimum values of the absolute error during the entire printing process containing the absolute error variation in each layer (curves depicted

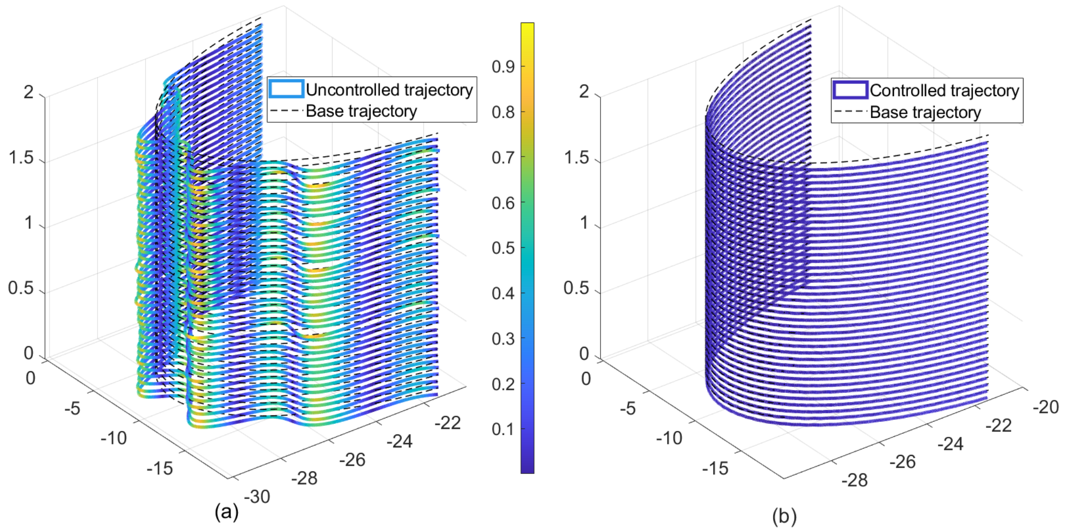


Figure 5.10 Absolute Error: a) non-controlled configuration, b) controlled configuration.

inside the envelopes). The uncontrolled behavior reaches 0.99 m of the absolute error with respect to the deviation from the task trajectory. The RL-controlled approach shows a good performance, with the maximum absolute error of 0.08 m in the worst case (at the end of the printing process) and an average absolute error of $0.045m$ during the process. As shown in Fig.5.11, the widths of the different envelopes, especially the limited width in the RL-controlled configuration, highlight the agent's ability to react successfully to the varying external conditions acting on the extruder. The RL-controlled approach also shows a better performance in terms of process duration: the RL-controlled configuration accomplishes the entire control task in each layer in about $52s$ instead of the $60s$ required by the uncontrolled system (see Fig.5.11).

The performance in terms of accuracy can be compared with the permissible tolerance allowed by Eurocode 6 EN 1996-2:2006 [361], which allows admissible values of deviation from the intended line (straightness) [362] respectively for each 1 meter and 10 meters masonry's portions. In this study it is applied to the curved wall application. Tab.5.2 reports the worst performance measures specified for both the RL-controlled and uncontrolled systems and shows that the former's accuracy results in line with the admissible tolerances of the EN 1996-2:2006. These results highlight the good performance of this preliminary feasibility and conceptual stage of the technological development.

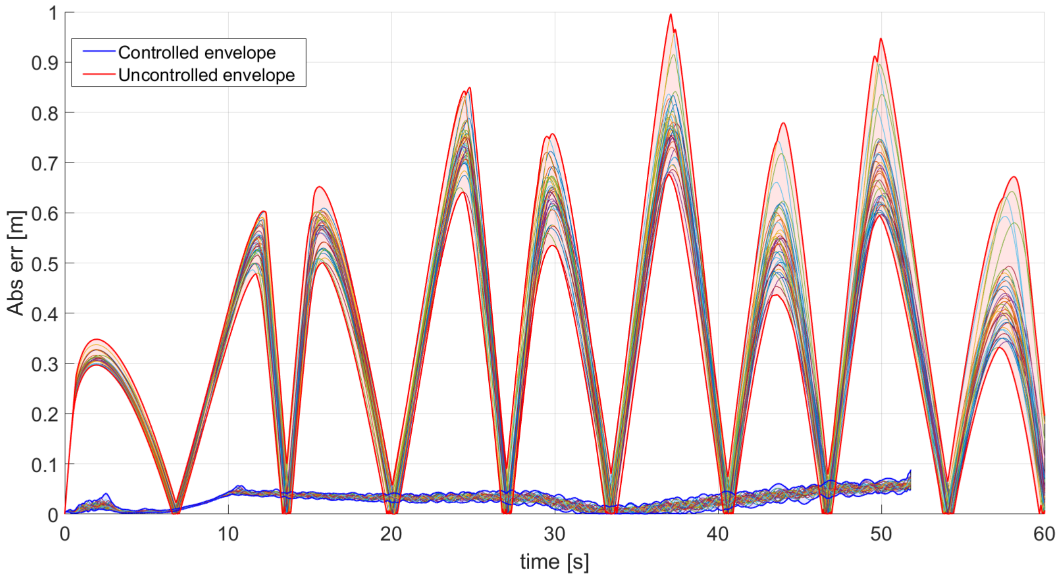


Figure 5.11 Comparison of absolute error between controlled and uncontrolled trajectories.

Table 5.2 Worst performance measures in RL-controlled and non-controlled systems for the first layer.

System	Deviation from intended line	EN 1996-2:2006 tolerance limit
RL-controlled	$10mm$ $49mm$	$\pm 10mm$ in any 1 meter $\pm 50mm$ in 10 meters
Non-controlled	$493mm$ $706mm$	$\pm 10mm$ in any 1 meter $\pm 50mm$ in 10 meters

5.5 Conclusions

This chapter proposes for the first time the concept of a TC-based 3D Printer. This new additive manufacturing system combines the tower crane (one of the most important machines used in high-rise building construction) with an “aero-pendulum extruder” consisting of a hanging extruder equipped with propellers controlled to counteract the swing effect. The principal challenge of such a new concept is the control system to produce an effective extruding toolpath for the 3D printer. This ambitious goal is reached by proposing an DRL-based control system. The simulated results show the feasibility of the concept by analyzing the training, simulation and validation of a Deep Reinforcement Learning based control of the TC extruder.

The DRL control system can obtain a tolerance for masonries building in line with Eurocode 6 with respect to the ideal trajectory compared with the case of the system without stabilization.
To sum up, the three main novelties of the new concept are as follows:

- the idea of upgrading a tower crane with an aero-pendulum extruder is proposed for the first time in the technical and scientific literature;
- the TC-based 3D printer represents the upgrading of the largest and most widely used building machine for high rise buildings to enhance additive manufacturing in construction;
- for the first time a DRL-based control system was modelled, trained and validated for the control of a tower crane machine equipped with an aero-pendulum extruder to support obtain a large 3D printer.

Proving the feasibility of the proposed system is the first step in the development of a new additive manufacturing system for multi-story constructions by large TC-based 3D Printing. The research work opens up new possibilities to activate experimental research for companies and research centers and lays the foundation to overcome the most relevant limitation of the additive manufacturing application in the construction industry, i.e. the build volume. The outcomes of this study will allow researchers to develop new easy-to-access technology for enterprises and manufacturers, and engineers to reach both freedom in geometry and build volume, features impossible to combine in the present state of the art. The results presented will allow working on the construction of a scaled-down prototype of the 3D Printer and its control system. Such work will be able to investigate practical aspects of the implementation and test the proposed system. Moreover, studies of the most effective printing material, concrete pumping system and extruder nozzle to obtain a practical building system can be performed together with the integration of a real-time image processing-driven control in the proposed DRL approach.

Chapter 6

General results discussion

In this chapter, the main results reached in the application of the 4.0-related technologies investigated in the thesis are presented. The literature findings about the application of technologies such as Big Data and Internet Of Things are presented in the IB context, considering also BIM and ST. The findings of AI and ML application in fault detection of structural systems and in robotics for additive manufacturing are then resumed.

6.1 ICT technologies for intelligent systems in life cycle management of constructions

The implementation strategies of ICT technologies in IBs and smart constructions aim to optimize the management of life cycle domains. IBs were investigated as an intelligent systems supporting the optimization of the whole building construction process. Such systems need specific features like: i) cloud-based architecture, ii) powerful data visualization, iii) real-time sensing and acting, iv) analytics on heterogeneous data, in order to build a consistent reusable and transferable knowledge. A technological framework in which to build such a system is proposed in Section 3.2.2 and is composed by the inner components in Fig. 3.6.

In the results discussion, we need to consider that the construction process during the whole life cycle is a complex process, due to the countless technical and management aspects involved. Mainly, this process is still conducted with an anachronistic approach if compared to other engineering research fields: operative tools allow for simulating many mandatory aspects in the design phase such as structural design, technological sub-system design and legal constraints in urban planning. After the design, the construction phase needs to follow strictly the design specifications; after the construction, a single time-defined testing step assures the correspondence between design and construction; the future development during operational stages is not usually investigated and monitored, and it is not usually and systematically compared with the pre-construction design simulations.

These observations lead to point out the following two challenges:

- engineers take decisions on the basis of simulations and their own personal experience, that are not formalized knowledge; being not formalized, it is difficult to reuse or transfer;
- the real construction performance during building life cycle is not matched with the pre-construction designed one, so that there is no evaluation of effectiveness of design decisions.

Regarding the first item above, the key to solving this drawback is the availability of systems capable of collecting data and enriching formalized and reusable knowledge. Their application to multiple buildings would allow the collection and the enrichment of unified, shared and usable knowledge.

Examples of this kind of system, providing automatic generation of knowledge bases from data, are available in the literature, such as [363–365]. These systems are presently introduced in general terms and applied in other research fields. Their application to the IB area and construction industry in general would provide the possibility of automatically creating and formalising real-time, up-to-date and reusable knowledge on which to build software and services to support building life cycle management.

Regarding the second item above, it is important to consider that the starting point in the performance evaluation of the construction life cycle is the collection of effective heterogeneous data. The actual flows and real-time event processing feature activities of all emerging intelligent systems in other research field areas. In a construction system, data are referred to as BIM general data, IoT sensors data, and third part service data from remote repositories, e.g. weather data. Each of these data types shows its features, like different granularity, semantic enrichment, and typical big data characteristic reported in Chapter 6: the big data paradigm is the most suitable one for this kind of application. In the state-of-the-art, IFC format is the *de facto* standard to represent the BIM model and is largely used also in cloud-based visualization applications. The distributed storage and retrieving best technological strategy is still to be investigated.

About the collection of heterogeneous data, a specific issue is related to interoperability and data format. The most used format for interoperability is still the IFC format, used to migrate from proprietary-specific platforms to common usable formats. Despite its effectiveness, the necessity of conversion between data formats creates issues in data management in the life cycle and between stakeholders. A change of paradigm of a global unified environment in which to completely manage data ranging from BIM to IoT sensors data should be investigated, to understand how to organically integrate the independent proprietary platforms in this ecosystem. To this aim, semantic web technologies may enhance the potential of construction systems, e.g. by improving non-technical stakeholders' involvement in data management and monitoring.

6.2 ML in fault detection of structural systems

In Chapter 4 a methodology to localize damages of a truss railway bridge was presented. This particular method features many characteristics: i) it does not need preliminary damage-sensitive feature extraction to prepare the data to feed the ML models; ii) differently from most of the approaches in the related literature [246, 245, 247, 249, 248], it uses raw strain sensor signals and not vibrational signals; iii) it introduces a distance-based criterion to investigate the most informative portion of the dataset and consequently to allow the CNN training with high-dimensional data. The dataset investigation is based on physical and geometrical observation of the system structure and has a crucial role because the dimensionality of multivariate strain sensor signals, without the investigation, makes effective CNN training difficult.

It features also some limitations. First, a proper updated FE model to generate data representative of the real infrastructure is necessary. To perform data-driven analysis on damaged conditions of infrastructures, data that refer to the damage conditions are needed. However, a real infrastructure in its operative condition cannot have “experienced” the totality of the damages that produce the needed amount of data. Hence, “real” data of damage conditions are usually not available. Therefore, the FE model is necessary because it represents the source to generate data to train the ML monitoring algorithms on scenarios of interest. An accurate FE model is requested by many other works in the related literature [243–246, 248, 251], thus the method proposed is in line with the studies on the use of ML methodology in SHM. A model updating phase is thus needed before performing damage scenarios simulations and data generations. The concept is the base of a digital twin approach, a challenging and emerging technology for maintenance and fault detection in main infrastructures.

Despite assessing its generality by randomly selecting structural elements, the proposed method can be generalized on different damage scenarios and the use of commercial software contributes to this generalization capability. A different rationale can be used to focus on peculiar damage scenarios of the structure considered in the investigation, e.g the fatigue propagation into riveted steel truss bridges [366, 239, 367]. A different rationale can also involve a large number of damage scenarios, and thus the effect of the classes numerosity has to be further investigated, e.g., the method scalability to large multi-class classification problems. However, as the authors state in [368], the classes numerosity is generally not considered as a limitation, since studies of large multi-class problems are present in ML research field, e.g., in [369] the trained classifier deals with about one thousand classes. In such cases, where a large number of damage scenarios are considered, the use of a “normal state” as a reference can be considered in the evaluation of better classification performance.

The method can be enhanced in future research by improving: i) the informative content of the collected data; ii) the adopted ML model architectures. Both these aspects are related to the physical structure of the investigated system. Informative content improvements can be obtained by focusing on control points location on the infrastructure. In this study two misclassified damage scenarios represent two structural elements physically close to each other (Fig. 4.4), and an optimal control points location strategy could thus maximize the sensitivity to different damages. In addition, the ML model architectures can be improved by feeding the algorithms with the physical important features of the system. A solution comes from ML models that perform computations with different data structures: the ML models can perform additional evaluations by employing further knowledge levels. To this aim future works will consider and utilize ML models working on different data structures, such as Graph Neural Networks [370, 371] that allow following the evolution in terms of geometry and relations between parts of the physical system.

6.3 AI in additive manufacturing for the construction industry

There is still much space for AM application in the construction industry, and many challenging problems still need to be solved. The TC-based 3D Printer system proposed in Chapter 5 represents a new concept for on-site large additive manufacturing applications, exploiting the extrusion-based material deposition with viscous material, as in most of the existing approaches.

6.3.1 Positive aspects

The basic idea was to avoid conceptualizing new machines and exploit the best existing technology, currently used in the construction industry.
In the academic and technical world, the only other attempt to convert one of the widespread construction machines into a 3D printer is the CONPrint3D [296], a new 3D printing system to convert truck-mounted concrete pumps into additive manufacturing machines. The similarities and differences between the present proposal and CONPrint3D highlight the novelties and positive aspects of the proposed system. Both these new concepts aim to adapt 3D-printing concrete technology to today's architecture and structural design, with a truck-mounted concrete pump or tower crane in the case of CONPrint3D. While CONPrint3D investigates the concrete composition and properties and printhead design to support quality and precision/tolerances, the current work focuses on the control feasibility of a tower crane customized with a controlled aero-pendulum extruder to configure a 3D printer capable of providing large build volumes with sufficient precision. Therefore, CONPrint3D main issue is not the control system but the improvement of printing precision with a novel printhead (experimenting with different nozzles).
In TC-based 3D printing, the first objective concerns the high-level intelligent control of the whole system, to manage the extruder path in synergy with the crane

movements. To counteract the inevitable swing effect of the suspended extruder, the system is equipped with an aero-pendulum extruder with propellers that directly react to the swing. The principal advantage and novelty of the proposed concept concern the use of large and widely used building machinery for high-rise buildings: tower cranes are the most used machines because of their reach, which is turned into printing volume within the system proposed; in this way, the main existing 3d printers' limitation, the build volume, is overcome without designing or inventing any completely new technology from scratch. From a practical point of view, the concept proposes an easy-to-access technology for construction enterprises: the upgrade of already existing tower cranes with the custom aero-pendulum extruder is only needed to potentially perform additive manufacturing.

Apart from the dimensions, the other difference regards the approach to control the machine based on a DRL system, which was modelled, trained and validated. The flexible Tower Crane-based 3D printing can be located internally to construct high rise buildings or externally to a building (being able to reach about 40 - 45 m high) and can include a "climbing section" to increase its height as the building work advances.

It is possible to compare the potential of the technology with already existing 3D printed buildings. Indeed, the larger 3D printed building [372] has a floor area of 640 square meters only and is achieved by moving a small 3D printer based on a robotic arm. Curved walls built with this technique can achieve 8 meters of diameter. The proposed technology instead shows how the tower crane 3D printed can effectively reach a curved wall of 20 m of diameter and higher.

DRL features many important aspects that lead the authors to choose such an approach for TC-based 3D printing control. Indeed, DRL can provide optimal control solutions like the other control techniques [373]. Moreover, an important peculiarity of the DRL is that it does not strictly need any formal and mathematical system model but may exploit strongly detailed system simulation environments (also considering uncertainties) or directly the real system outputs to train the controlling agent [374–376]. Hence, the DRL is particularly effective in the case of complex and non-linear systems. In addition, the DRL is an effective tool to include real-time image processing-driven control, because of its capability of processing images or videos by the Deep Learning architectures. For example, in autonomous vehicle control and in the robotics area, there are many successful applications in this direction: in paper [334] a DRL control agent is developed using real-time semantically segmented RGB camera images; the work [335] deals with object picking with a robotic manipulator learning a closed-loop policies mapping depth camera inputs to motion commands. In [333] authors employ high dimensional data to train a speed DRL control, including road information processed from the video data and the low dimensional data processed from the sensors. Furthermore, [336] presents a DRL based method to solve the problem of robotic grasping using visio-motor feedback. Summing up, in this work, the DRL is chosen for two reasons: i) the DRL provides optimal results for managing such a complex 3D printer; ii) it allows future research to integrate real-time image processing-driven control. Indeed, a DRL-based controller exhibits the important feature of determining the control actions also based on the graphical information about the printing procedure. For instance, the printing parameters can be automatically tuned, such as the material flow tuning by considering the printing speed and quality perceived by images. Many examples already presented in the literature review and dealing with such approaches [337–339], highlighting the importance of such technique for future mandatory integration in the control strategy.

6.3.2 Limitations and recommendation for future researches

The present study represents a technological conceptualization and feasibility investigation: it demonstrates the consistency of the integration of tower cranes and the aero-pendulum extruder to obtain the biggest possible 3D printer for the construction industry. Its outcome opens up the possibility for researchers and practitioners to develop it based on already wide technological knowledge of the process. In particular, tower cranes are already wide-used machines and their technological readiness is noticeable. On the other hand, the aero-pendulum extruder design involves studies about the aerodynamic evaluation of the propeller system, the low-level control of the electric motors driving the propellers, and the sensitivity requirements of the extruder-mounted sensors to promptly react to any swing: its development can largely benefit from the UAV-related literature and the enhanced technologies available for drones. The aero-pendulum extruder design also includes the identification of a suitable printhead and nozzle to comply with the printing behavior.
Other aspects to consider are the material supply strategy to feed the extruder during the printing phase (concrete pumps and power supply), and printing material requirements and specifications. The material supply strategy development can benefit

from specific applied research, such as the CONPrint3D and other systems already available.

6.3.3 Comparison with classic 3D printing approaches

In Chapter 5, we trained an intelligent agent to supervise the entire printing process by activating jib rotation and the propellers to counteract the swing and minimize the extruder deviation from the designed trajectory. Because of the stated problem and the system features, the classic concept of a “toolpath” from standard 3D printing does not apply to the present system. In fact, in a standard 3D printing task the geometry is first “sliced” by deciding the extruder speed in advance, so that it is already set as a parameter. The trajectory (toolpath) is then generated, which the machine follows with high precision since it is completely controllable. During the printing process, there is no control matching between the designed and the actual trajectory: the toolpath is a prescription that the machine is not aware of accomplishing properly. In the presented application, the jib rotation speed is not considered as a pre-determined parameter but is an output of the intelligent agent’s control task together with the thrust force on the extruder. This further degree of freedom adds flexibility to the agent’s control and allows it to manage the whole process to deal with the external conditions sensed. On the other hand, the agent is trained in a specific circular trajectory, chosen because of the challenging continuous variations of acceleration involved, and is able to perform the control task only in that specific trajectory. This means that each specific control task, and each specific trajectory needs specific training, although each already trained agent can be used as a starting point for the following training requirement, so reducing the computational effort and speeding up the printing process.

Chapter 7

Conclusions

In this Thesis, Industry 4.0 technologies application and potential in the construction industry are investigated (i.e. Construction 4.0), with a focus on the ones more involved in the digitization of the sector. A brief analysis of the literature reported in the introduction highlighted the importance of such topics both in the academy and the industry.

An introductory description of the technologies investigated was given in Chapter 2. First, Information and Communication technologies such as Internet of Things, Big Data and Semantic Technologies employed in specific construction-related software environments were introduced focusing on their main operative tools, i.e. technologies adopted in the literature. A focus on Artificial Intelligence and Machine Learning was then presented, dealing with the basic concepts of Artificial Intelligence and contextualizing the paradigms of supervised learning and reinforcement learning. Finally, an overview of additive manufacturing in the construction industry was introduced.

Big Data, Internet of Things and Semantic technologies are being integrated into BIM environment in an intelligent system-fashion approach, enhancing services availability and potential. In Chapter 3 a review of this kind of integration was presented, and the main specific technologies involved in detailed implementation were investigated. It was shown that complete integration of these technologies is not yet reached in an available commercial application, mainly due to the trend of proprietary software developing in a closed and low-interoperable environment.

In Chapter 4 a methodology for locating and assessing the severity of damages in railway steel truss bridges using artificial intelligence and raw strain sensor data was presented. A preliminary feature selection phase allowed us to identify the most informative portion of data to train a CNN classifier. The results showed the feasibility of the methodology and good potential for real-time application in similar infrastructures.

In Chapter 5, the concept of a new technology to employ in additive manufacturing in construction was presented. It modifies tower crane technologies with a custom extruder and features an intelligent control strategy based on Deep Reinforcement Learning. This preliminary analysis fulfils the requirements in terms of the accuracy of the technology and identifies the first effective step for a low-level feasibility investigation.

The thesis work highlighted that there is still space and need for investigation in Construction 4.0. It represents a research field that could largely benefit from strongly oriented academic investigations that however remain detached from real-world applications. The study carried out outlines different fields of investigation focusing on applications in construction life cycle phases: i) whole life cycle management, ii) operation & maintenance and iii) integrated design with construction.

Concerning the whole life cycle management i), intelligent systems for knowledge extraction and reuse are only theorized in many research papers, and BIM-centred architectures featured by IoT and BD are mainly described and identified in their components. Industry-standard software is instead pushing towards adding more features and services to their proprietary platform, and the main attempt to enrich the capability of these platforms is described by the increasing number of "dimensions" of BIM software (e.g. n-dimensional BIM). Due to the lack of effort towards a unique integrated knowledge collection and reuse through these platforms, to the best of the author's knowledge there is still no example of consistent application of BD-based architecture supporting IoT data in construction. Despite being driven by proprietary services and development environments exposed to users, the customization of leading proprietary platforms remains currently the most practical way to aim for such systems.

Artificial Intelligence-driven Big Data processing in the operation and maintenance stage ii) of strategic infrastructure is a massively investigated research field because of safety concerns-related and shows high potential in terms of achievement in short time. It benefits from the sensorization trend enhanced by the IoT approach and the massive development and appeal of data analysis techniques in the academic literature. The methodology proposed in Chapter 4 is fully integrable with current approaches employing vibrational signals from accelerometers that apply data analysis on dynamic features extracted. Despite enhancing the possibility of successful fault detection of structural systems in comparison with other methodologies, it shares the necessity of a high-accuracy updated FEM model in order to properly simulate the damage scenarios of interest for the particular system analyzed.

The integrated design/construction phase iii) is investigated with additive manufacturing for the construction industry, one of the most studied Construction 4.0-related technology. The main trend in research and industry is to design new technologies, borrowing expertise from small-scale additive manufacturing, that have some limitations in terms of build volume, movability and costs. On the contrary, the conceptualization proposed is important to overcome the state-of-the-art limitation in additive manufacturing in the construction industry, i.e., the build volume. There are many different applications of 3D printed geometries difficult to achieve with standard constructive technologies. All these updated case studies are characterized by limited dimensions because of technological limitations. The complete development of the technology conceptualized in Chapter 5 will allow reaching both freedoms in geometry and build volume, features impossible to combine in the present state of the art. From a practical point of view, the technology will be an easy-to-access technology for construction enterprises. They will only need to upgrade their already existing tower cranes with the custom aero-pendulum extruder to potentially perform additive manufacturing.

The investigations presented can be read as an approach to cross the gap between the academy and the construction industry on the topic of Construction 4.0. They look towards challenges currently detectable and suggest practical directions for their solutions. The complete and successful engineering and development of the proposed studies can contribute effectively to specifying the Construction 4.0 concept and to the construction industry's performance.

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