Automatic intelligent inspection systems for quality control: A case of defects in light-gauge steel frame assembly manufacturing

by

Pablo Martinez

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Department of Civil and Environmental Engineering
University of Alberta

Abstract

Offsite construction has become a viable alternative to traditional construction methods by establishing controlled and automated manufacturing environments for construction products. To reap the benefits of industrialized construction, manufacturing execution and quality play an important role. However, most quality control processes remain manual, relying on visual inspection and operator's expertise. Automated manufacturing processes in offsite construction facilities and their corresponding machinery would benefit from smart manufacturing, information, and communication technologies to control quality and, ultimately, reduce defects and optimize production.

This study presents a framework for the automatic inspection and quality assessment of BIM-based construction products as a knowledge-based cyber-physical system that bridges Industry 4.0 principles with zero-defect manufacturing and lean techniques. The proposed methodology is based on the well-known 5C cyber-physical architecture, adapted to a building information modeling environment. In this research, light-gauge steel frame assemblies manufacturing is selected as the case study.

At first, a knowledge model for steel frame assemblies manufacturing is proposed to link, at the design stage, product information, manufacturing operations, and quality specifications. By enhancing building information models with the developed ontology model, offsite practitioners can access quality information at the design stage and prepare adequate quality control strategies beforehand. Then, a vision-based cyber-physical inspection system is proposed that generates quality-related information as required by the BIM model. The designed CPS system employs visual sensors (cameras) to provide real-time inspection and quality control of the frame assembly manufacturing process, in addition to providing a platform for data storage and future analysis of quality-oriented data. Finally, in an effort to integrate human input and knowledge into the system, cognitive and supervisory roles are discussed. The implementation of the proposed system enables quantification of quality issues, as well as analysis of the source of defects in steel frame assemblies manufacturing.

Preface

This thesis is an original work by Pablo Martinez. 5 journal papers and 1 conference paper related to this thesis have been submitted or published and are listed below ordered chronologically.

1. Martinez, P., Ahmad, R. & Al-Hussein, M. (2019). A vision-based system for pre-inspection of steel frame manufacturing. *Automation in Construction*, 97, 151-163. (Chapter 5).

2. Martinez, P., Ahmad, R. & Al-Hussein, M. (2019). Real-time visual detection and correction of automatic screw operations in dimpled light-gauge steel framing with pre-drilled pilot holes. *Procedia Manufacturing*, 34, 798-803. (Chapter 5).

3. Martinez, P., Ahmad, R. & Al-Hussein, M. (2019). Automatic Selection Tool of Quality Control Specifications for Off-site Construction Manufacturing Products: A BIM-based Ontology Model Approach. *Modular and Offsite Construction Summit Proceedings*, 141-148. (Chapter 4).

4. Martinez, P., Al-Hussein, M. & Ahmad, R. (2019). A scientometric analysis and critical review of computer vision applications for construction. *Automation in Construction*, 107, 102947. (Chapter 2).

5. Martinez, P., Al-Hussein, M. & Ahmad, R. (2020). Intelligent vision-based online quality inspection system of screw fastening operations in steel frame manufacturing. *International Journal of Advanced Manufacturing Technology* (under review). (Chapters 5 and 6).

6. Martinez, P., Al-Hussein, M. & Ahmad, R. (2020). Vision-based cyber-physical system for automated inspection and quality assessment of steel frame assemblies. *International Journal of Industrialized Construction* (under review). (Chapter 6).

Quality is never an accident. It is always the result of an intelligent effort. There must be the will to produce a superior thing.

- John Ruskin

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Chapter 1

Introduction

1.1 Background

During the last decade, offsite construction (OSC) has become increasingly popular in North America as a viable alternative to traditional construction [1]. OSC refers to a construction method that "brings onsite construction works into a climate-controlled facility where advanced machinery and manufacturing technologies can be used to prefabricate buildings in a standardized and efficient manner" [2] and will serve as a platform to overcome the limits in growth, performance, quality and productivity associated with conventional construction [3]. The growing attraction of OSC from both industry and academia is explained by the shortened schedules, higher efficiency, reduced waste, lowered health risks and physical extenuation of the workforce, and increased productivity [4]. As modern markets impose mass customization of products [5], OSC provides customers with the possibility of "one-of-a-kind" flexibility. Given those benefits and combined with a stable and controlled factory environment, digitization and automation of construction processes is in high demand.

In an OSC facility, construction products are customized based on client requirements and various design parameters, as well as construction codes and specifications. As such, the complexity of OSC projects lies on the number of professionals and disciplines involved to manufacture the necessary components of the product. An established framework that would allow an input-to-output analysis of the OSC processes at the project level, but more importantly, at the component level is still needed [6]. In the past decades, Building Information Models (BIM) for OSC projects have been developed to enhance design, improve data exchanges, and reduce waste [7]. However, limitations are encountered in the transition between the digital and the physical worlds, and specially obtaining relevant feedback on the state of the project [8].

Nonetheless, the implementation of BIM, a major unifying concept within the construction industry nowadays, has been very important in raising awareness and progressively changing construction practitioners mindsets, and the Architecture, Engineering and Construction, and Facilities Management (AEC/FM) industry in general, around the adoption of new technologies [9]. A swift transition to Construction 4.0, the counterpart of Industry 4.0 in the construction sector, seems necessary to enable industry to move beyond the limits of the BIM approach as currently developed [10]. The coming fourth industrial revolution, also named "Industry 4.0", presents changes in manufacturing systems through integrated information systems, smart technologies, and an advanced digitalization within factories [11]. Similar to other industrial sectors, the OSC digital transformation is driven by a physical-digital-physical connection enabled by the use of sensors, controls, augmented reality systems, cognitive and high-performance computing [12] and finally allows to introduce different technologies from the manufacturing domain onto the OSC domain [13].

Although digitization in the OSC sector is bringing improvements to quality of construction elements, issues still remain. Given a recent survey in New Zealand, 68% of new homeowners claimed that rework was needed in their homes at handover [14]. Moreover, it is reported that the cost of poor quality in offsite construction projects remains high (8%-16% in New Zealand [14] and 8%-21% in the UK [15]). Quality of construction outputs has always been criticized even with the great efforts that have been done in the past decades to promote quality within the construction industry.

Furthermore, evidence suggests the possible misconception that faster construction time in OSC projects is a result of lower quality workmanship [16]. Considering that most offsite practitioners identify quality as one of the main improvements when switching from traditional stick-built to offsite construction methods [17], there is a clear gap between the perspective of quality in offsite construction and the final end-quality of the construction project as-is. Quality of offsite construction products should be a selling point for the industry, however, that is not the case yet.

Conventional quality inspection methods in OSC facilities are manual, paper-based, and error-prone. Such approaches are labor intensive and, sometimes, cost-prohibitive. Moreover, manual inspections are typically based on sampling: a slow process that opens up the chances of mistakes going downstream as only a few selected products are inspected. Overall, the effects of relying on manual inspections for quality control potentially suppose a loss of material due to defects, loss of production time, and inefficient quality resolution actions. To improve quality of products and mitigate the impact of defects in the production line, online automatic inspection has been promoted in academia and industry alike [18]. A real-time quality control approach that has been widely adopted by several industries, specially manufacturing, is computer vision [19]. Computer vision seeks to mimic human perception through the use of visual sensors. These visual sensors and their corresponding systems are responsible to generate rich data-sets that would enable an accurate digitization of construction components in real-time. Such information would enable automated assessment of the quality of each product within the production line, as well as support the mitigation or elimination of defects during production.

In summary, quality control procedures in offsite construction facilities need to be adapted to the new paradigm, introducing digital technologies, automating the inspection systems, and providing quality engineers access to smart tools to trace defects from the bay to its source. This thesis aims to research the development of a framework that supports comprehensive inspection of offsite manufactured products that mitigates of the negative effects of defects in the production line and enables a continuous improvement culture towards eliminating defects in the shop floor by involving all the effecting agents of the end-product quality.

1.2 Motivation

One of the major concerns for the construction sector in the following decades is the stagnant productivity. With current labor shortages and increased costs, workers' health and safety or product quality may be compromised to compensate productivity numbers. Regarding quality, a possible solution is the integration of automated processes in the construction environment. Although adaptation of automation in construction has been a slow process, principles of industrial automation are applicable to this domain, especially in the prefabrication of construction components [20]. With the development of intelligent automated systems within academia and their practical implementations in other industries, such as automotive [21, 22] or aerospace [23], the introduction of intelligent inspection systems to the offsite industry can be a step forward towards a quantifiable increase in the product quality.

However, several challenges would need to be addressed in order to reach such goals:

- Production quality is a complex problem that is intertwined with many other factors. To provide a comprehensive quality control procedure that considers all potential sources of defects, information from those sources needs to be accessible from a common framework. The information exchange regarding quality in the context of offsite construction and its information workflow would need to be researched to integrate in an automated manner the constraints of quality specifications.

- Quality data is often generated via inspection systems. To have a continuous flow of such data coming from offsite construction production lines, automated inspection systems are required. Following other industries' trends, vision-based algorithms need to be developed to accurately and contactlessly inspect prefabricated construction products.

- Quality control procedures make use of inspection data to ensure conforming products out of the production lines. Decision support systems can help machines or operators to determine an optimal course of action to deal with potential defects. Developing such decision support systems for offsite construction would enable the mitigation and elimination of defects from the manufacturing phase.

- Certain actions need to be taken in order to mitigate the impact of defects in the end-product. In cases like offsite construction, defects can be easily addressed if they are detected on-time and rework procedures are in place. An integrated system that monitor and control rework operations would be required to maintain control over the quality of the end-product, and assist in eliminating defects on the production line.

Regarding steel framing, it represents the most challenging engineering problem to practitioners nowadays [17]. This is due to its various design patterns and assembly complexity when compared to other options, such as wood-based frames. The inherent complexity of steel frame assemblies presents a complex scenario for the various quality control procedures needed. As an example, Figure 1.1 shows common quality issues in light-gauge steel frame assemblies.

The following section explicitly addresses the research objectives presented in this thesis based on the existing gaps in the academic literature and industrial practices.

1.3 Thesis Objectives

The main objective for this research is stated as follows:

"Provide an integrated framework for automated quality control and assessment of steel frame assemblies manufacturing in offsite construction facilities"

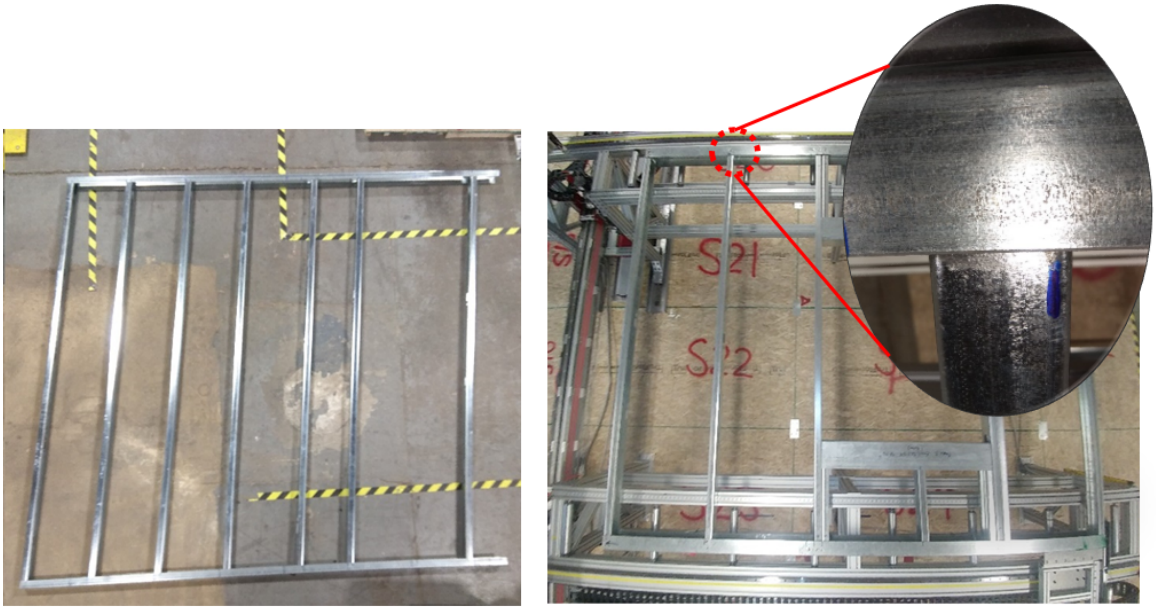


Figure 1.1: Example of potential quality issues in steel frame manufacturing. *Left*: image of a finished non-squared frame. *Right*: image of a finished frame with a missing screw.

As such, this research objective includes the following tasks ($\mathbf{O}_X$):

- $\mathbf{O}_1$: Develop a knowledge model to support automated identification of quality specifications within a BIM framework by formalizing the link between construction-related products, manufacturing processes, and quality constraints.
- $\mathbf{O}_2$: Develop novel computer vision and machine learning algorithms for automatic offline/online real-time inspection of steel frame assemblies at its pre-manufacturing, online, and post-manufacturing stages.
- $\mathbf{O}_3$: Develop decision-support and monitoring systems based on inspection results for quality control operations in steel frame manufacturing.
- $\mathbf{O}_4$: Provide a smart approach to integrate and monitor rework operations in offsite manufacturing of steel assemblies.

1.4 Thesis Outline

This chapter provided a concise statement on the current state of offsite construction, focusing on the limitations in light-gauge steel frame assemblies manufacturing, and the motivations for undertaking this research. A brief statement on the objectives of this thesis is also presented in this chapter.

Chapter 2 is a general state of the art summary on the main topics covered in this thesis. First, the main contributions in the area of Construction 4.0 are discussed, including building information modeling, knowledge modeling, cyber-physical systems, and its impact on industrialized and offsite construction.

In chapter 3, the proposed framework towards improved quality and manufacturing of light-gauge steel frame assemblies based on cyber-physical systems and zero-defect manufacturing is presented. Starting by looking at current practices, the proposed research methods and framework are explicitly reported.

Chapter 4 presents the knowledge model formulated for steel frame assemblies. From its original BIM schema, knowledge is expanded towards manufacturing and quality domains. Then, a full ontological model is presented and integrated back into the BIM software that enables manufacturing and quality analysis of steel frames at the design phase (O_1).

Chapter 5 proposes a vision-based inspection system for light-gauge steel frame assemblies. The proposed approach divides the inspection system in 3 steps: 1) pre-manufacturing inspection; 2) online inspection; and, 3) post-manufacturing inspection. For each system, the machine vision algorithms and their integration in the semi-automated use case for steel frame assemblies manufacturing are presented (O_2).

Chapter 6 describes the cyber-physical system built around the inspection systems aforementioned. Each level of the cyber-physical system is identified and explicitly described, including algorithms, information flowcharts, and decision-support systems that support quality control and rework in offsite construction manufacturing of steel assemblies (O_3 and O_4).

Finally, chapter 7 summarizes the work done in the thesis and the resulting findings. Furthermore, future research directions which build on the presented work are discussed.

Chapter 2

State of the Art

2.1 Construction 4.0

Modeled after the concept of Industry 4.0, the idea of Construction 4.0 is based on a amalgamation of trends and technologies from different domains that promise to reshape construction frameworks. Such a transformation is only possible through the use of existing and emerging technologies that take part in the Industry 4.0 paradigm [24]. Construction 4.0 uses the main core principles from Industry 4.0, such as cyber-physical systems, and links it with the construction ecosystem of digital platforms, i.e. building information model, to close the cyber-physical gap that exists in the built environment [25]. The Construction 4.0 framework then provides a mechanism from which digitalization of built assets and the use of such digital models support efficient planning, design, and delivery of construction products.

With the necessary call to 'modernise or die', the architecture, engineering and construction (AEC) industry faces an urgent transformation and requires improvement plans to reach modern society goals of sustainability, development, and performance that Construction 4.0 is believed to solve [26]. Real-time progress monitoring, enhanced quality and safety of construction operations, and improved communication between stakeholders are just a few of the benefits that are expected to come. The following subsections target the state of the art for the Construction 4.0 main themes discussed in this thesis.

2.1.1 Building Information Modeling (BIM)

AEC models from diverse professional domains may possess some identical or related parts, or, in some cases, link the results of other analysis. The variety and heterogeneity of models with common features led to the idea of creating a universal model to be used by several tools in construction projects. The solution was initially termed 'building product modeling' (BMP) [27], finally labeled as 'building information modeling' (BIM). BIM itself has become an essential concept for modeling, visualization, analysis, simulation, and documentation that covers a broad set of interacting policies, processes, and technologies.

BIM brought the revolution of digitalization and informatization to the entire construction industry. By digitizing and parameterize different building information, it provides a clear visualization as a 3D model. BIM integrates models, databases, assets, and material and spatial relationships into an environment capable of simulation, progress management, cost estimation, energy analysis, among others [28]. BIM enhances not only planning, design, construction, operation, and maintenance processes, but also the whole project life cycle [29]. In summary, BIM is emerging as the key technology for digitalization of the AEC industry [30].

Within BIM, the total sum of information about a building is provided in the form of a model and a schema (or meta-model) [31]. The model is the digital representation of an actual building (or project) over its whole life-cycle and the schema is the non-linguistic data structure that describes the interactions, properties, and states of the information within the model. A typical commercial BIM tool provides its 3D visualization using different constructs and features that are usually proprietary (with some exceptions, such as OpenBIM [32]), however the exchange and use of data is guaranteed by agreed formats and schemata. As such, BIM schema is the key to harmonize data and information exchange, enabling interoperability between project stakeholders.

The focus of the BIM schema is to standardize the building-model data exchange. Currently, the most extended approach for commercial BIM standardization is the ISO/IFC STEP EXPRESS model [33], however, continuous efforts in the past decade from academia and practitioners look to expand further the capabilities of information exchange within BIM environments. By expanding the BIM schema through several extra information layers, distributed and modeled using different approaches, the capacity of BIM modeling to understand and visualize data increases. For example, an IFC-based extension was presented to achieve building life-cycle management within a BIM environment [34], or, more recently, geographic information system (GIS) data could be retrieved through IFC scripts and linked to BIM data for improved geo-localization of building elements [35]. Overall, expanding and modeling all the required information for AEC projects is still a work in progress, however matching newer data structures to current schema may prove itself a very tedious task as the model grows [36].

To develop a novel extension for BIM requires to define a map between internal and external schema. The internal schema is imposed by the BIM software chosen, i.e. Autodesk Revit, and usually limits authors to comply with its features and interfaces that follow a specific methodology or application programming interface (API). The external schema, however, is left to the authors intentions, as long as it complies with the specific standards, e.g. IFC, or the selected modeling language can be interpreted correctly, such as XML Schema, RDF, UML, OCL, or Object-Z [37–40]. Alternatives exist that can provide a better handling of contextual statements, narratives, and states that could enable greater formal reasoning, i.e. OWL, to permit a larger semantic BIM model. In fact, recent BIM developments have been centered around the development of semantic knowledge models that are later integrated in the BIM environment. For example, a formalization of risk knowledge management is linked to BIM through an ontology model, a type of knowledge model, that enabled the authors to facilitate risk analysis and prevention through BIM [41]. BIM and knowledge management are often treated as stand-alone processes that may interact at a cognitive or human level, but a deeper integration and automation of exchange of knowledge may be required for more complex domains, such as safety, offsite production, or quality. Recent research has shown that extending BIM to a knowledge management base is capable of capturing, sharing, reusing, and maintaining knowledge simultaneously with BIM collaborative processes [42]. The integrated platform, baptized 'building knowledge model' (BKM), is still in very early stages and most approaches still prefer consolidated models.

2.1.2 Knowledge Modeling

The essence of knowledge modeling was defined in the late 80's as a representation of an object, i.e. system or operation, at an abstract level, targeting at the how and what an object may know. Conceptually, a knowledge model is a complex set of facts, theories, heuristics, explanations, justifications, and control of an object based on a predefined structure [43]. All kinds of knowledge, including construction-related knowledge, can be represented using one or more techniques. Users in the AEC industry, however, find it difficult to clearly differentiate knowledge modeling from what they recognize as data models [44]. Data models, such as BIM, have a clear conceptualization of a product, i.e. building, while knowledge models provides multiple interpretations of a product that factor in experiences and perspectives of a broad range of users [45].

These modeling techniques are interrelated knowledge elements, that can range from primitives (frameworks, rule-sets, logical expressions, or procedures) to complex knowledge elements. The complexity of a knowledge model is gained by aggregating different combinations of primitive knowledge elements. By describing and formalizing complex information processing systems, knowledge can be inferred to provide a solution in regard to an specific task or goal. Knowledge modeling for that particular task or goal is then facilitated by this task structure: the knowledge and strategies required to achieve such task is required to be known, as well as the terms of analysis to model the knowledge [46]. In this sense, the knowledge model eases the automation of complex tasks by simplifying and formalizing the information channels between collaborative systems.

The usefulness of knowledge modeling is not, however, limited to the automation of problem-solving. The analysis of the task itself requires a decomposition and understanding of what kind of knowledge is needed. It is possible that some task may require methods that are not available in a computer-processable form, specially in human-machine cooperation [47]. Aiming at overcoming such limitations, interdisciplinary advancement of knowledge modeling in specific fields has helped lay the ground to develop advanced knowledge techniques. These fields include intelligent agents, ontology engineering, databases, among other major trends in computer engineering and research.

On the one hand, intelligent agents, also known as smart or autonomous agents, are computer systems that operate robustly in a rapidly changing, unpredictable, and open environments, where there is a possibility that actions can fail. In general, agents are able to perceive something out of the environment it is in, usually through sensory input, and produces as output actions that affect it through a continuous action [48]. Although reactive in origin, intelligent agents have been used for real-time control tasks since the 80's and have been at the source of solving problems in knowledge-rich domains, integrated as expert systems [49].

On the other hand, ontology is defined as the explicit and formal specification of a concept, and can be used for various reasons: support interoperability of information in multi-domain knowledge models; consistency checking and reasoning of knowledge models; and concepts can be mapped and represented in an intuitive way [50]. Considering the heterogeneity and diversity in knowledge representation and formalism, research in ontological engineering has provided a standard basis in which to build higher-level knowledge models, with taxonomical and terminological mismatches between different domains [51]. By providing a clear formulation and declared representation of a subject, via defining classes, entities, properties, attributes, relationships, and function, the ontology model provides conceptual knowledge with a standard vocabulary and logical terms about how information is related (or not) to each other [52].

The two described techniques are the most common approaches to knowledge modeling in modern applications for product-based manufacturing, however more information regarding the development of such techniques can be found in [53, 54] and summarized in the table below:

Table 2.1: List of knowledge modeling approaches and technologies.

Type	**Description**	**Examples**	**References**
Linguistic Knowledge Base	Modeling of the knowledge of human lexicon	*FrameNet, WordNet, ConceptNet*	[55]
Expert Knowledge Base	Modeling of knowledge applied to problem solving (rule-set)	*Prolog, WUENIC, KnowRob, Fuzzy Petri Net, Matlab*	[56–58]
Ontology	Modeling of knowledge as a taxonomy of concepts	*Protégé (RDF,OWL), OntoLearn, SymOntos, PRIMA, OntoEdit*	[59–62]
Cognitive Knowledge Base	Model of knowledge as dynamic neural networks	*Knowledge Manipulation Engine (KME)*	[63]

In the actual context of Industry 4.0, manufacturing systems are being updated to an intelligent level. Intelligent manufacturing benefits of advanced information and manufacturing technologies to achieve flexible, smart, and re-configurable manufacturing processes in order to address ever-changing and dynamic global markets [64]. The development of autonomous intelligent manufacturing units is very important for the future efficiency and integration of the manufacturing industry in a data-driven future [65]. Such level of intelligence requires, however, certain expertise or knowledge in order to enable machinery to vary and adapt their behaviors in response to different scenarios based on past experiences and learning capabilities [66]. Proper presentation of the acquired knowledge to users support the correct decision-making and eases the transfer of knowledge from experts to machinery and from the knowledge systems back to users [67]. As such, the base of all 'Industry 4.0' smart manufacturing systems is the knowledge acquisition and posterior decision-making systems regarding manufacturing processes.

Applied to the construction industry, the richness of design information offered by BIM has helped in the delivery of improved quality buildings. BIM itself is a purpose-built, product-centric information database, and has proven itself as one of the key enablers of Construction 4.0 [68]. Specific to off-site construction, the ability to extract construction manufacturing specific information from a BIM model is critical to support productive workplaces [69]. The complex and dynamic nature of construction manufacturing and its off-site work patterns are widely known. However, in order to take correct decisions, the appropriate knowledge needs to be captured, stored, and analyzed afterwards: the requirements imposed by construction specifications are known for both planning and quality control [70]. In fact, when considering the multi-disciplinarity of offsite construction, selecting an adequate knowledge model approach is key to obtain a streamlined performance.

The integration of intelligent systems on BIM-based construction processes has facilitated a deeper understanding and control over the quality control of construction related manufactured products. In regard to automated quality control processes, several examples can be found in the literature showcasing the capacities of vision-based intelligent systems [71–74]. However, most of these current systems, specifically designed for the construction industry, are product-specific or task-specific and cannot be utilized for general offsite manufacturing purposes. To address such shortcomings, ontology models have proven effective in the construction environment by providing a re-configurable and more generalistic approach. Several ontology-based models have been proposed to formalize the knowledge in the offsite construction and manufacturing sectors [75–78].

Production quality is a paradigm of innovative and integrated quality control where production logistics, maintenance design, management and control, as well as the advanced manufacturing processes are involved [79]. For construction, BIM is a necessary source of product knowledge that enables product-oriented manufacturing [75]. However, an extension of the existent knowledge models is necessary in order to target quality control of offsite construction elements from all the involved knowledge domains, as seen in Figure 2.1. Initial knowledge-based systems have been developed to bring robust advantages in manufacturing environments to facilitate real-time inspection, condition monitoring and control–diagnosis at the shop floor [80], but research is still needed to adapt such environments to the offsite working environment. As an 'Industry 4.0' approach, a knowledge model for quality analysis based on computer-aided design (CAD) has enabled model-based definitions of defects for parts at the design stage [81], however, the proposed rule-based models have a limited effect on the shop floor when considering mitigation and prevention of defects. Rule-based systems are a feed-forward communication method and bi-directional knowledge models are targeted to provide not only detection and correction of defects, but also traceability to its source.

2.1.3 Cyber-Physical Systems (CPS)

Intelligent manufacturing or smart manufacturing is a broad concept of manufacturing with the purpose of optimizing production by making use of cutting-edge information, communication and manufacturing technologies [82]. Such initiative falls under the well-known Industry 4.0 strategies to upgrade manufacturing technologies by cyber-physical systems (CPSs), the Internet of Things (IoT), and cloud computing [83]. Providing manufacturing systems with monitoring capabilities and the possibility of taking smart decisions autonomously through real-time communication and cooperation with humans is the goal of the Industry 4.0 era [84]. As such, the

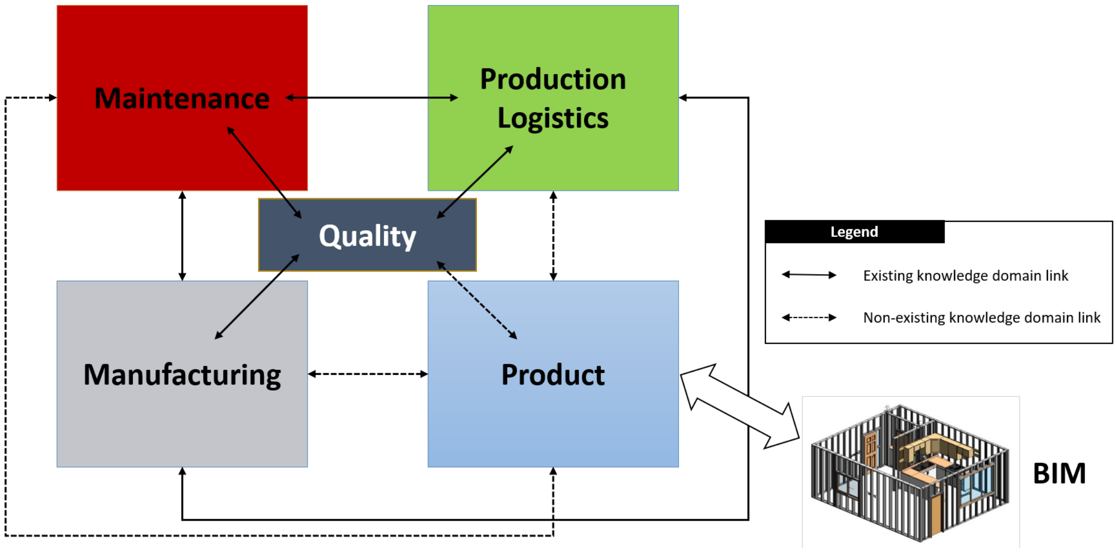


Figure 2.1: Summary of knowledge domains and relationships for quality control of offsite construction products.

combination of embedded production technologies with real-time decision making will fundamentally transform machinery first and, consequently, the manufacturing industry. Cyber-physical production systems (CPPS) are the next step to further integrate manufacturing science and technology with computer science, information and communication technologies [85].

Cyber-physical systems are an intensive network of collaborative computational entities that link the surrounding physical world and its on-going processes. It provides at the same time data-driven insight onto the physical world by applying computational approaches. As such, the intersection between the physical and digital world is the key factor in the development of such systems [86]. A successful implementation of such systems in industrial environments offer several advantages at three different levels: 1) individual components or subsystems; 2) machines; and, 3) the production system as a whole. CPSs are a multi-disciplinary emerging research area that will involve the integration of multiple fields of science and engineering. For the last decade, cyber-physical systems have been developed to cover a large range of applications, from digital medical applications to control of energy distribution in complex grid systems, with potential huge economic benefits [87]. Current CPSs applications are supported by trendy technologies for cyber applications, such as Internet of Things (IoT), blockchain, 5G, virtual reality (VR), and artificial intelligence, as well as recently developed physical devices such as UAVs, additive manufacturing (AM), RFID, or robotics [88]. An overview is presented in Figure 2.2.

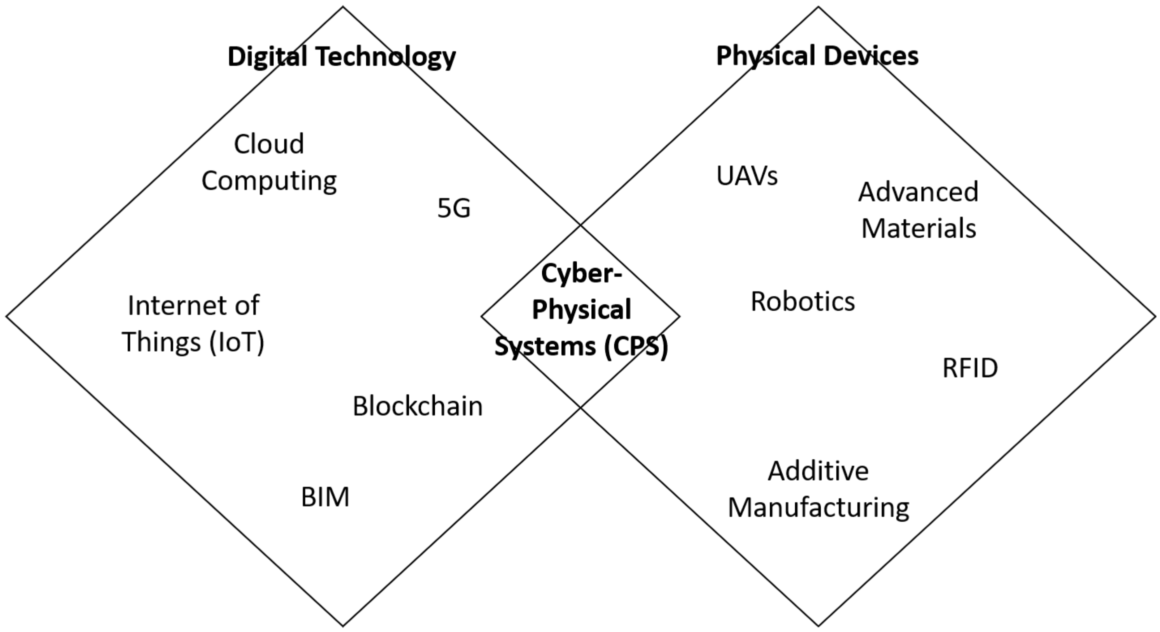


Figure 2.2: Supporting technologies for cyber-physical systems.

CPSs for manufacturing can be structured around a 5C level architecture, as shown in Figure 3. This CPS architecture enables computational entities and systems to collaborate and infer knowledge into the surrounding physical systems and their on-going processes. As such, the CPS structured system designed using 5C structure can monitor, control, coordinate, and communicate the status of the machine and its manufacturing product in an automatic and fully integrated manner. However, the defined interactions between the physical and cyber elements are the limiting factor of such systems and of key importance to impact the performance of the machine and product quality [89]. The 5C architecture provides a step-by-step guideline for developing and deploying a CPS for manufacturing applications. In contrast to generic CPS descriptions [90], the architecture presented clearly defines CPS systems by layers of functions and attributes. The architecture consists of 5 levels in a sequential workflow manner and illustrates how to construct a CPS from the initial data acquisition through analytics to the final value creation.

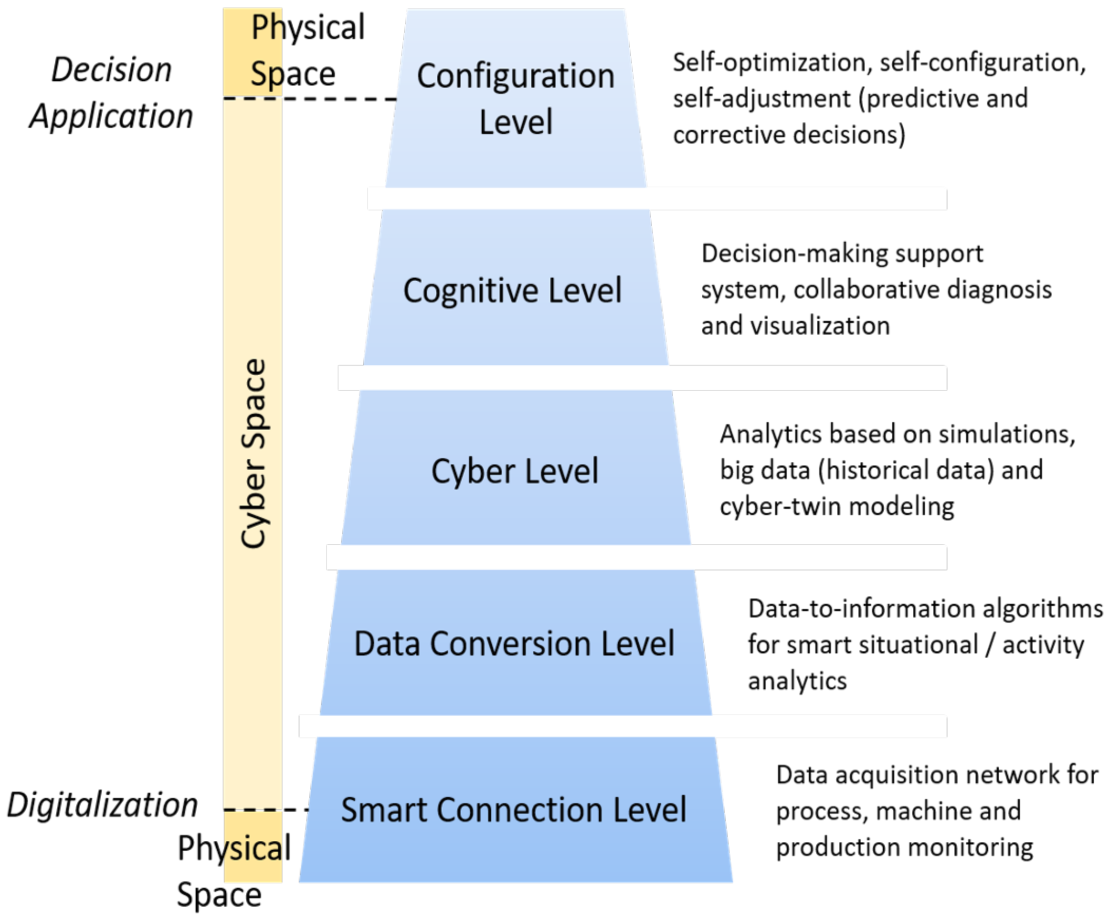


Figure 2.3: CPS 5C architecture, after [67].

However, the expectation towards CPS are manifold, sometimes exaggerated and often unpractical, from robustness at every level to self-organization, self-maintenance, and self-repair. The potential applications of such systems are almost endless but its integration in current production lines and machinery may encounter difficulties due to changes in the nature of the organization and control of production systems [85]. At an industrial level, the investment necessary to implement CPS is not easily justified and limits the advancement of CPS technology [91]. However, CPS is still seen in industry as the solution to overcome limitations of the current operating machinery [92] and online automatic product inspection is a necessary requirement of any manufacturing process nowadays [18], especially when internet-based connectivity and communication are key codes in Industry 4.0.

In the construction industry, academics and practitioners alike have striven for a deeper integration of virtual models and physical construction. The benefits of such integration have been previously identified: extension of virtual modeling to construction and operational phases, bi-directional consistency between virtual and physical modeling of construction components, ease of coordination and management of construction projects, and improved project monitoring and control [93]. Early examples of CPSs integration in the industry are built around Industry Foundation Classes (IFC) and the Building Information Model (BIM). IFC is becoming the preferred method to exchange building information and BIM-based processes are widely being integrated to automate repetitive construction activities, such as safety operations. However, clear frameworks for the bidirectional integration of BIM and CPSs are still in process [94].

In fact, BIM is currently considered the specific digitalization tool for the construction industry, while most of the other technologies available have been adapted from other sectors, mainly the manufacturing industry [88]. While the potential of BIM to promote digitalization and revolutionize the industry is enormous, especially if reinforced by Industry 4.0 technologies such as computer vision, the impact in physical activities and construction processes is still limited to a few applications, for example, structural [95, 96] or progress monitoring for masonry activities [97]. Considering that the advancement and deployment of CPSs has already had a great impact in the manufacturing area [91, 98], a potential bridge that connects leading CPSs research and the construction sector is the manufacturing activities that occur in offsite construction facilities. Offsite construction (OSC) is an ideal mix of a clearly identifiable and recognizable manufacturing environment embedded with the complexity of construction products, information, and data structures.

In summary, CPS consist of interconnected and integrated smart systems that include both physical and digital parts. The physical and cyber environments are reciprocally interconnected and synchronized through sensors and actuators. The key potential of CPS is the opportunities that it provides towards data analytics that can be performed over the sensory input. CPS is, then, the "heart" of Construction 4.0 and will transform all phases of a project life from design intent to construction and operation [25].

2.1.4 Industrialized & Offsite Construction

Industrialization has demonstrated countless times its capacity to offer mass customized products at affordable prices. Almost all the products available today on the market are produced in industrialized facilities. Whereas some construction components are manufactured in such environments, i.e. trusses or joists, it is not the case for most building components. Buildings are quite different from most other industrialized products: its manufacture only can end at the construction site. As such, industrialization of the construction sector can solely focus on the means and systems that generate those buildings [99]. Nonetheless, industrialized construction promotes the advancement of construction processes by employing mechanization and automation. There are several intents behind such changes, such as increased labor productivity, reducing costs, fast commissioning of new projects, lean construction, ease the incorporation of novel technologies, and improving overall quality [100]. It is projected that by 2035, the majority of buildings and construction projects will be constructed using industrialized construction, specially as manufacturing and construction converge. Among other trends, offsite construction and prefabrication remains one of the key enabler technologies for the future of the construction industry. By adapting the fabrication of large building elements, i.e. walls or roofs, into a mechanized and seamless process of assembly in offsite facilities, transportation, and onsite installation of prefabricated parts, current issues that define the construction industry today may be circumvented [101]

During the last decade, offsite construction (OSC) has become increasingly popular in North America as a growing alternative to traditional onsite construction. According to a recent survey in the US, the market share of OSC will continue to increase in North America in the near future due to a serious shortage of skilled labor in construction and its built-in integrated design and manufacturing processes, with emphasis on planning for efficient production [102]. The growing attraction of OSC from both industry and academia is explained by shortened schedules, higher efficiency, reduced waste, lowered health risks and physical extenuation of the workforce, and increased productivity [4]. As modern markets impose mass customization of products [5], OSC has become a viable solution for the construction industry that provides customers with the possibility of increased flexibility [103]. Several analysis on culture and market adaptation to OSC in different countries have been performed to understand its acceptance as an alternative to traditional construction [104–107].

Among the driving technologies in OSC, BIM has been identified as a key component. BIM research has synergized with OSC needs in several specific areas: BIM-based logistic and assembly planning; BIM-enabled product design and manufacturing; AI-based generative design for prefabrication; *as-built* BIM; data exchange through cloud-BIM; robotics and 3D printing; and BIM-enabled big data analytics [7]. Improved efficiency and quality of design, increased automation and productivity, reduced waste, or to provide data-driven reasoning towards best practice are a few benefits that BIM yields for OSC. In most cases, prefabricated components set the design decision-making for OSC and BIM standards ease the communication between projects [108]. In summary, the level of BIM integration in OSC practices determines the level-readiness for Construction 4.0 applications [109]. However, at present, an evaluation of the impacts of Construction 4.0 in the offsite construction sector still needs to be researched, from cyber-security issues related to the inter-connectivity of shared BIM models to changes in the supply chain, organizational structures, and business models

[13].

Modular construction is a form of OSC that involves the prefabrication of volumetric components, prior to their shipment and installation on construction sites. Alternatively to other modular approaches and aiming to optimize transportation and installation equipment costs, wall or floor components may be prefabricated in panels. Panelized construction, in either wood, steel, or precast concrete, is currently the preferred approach for residential and low-rise commercial buildings [110]. In such facilities, however, the introduction of Construction 4.0 technologies on its manufacturing floor has barely started. Challenges in material flow due to rapidly changing design parameters were recently addressed by introducing state-of-the-art tracking approaches in an IoT (Internet of Things) framework [111], but numerous other challenges still remain unresolved: real-time monitoring of OSC activities or inventory control, to name a few. In general, OSC practices cannot deal with manufacturing issues that may arise in real-time. This lack of real-time information limits the impact of OSC beneficial aspects, such as increased quality, and prevents quantifying the effects of any attempted improvements in the short term.

2.2 Quality in Construction

2.2.1 Zero-defect Manufacturing

Zero-defect manufacturing (ZDM) was introduced more than 50 years ago as a mentality, a philosophy, or a movement that aims to minimize the number of defects in manufactured products and services as much as possible [112]. The ultimate aim is to reduce the number of defected products to zero and to "do things right in the first time". The expected benefits of a complete integration of ZDM principles include a higher productivity of manufacturing processes, reduced cycle times, provide feedback information of production and process parameters to the product design phase, and enable data-driven causality analysis on defects [113].

The reasons why ZDM principles are interesting to industry are numerous, including: 1) it can considerably reduce the overhead costs related to the organization and treatment of defective products, i.e. rework or increased inventory [114]; 2) it can maximize productivity within the stream map of the production lines, eliminating any non-added value processes, i.e. defective machines and tools, inefficient processes, etc.; 3) significant reduction of waste and therefore initial investment can be realized with ZDM [115]; 4) continuous improvement within the manufacturing floor is enabled, thus, product manufacturing would get closer to the initial goal of ZDM; and, 5) an improved quality in final products strengthens customer satisfaction and soars client fidelity [116].

One of the main conditions for the ZDM approach to be enabled is that all the factors influencing quality around the whole process should be monitored and optimized as far as possible. In the 90's decade, a supervised learning methodology for ZDM was already proposed to enforce quality-oriented process controls and integrated strategies to deal with both, systematic and accidental, non-conforming products [117]. However, the authors questioned the cost-effectiveness of such a complex and time-consuming solution with their actual computational performance, thus it was primarily applied in manufacturing processes of industries where the consequences of part failure suppose an unacceptable risk, i.e. aerospace industry.

However, computational limitations should be less of an issue nowadays. In fact, ZDM is becoming a common practice in the manufacturing domain to reduce and minimize the number of defects and quality errors by using large data-sets and complex knowledge discovery techniques, such as data mining [118]. ZDM has evolved since to be a disruptive concept that is able to reshape entirely the manufacturing ideology and can be implemented in two different levels: at the product level, where identified defects are analyzed to find mitigating solutions, or at the process level, where the manufacturing equipment is studied in relation to manufacturing results [119].

An overview of the ZDM concept and dual integration in manufacturing environ-

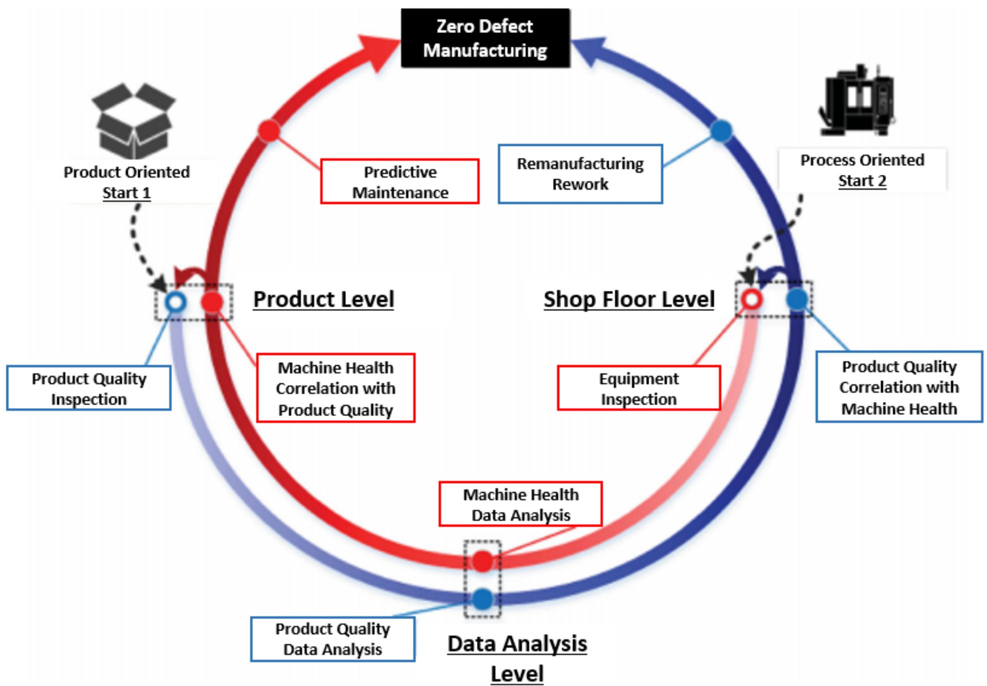


Figure 2.4: Zero-defect manufacturing concept, after [119].

ments can be found in Figure 2.4. Considering the two levels aforementioned, namely product and shop floor, both integrated approaches provide feedback to each other: product quality is correlated to equipment health and vice-versa. Therefore, by having a dual inspection system in place, zero defects may be achieved by predictive maintenance routines and establish re-manufacturing and rework procedures. This concept relies on an increase in the level of automation, 100% accurate equipment, and process capabilities to reach its goal. However, minimizing the impact of human intervention in manufacturing systems is not a realistic approach as long as human operators are required to manually assemble components, handle or transport components, or operate equipment and machinery. In fact, most construction operations are still a manual process. Nonetheless, ZDM can be used to detect human errors, yet operators are not usually involved in the development of this technology. A better integration of ZDM is required that involves human knowledge and cognitive response from operators [120].

ZDM can be integrated using four different strategies, based on the concept shown in Figure 2.4: 'detection', 'repair', 'prediction', and 'prevention' [119]. The most dominant approach in literature due to its simplicity to integrate is the detection of defects, mainly because it represents the starting point for implementing ZDM and the foundation for the implementation of the other strategies. As of today, monitoring systems for ZDM have been the most significant developments in the area [121], whereas prediction of defects, repair strategies, and prevention of defects are very difficult and complex tasks that require a vast amount of data in order to be accurate, hence limited results can be found around such applications of ZDM. In most cases, virtual prediction models are used in cases where the physical detection of defects is not possible or not cost-efficient [122, 123].

Anyhow, the ZDM concept has been implemented partially so far due to numerous technological limitations that were hindering its implementation in industry. With higher computational power and data storage available at reasonable cost and the evolution of Industry 4.0, ZDM is cheaper and easier to be implemented as a large amount of data is required for techniques such as machine learning to work properly [124–127]. Although applying ZDM principles to a single system is a straight-forward process, multi-stage production systems (such as OSC assembly lines) bring more complex challenges for defect compensation and inspection. In contrast to single processes, defects occurring in multi-stage production lines propagate throughout the system, making defect inspection system more sophisticated and complex [128, 129].

2.2.2 Quality in Lean Manufacturing Processes

Lean production has its origins in the philosophy of achieving continuous improvements in the most economical ways, with special focus in reducing waste (or *muda* in Japanese). To err is human, thus people can and will make unintentional mistakes, despite their best intentions. Waste is then naturally generated in any human-thought process. The concept of reducing waste became one of the most important concepts in quality improvement activities. This philosophy was widely known as Toyota Production System and it became labeled as lean thinking later [130]. In fact, by defining waste as the excess resources used compared to perfection, one can conclude that waste is everywhere and that the aim of lean production is to eliminate all waste.

Initially, an index was defined to quantify the impact of poor quality in manufacturing lines, known as "the cost of poor quality" (COPQ). COPQ was defined as the sum of all costs, no matter its source, that would disappear if there were no quality issues [131]. Quality control is then a holistic management philosophy that deals with production from several aspects: from manufacturing processes or leadership to any necessary services. Such practices have been developed from the initial Japanese total quality management (TQM) methods, which can be found in most modern quality improvement approaches such as six sigma quality or lean production [132].

In general, lean practitioners rely on mistake-proofing (or *poka yoke* in Japanese) to deal with quality issues in their manufacturing processes. Mistake-proofing was defined, in the early 80's, as the use of any automated device or method that makes it impossible for an error to occur or makes the error immediately obvious once it has occurred [133]. Therefore, mistake-proofing can be applied both to prevent the causes of defects, which will result in lesser subsequent occurrences of errors, and to carry out control of the final conformity of end-products. Following such lean practices, the monitoring and control of the quality issues should be autonomous, over the 100% of the manufactured products, and inexpensive. However, ensuring eliminating all errors is not always possible, hence it is necessary to have a framework that detects errors as soon as possible, provides the inspection information (error signals) to the relevant operators, and ultimately tries to eliminate the possibility of such error to occur independently of the operator's attention span [134].

However, since its first definition, several formulations for mistake-proofing applications have been given in literature. Grout defined a *poka yoke* process as a system that had designed features to prevent errors or mitigate its negative impacts [135].

Middleton defined it as a systematic practice of eradicating errors by locating its root cause [136]. Plonka considered that a system with a mechanism for detecting, eliminating, and correcting errors at the source, before reaching the customer, followed the mistake-proofing approach [137]. More recently, Saurin defined *poka yoke* as a device that either prevents or detects abnormalities that are detrimental to product quality or to employees health and safety [138]. In this thesis, mistake-proofing systems are understood as a system proactive or reactive to defect generation and that is functional, namely having correct and prompt communication of any quality issues to enable continuous improvement towards minimizing waste.

Poka yoke is based in six principles, starting from the most desirable one: elimination, prevention, replacement, facilitation, detection, and mitigation [139]. Each one has a different impact at different points in time during the manufacturing operation(s) of a product. Elimination aims to remove the chance of defects by redesigning the operation or product. Prevention is to design and engineer the product or task so that defects are not possible. Replacement is to substitute an operation with a more reliable one to improve consistency and reduce quality issues. Facilitation is to ease information usage to make fewer mistakes during the operation. Detection is to identify the mistakes so that corrective operations can be performed. Mitigation aims to minimize the effects of errors. A visual representation of the mistake-proofing principles is shown in Figure 2.5.

As observed, the ease of data generation is inversely proportional to the desirability of intervention of mistake-proofing principles: in other words, it is easier to generate quality-oriented data by inspecting products looking for defects (quality-at-bay) that it is to associate those defects from the planning stage of the work operation (quality-at-the-source). Given that manufacturing approaches are leaning towards data-driven decisions, prevention and elimination principles are rarely applied based on data, but based on expert knowledge. In fact, academics and practitioners alike tend to link *poka yoke* principles to other methodologies for ease of integration, such as the theory

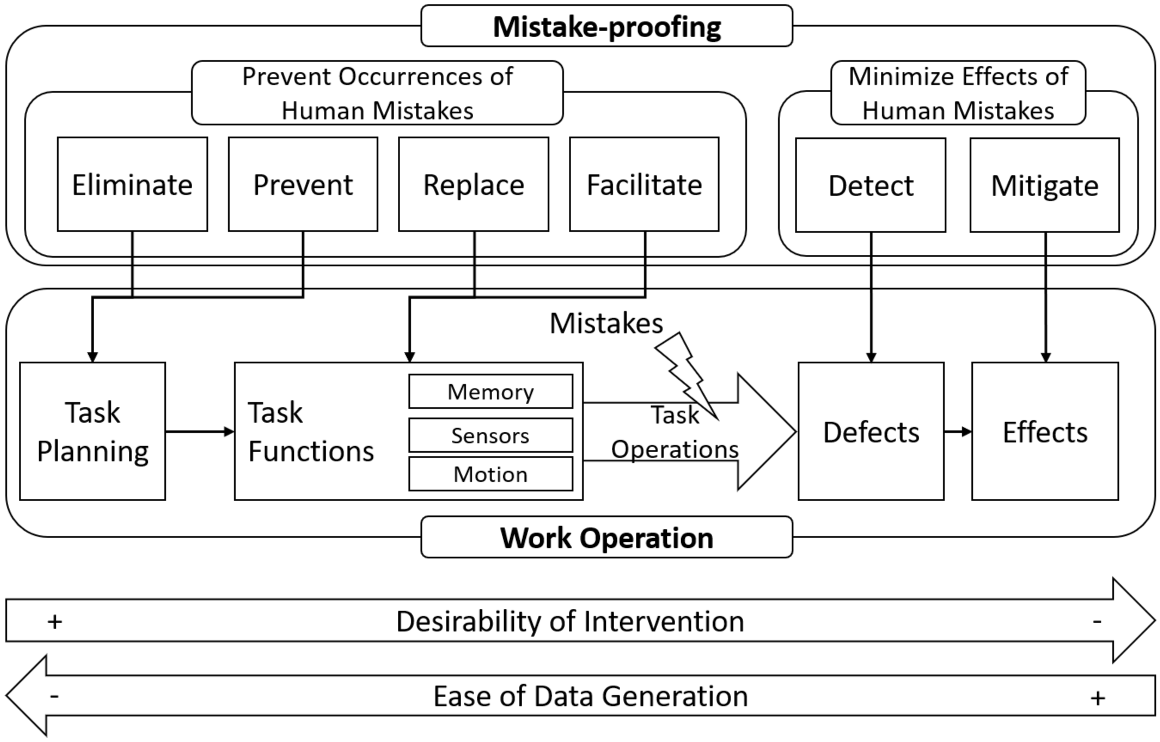


Figure 2.5: *Poka yoke* principles applied to manufacturing operations, after [140].

of inventive problem solving (TRIZ) [139], or plan-do-check-act (PDCA) continuous improvement cycle [141]. In most cases, application of these principles is restricted to qualitative measures that are not tangible and difficult to quantify. Considering industrial needs and looking to provide a clear justification to investment in mistake-proofing devices, cost models to implement such approaches have been designed [142, 143] and a discrete-event simulation model was proposed to estimate its impact on production lines [144].

Nonetheless, most applications of mistake-proofing rely on robust detection and mitigation methods. A tool for visualization, analysis, and design of quality assurance methods, based on reliable data, is the innovative approach of quality value stream mapping (QVSM). Based on the well-known design elements of value stream mapping (VSM), the implementation of such approach supports and facilitates the identification of effective (or ineffective) equipment, testing strategies, or quality control loops [145]. Another approach is the popularization of autonomation (*jidoka* in Japanese) and autonomated machinery is a clear example of *poka yoke* intervention in production operations design. The concept of autonomation is a combination of automation and autonomy. In general, autonomation prevents the production of defective products, eliminates overproduction, by incorporating machinery with self-identifying systems that allow the machine to stop when any malfunction or unusual process occurs [146]. From a manufacturing perspective, human intervention is only required when the quality issue cannot be self-rectified. Autonomation, then, can be integrated as a sequential process into any machine logic: 1) detection of defects; 2) stop the production sequence; 3) immediate corrective actions; and, 4) investigate root causes and install countermeasures. Such approach is usually due to overproduction, waste of time during the manufacturing of defective products, transport of defective materials, and reprocessing, alongside with inventory waste.

In summary, lean principles consolidate and guide quality control procedures to reduce waste, in a similar direction of the ZDM approaches reviewed in Section 2.2.1. However, current research shows areas where methodologies are still missing: pro-active defect repair policies, correlation analysis between product quality and system dynamics, or preventive maintenance, among others [79]. For example, digital image acquisition systems are state of the art tools that can be used to facilitate autonomation of certain manufacturing processes via mistake-proofing. The capacity of visual inspection systems to provide the pertinent information is leading to the increase in quality levels and reducing the amount of defects being produced [147].

In fact, technologies related to the Industry 4.0 have been integrated with lean practices in order to ease its implementation in the industry. That is also true for the construction sector, in which a synergy between BIM and lean practices has been identified [148]. In most cases, newer technologies such as cloud databases or cyber-physical systems have been useful to digitize lean tools and techniques. The concept of Lean 4.0 represents the conceptual conjunction of lean manufacturing and Industry 4.0 technology from the commonalities that both approaches have in industry applications [149]. As a general consensus, lean manufacturing has been considered as an prerequisite and enabler of the digitalization of industrial facilities, but also the introduction of Industry 4.0 principles has improved the effects of lean techniques [150]. Just-in-time 4.0 [151, 152], *Heijunka* 4.0 [153], *Jidoka* 4.0 [154], value stream mapping 4.0 [155], or *Kanban* 4.0 [156] are just a few examples of applications of Lean 4.0 that can be found in the literature. In regards to advance the quality of manufacturing using Lean 4.0, there is still not a fully integrated solution based on *poka yoke* 4.0, although it has been recognized as a key component of future 'smart machines' [157].

2.2.3 Automated Inspection Systems in Construction

The lack of automated manufacturing and installation quality inspection systems has been identified in the past years as one of the main key elements missing in construction, and more specifically, in industrialized construction [158, 159]. This lack dampers the performance of industrialized construction methods and hinders the process of replacing traditional approaches. To tackle the issue, there has been a dramatic increase in the development of vision-based inspection systems for construction operations, in both indoor and outdoor conditions [160]. The industrial need to monitor construction operations with different purposes initiated a stream of research on data collection using different forms of the subject media. As an example, image processing techniques have been proven to be cost-effective and efficient for automated recognition and tracking of construction resources [161], workers [162–164], construction equipment [165, 166], classification of materials [167, 168], productivity analysis [169, 170], recognition of structural elements [171, 172], and condition assessment [173]. While most studies have focused on the use of computer vision techniques at job sites, the indoor applications faces many challenges including highly cluttered scenes, occlusions, and diverse illumination conditions [174, 175].

Previous works have generally improved the visualization and analysis of construction operations, enabling construction managers to take decisions with a better and more realistic view of site operations. A scientometric analysis is performed to visualize the research maps on computer vision for the AEC industry (see A). As a result of that analysis, very few inspection systems that target construction products can be found in literature, and even fewer that work in indoor environments. For instance, an algorithm was developed to detect concrete columns in images using a hybrid shape and color approach [171]. Other important contributions include the recognition of objects and construction elements, such as bricks [176], windows [177], doors [178], or drywall sheets [179]. However, the use of such indoor inspection systems was to provide reliable information of the construction status to facilitate maintenance or construction operations.

In regard to inspection systems that target quality assessment or defect detection, 3D laser scanning is the widely accepted approach. The resulting point clouds contain large amounts of data with high accuracy, high density, and a lower sensitivity to changes in environmental conditions, e.g. lighting [180]. Because of this advantages, the quality assurance procedures of several prefabricated components can be automated, i.e. precast concrete panels [181] or modules [182]. However, due to the general large sized components in construction, 3D reconstruction and digitization of such elements are long quality processes. This makes the available automatic inspection systems not viable for online continuous defect detection, which is a common solution for several other manufacturing industries. Current OSC facilities would benefit of an integrated framework that would provide real-time supervision and quality control without hindering overall productivity.

Chapter 3

Towards Zero-defect Manufacturing of Steel Frame Assemblies

3.1 Proposed Framework

The proposed framework aims to facilitate the integration of automatic quality inspection, assessment and control of construction elements or products as an extension to the current established OSC manufacturing modus operandi. Given the literature review provided, existent frameworks can be improved for such purposes by introducing novel principles of the Industry 4.0 era. Focusing on the construction product and introducing the robust data architecture of cyber-physical systems, a generic framework for defect detection and quality assessment in construction products is proposed to enable continuous improvement towards zero-defect manufacturing following, for example, *poka yoke* principles. An overview of the proposed framework is illustrated in Figure 3.1.

Taking as the only input to the system the BIM model of the construction product, the process proposed to integrate automatic quality inspection in OSC manufacturing lines can be described as follows:

1. To assess product quality, following zero-defect manufacturing principles, a product-centric cycle is proposed: 1) product inspection generates continuous

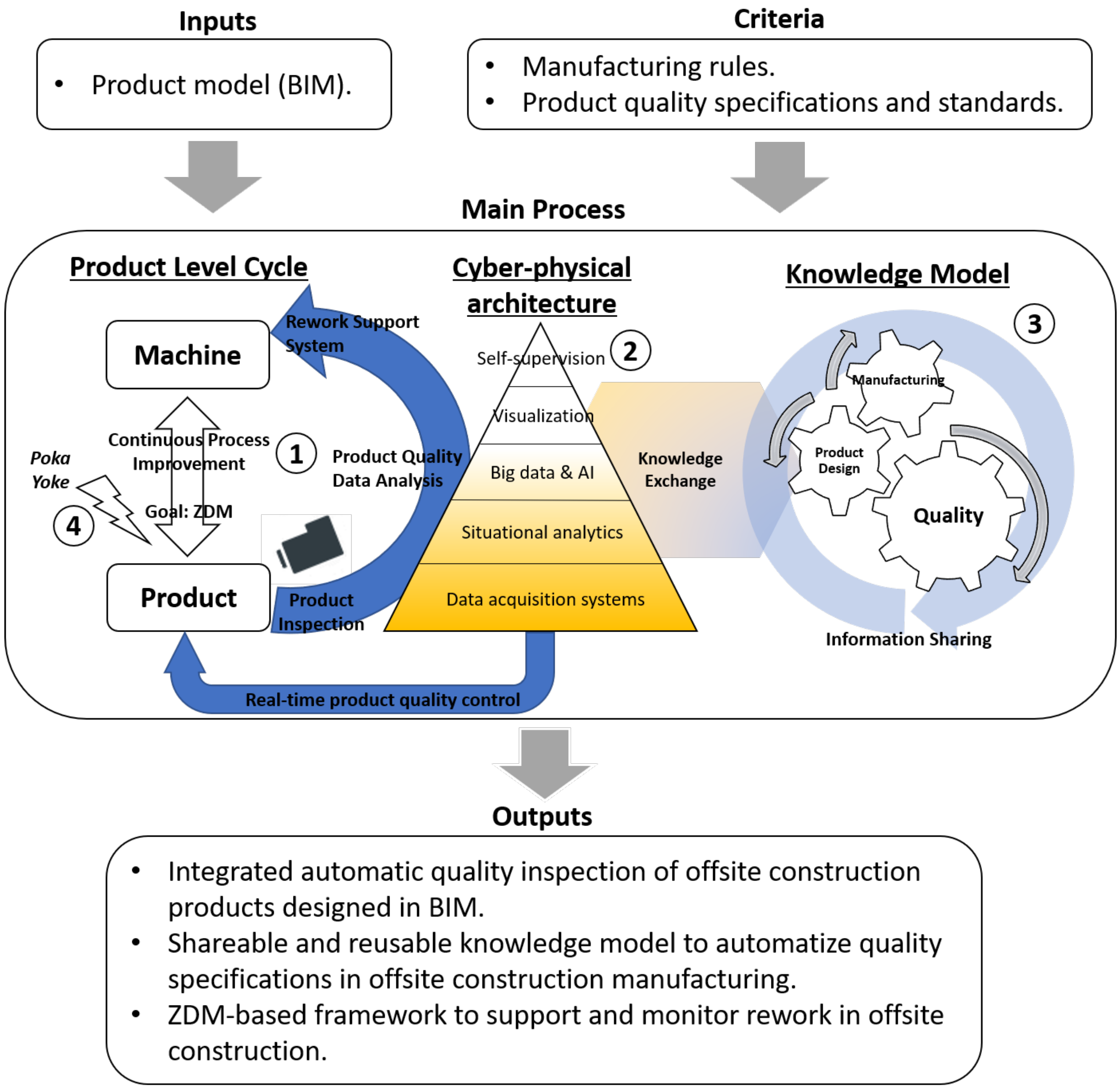


Figure 3.1: Overview of the proposed construction product quality-oriented framework.

quality-oriented data; 2) obtained data is analyzed to understand the impact of the manufacturing process on the quality of the product; and, 3) defect mitigation through rework orders is supported and monitored.

2. The product level cycle is structured as a cyber-physical system, enhancing the information transference and augmenting the interactivity between the digital and physical worlds: 1) the vision-based product inspection serves as a platform to digitize the product in real-time (data acquisition system); 2)

data obtained can be rapidly analyzed with situational conditions to provide real-time quality control on an individual basis; 3) quality-oriented historical data may be stored so that knowledge discovery techniques (big data and/or artificial intelligence approaches) can be applied; 4) data can be visualized as a human-machine interface so that human input is considered; and, 5) a supervisory agent monitors the system results to maintain quality levels at the manufacturing line.

3. The BIM model is enhanced by incorporating manufacturing rules and quality specifications as a knowledge model. This modeling enables dynamic information sharing with the system developed through the middle layers of the cyber-physical architecture and support dynamic decision support during inspection processes.

4. Continuous improvement of the quality of end-products in manufacturing lines is enabled and monitored, allowing practitioners to implement data-driven decisions that make the final goal of zero-defect manufacturing possible through any quality principles, for example, *poka yoke*.

Therefore, the developed framework provides an integrated quality inspection system for pre-designed offsite construction products, that extracts quality information from a shareable and reusable knowledge-enhanced BIM model, and supports and monitors rework operations in offsite manufacturing lines. Each one of the process components aforementioned is presented in the following chapters.

3.2 Research Methodology

The research methodology adopted to achieve the goals proposed following the framework presented is design science research (DSR). As a scientific problem-solving process, DSR is based on the development of an artifact: something that is useful and improves the problem identified through research gaps [183]. The process of developing an artifact deals with a rigorous procedure of, first, identifying gaps in the literature, then developing the artifact while applying evaluation methods in a reproducible manner and communicating its outputs clearly [184]. Further, limitations to the scientific contributions made are to be stated and discussed. DSR has been proven to be a suitable method for research in construction management, especially when developing solution artifacts to problems and implementing those solution in the construction domain [185, 186].

The methods applied in this research are demonstrated in Figure 3.2 and are divided in four stages: 1) descriptive: identifying the necessary information to be extracted or generated from quality specifications and the BIM model; 2) modeling: extracted information, namely expert knowledge (or know-how), is modeled through knowledge modeling techniques, and generated information is obtained through the digitalization of the construction manufacturing process; 3) implementation: applying novel system architectures, such as cyber-physical systems, the inspection systems required can be developed; and, 4) evaluation: test the overall framework using virtual and/or real scenarios as case studies.

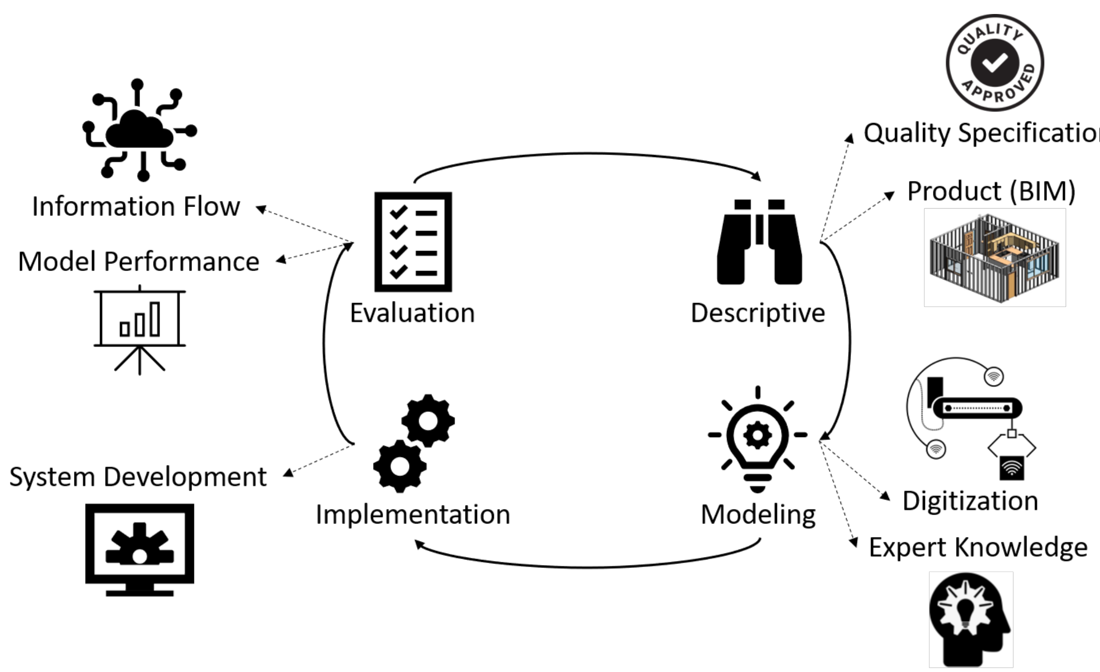


Figure 3.2: Overview of the proposed research methods.

For each one of the research objectives of the thesis, the following subsections present the DSR methodology followed to achieve the expected outcomes. The DSR methodology is presented following the guidelines as proposed by Hevner et al. [187]: 1) design an artifact; 2) present the problem relevance; 3) design the artifact's evaluation procedures; 4) present the research contributions; 5) use rigorous methods to support the application of the artifact; 6) provide the necessary means to reach the desired implementation and evaluation of the artifact; and, 7) communicate the research effectively.

Objective 1

The first artifact developed in this thesis consists of a knowledge model containing the information links between quality, manufacturing, and product design in the offsite construction domain. In possession of this artifact, OSC practitioners can access all the relevant quality information from a common software tool that eases the traceability of defects and other potential quality issues throughout all the knowledge domains involved.

To start its development, a comprehensive literature review is performed around knowledge models for related individual knowledge domains, i.e. BIM or manufacturing operations. This step clearly allows to present the current state of knowledge models in the area and identify which knowledge domains and links are missing. Hence, efforts can be focused on the establishment of novel knowledge links from already tested knowledge domains towards obtaining a comprehensive quality model.

Next, the required knowledge model is designed as an ontology model. Ontology models are formal descriptions of knowledge as a set of concepts and the relationships that hold between them. In this case, a knowledge graphical representation is used due to the need of linking several types of relationships to a same concept, an impossible task for other knowledge models such as relational databases or taxonomies. The ontology is then expressed following open-source formats, such as the ontology web language (OWL), to be able to connect the knowledge model to the current construction management workflow. For example, quality knowledge should be accessible from the BIM design software used by practitioners.

Finally, a set of BIM products are designed to test the information flow of the knowledge model. Each concept, relationship, and link is evaluated one-by-one to check how the proposed ontology model is accurately representing the knowledge domains and information flow. A quantitative approach is taken by using semantic queries that can evaluate each concept relationship by pulling information at different levels.

Objective 2

The second artifact developed in this thesis consists of several vision-based and machine learning algorithms for automatic inspection of steel frame assemblies throughout its manufacturing process in offsite construction facilities. In possession of this artifact, quality-oriented data is generated in an individual, automated, and continuous fashion, instead of the current manual sampling procedures.

First, an extensive literature review is performed to identify the previous vision-based approaches in the area, specifically in the identification and measurement of large construction components using monocular cameras. Once similar works are identified, the algorithms used can be analyzed to extract the base image processing techniques from which the proposed algorithms can be built upon.

Then, based on the manufacturing process studied (semi-automated steel framing), an inspection setup is designed based on the features to be extracted as specified in quality specifications. With the setup in place, resulting images can be obtained to serve as an experimental setup for the developed algorithms. further images can be obtained by simulating the setup results in CAD software. Those images then are used to test the algorithms.

Finally, the inspection results are bench-marked against the minimum tolerance required out of the quality specifications. Then, a quantitative analysis on the inspection results allow to measure the stochastic nature of the algorithms so that the results' variance can be considered.

Objective 3

The next artifact developed in this thesis consists on a decision-support system based on inspection results for quality control of steel frame assemblies. With this artifact, decisions regarding quality control, such as rework orders, corrective actions, and defect mitigation, is supported by data-driven systems, reducing uncertainty in the decision-making, as well as idle production time.

To obtain this artifact, an initial literature review on decision sciences for application of quality tolerances is explored to understand the underlying decision-making required in those instances. As a rule-based system, in this case, decision-support systems do provide 'best probable course of action' based on the available data. Such system can be graphically visualized as flowcharts to ease understanding and implementation.

To evaluate the proposed decision-support system, the inspection data obtained with the previous artifact is used. By introducing experimental data into the system, a qualitative analysis of the results and final decision-making can be performed to check the performance of the system proposed.

Objective 4

The last artifact developed in this thesis consists on an intelligent system that integrates and monitors rework operations based on machine learning results and user input. In possession of this artifact, OSC practitioners can automatically quantify the quality of their manufacturing processes, understand its impact on the end-product in an individual basis, and introduce suggested rework operations in the work flow. A similar methodology has been successfully applied in recent studies to introduce rework stations in regard to imperfect quality in monitored manufacturing operations

[188, 189].

From the previous artifact, rework orders are automatically suggested. Those suggestions can be followed by the operator or not. The rework operations are then independent from the decision-support system and would benefit from a monitoring system to track its effect on the end-product. To develop this last artifact, first, current methods to monitor decision-making systems based on machine learning and vision-based inspection data are explored. Common performance metrics for machine learning algorithms should be continuously updated while production is on-going.

Then, a mathematical model is proposed to obtain from those performance metrics quality indicators of the end-product, enabling management to monitor the current manufacturing conditions. The results are analyzed from a quantitative perspective to showcase the stochastic nature of the metrics obtained.

Chapter 4

Steel Frame Assemblies Knowledge Modeling

4.1 Overview

This chapter addresses the necessity of formalizing a link between quality inspection systems and the designed construction product through knowledge modeling within a BIM environment. Although Section 2.1.2 refers to quality as a domain connected to manufacturing, maintenance, design, and logistics, the provided model only considers design and manufacturing information due to limitations in the testing environment available that would, otherwise, bias the model provided. The proposed approach entails an ontology model that represents the steel frame assembly components, linked to its BIM model, and that identifies the quality specs required to manufacture a conforming product. Ontology is employed to enhance the steel frame model (in BIM) in terms of domain semantics for quality, including: 1) domain terms, 2) properties, and 3) interrelationships. Domain terms such as 'Stud' or 'Track' in the steel frame building industry, which are not IFC complaint nomenclatures, are generalized in the ontology model. Their relationships and properties are defined explicitly, providing semantic foundation for the quality specification retrieval process, as well as including industry specific vocabulary within the BIM model. This allows for construction practitioners to semantically query a BIM design model for quality-related explicit and implicit BIM data using their domain vocabularies without the need of understanding the technical structure of the underlying complex BIM schema.

The system architecture for implementing the proposed semantic quality approach is presented in Figure 4.1. Generally, it includes a BIM design model (of a steel frame assembly), a BIM data parsing tool, an ontology editor and reasoner, and a RDF tool. In this case, the BIM design model is developed using Autodesk Revit, due to its modeling flexibility and its available application program interface (API) to develop add-ons. The ontology is formalized and established using Protégé, a free open-source ontology editor from Stanford University. All the required BIM data is parsed using the Revit API and the connection between BIM and the ontology model is secured by employing dotNetRDF, an open-source .Net library that supports the population of ontology individuals with extracted BIM information. A default ontology reasoner in Protégé is used to infer new facts, i.e. implicit design features such as frame connections, from the explicit BIM data. Finally, SPARQL (which is supported by dotNetRDF) allows the end-user to query the ontology-augmented BIM model for quality related information. A more detailed explanation of the BIM schema and the ontology model proposed is presented in the following sections.

4.2 BIM Schema for Steel Frame Elements

Generally, building product information in the BIM model can be categorized into three groups: geometric, spatial, and functional. Geometric information refers to the vertices, edges, and other geometrical features that allow the full definition of building components. Spatial information elaborates on the specific location and relative position and spatial relationships between elements. Functional information relates to additional attributes or properties that infer information that describes the environment of the building element, such as the host information (element contained within another element). For the software used in this study, Autodesk Revit, those groups are identified as families (or classes) [190]. Namely, the geometric information is stored within the 'GeometryObject' family, the spatial information can be found

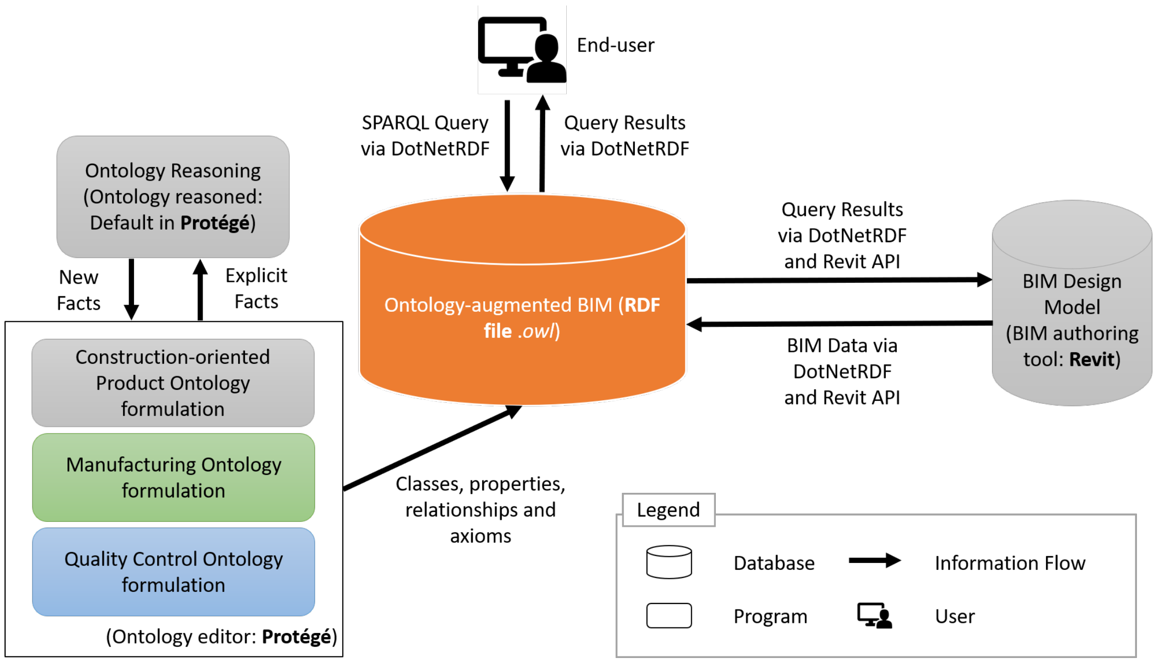


Figure 4.1: Proposed ontology-based BIM architecture.

in the 'Location' family, and the functional information is spread out between the 'HostObject', 'Instance', and 'ElementType' families. The exact building element information structure for each family and its categories and properties can be extracted according to the class diagram found in Figure 4.2.

Taking the case study selected, steel frame assemblies, vital information comes from the explicit information contained within an IFC wall element. In Revit, walls are instances of 'Wall' class and a subclass of 'Element', hence all the generic available information regarding geometry or location can be extracted, as well as functional information such as 'Material', 'ID', or 'Name'. Within the open BIM schema, IFC, all studs and tracks are represented as an 'IFCMember'. Without domain semantic awareness, all the model elements for wall frame sub-components are identified as the identical entity, as such, without understanding of the complex BIM schema and human intervention by BIM experts, it is not possible to, for example, identify correctly all the individual filter the frame elements contained in walls, including cripple studs, king studs, and jack studs. Similarly, there is no modeling element

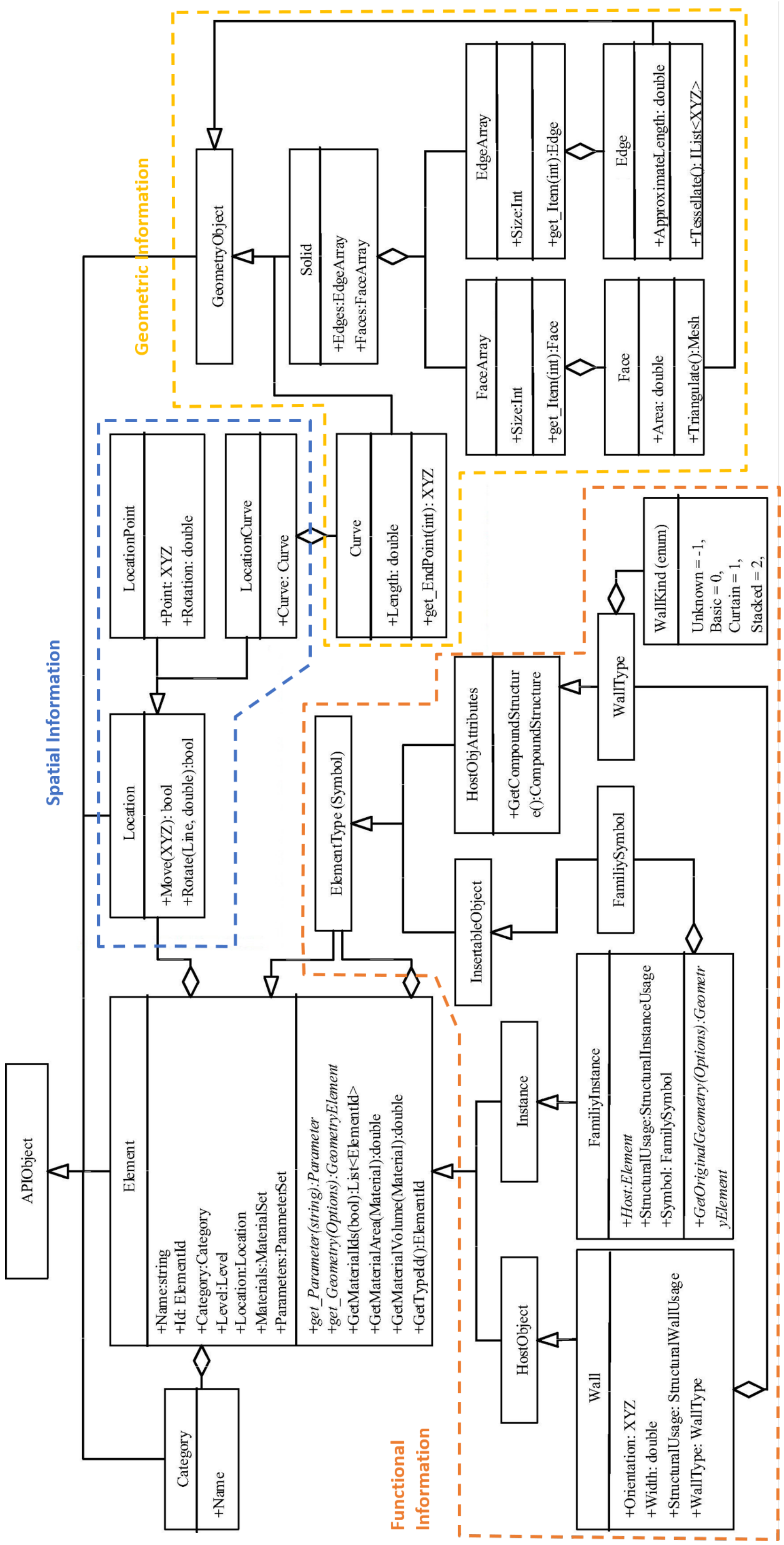


Figure 4.2: Autodesk Revit BIM Schema in UML format.

named ’Stud’ or ’Track’ in Revit. ’Structural Column’ and ’Structural Framing’, each a type of ’FamilyInstance’, are IFC elements that haven been used by practitioners to model, for example, ’Stud’ and ’Track’, and its geometric and spatial information is described using its parametric ’Location’ and ’GeometryObject’. However, such subjective decisions impede a streamlined potential automation of such processes.

To obtain a steel frame from its host element, a wall, an Revit add-on developed by the Modular Construction Lab at the University of Alberta is used, FrameX [191]. FrameX designs, for each host ’Wall’ element, the appropriate light-frame components, in this case steel frame assemblies, as defined by some user-parameters and by following the building code design rules for the spacing between elements, connections, and framing specifications around openings. Once the frame is designed and its geometric and spatial parameters defined, the information regarding the host wall can be ignored moving forward as the knowledge model presented solely deals with the frame components at this stage. This simplifies the amount of information to be modeled by limiting the functional information associated to walls which is not required moving forward.

Given the mentioned limitations of current IFC elements for frame components as a sub-element of a wall and the underlying complexities of using alternative options [192], the proposed knowledge-model approach defines and explicitly models each type of steel frame sub-component with distinguishable entities. Based on the BIM schema shown in Figure 4.2, an ontology model with initial set of classes, properties, and interrelationships is required to extract the required data regarding any steel frame using a similar structure. This not only allows to ease the data transfer between models (BIM and ontology) but also enhances the model with knowledge that could be inferred by the ontology reasoner. The ontology model proposed is defined in the following section.

4.3 Ontology Model for Quality of Steel Frame Assemblies

The ontology model proposed in this research is intended to allow construction practitioners, particularly quality managers, to access quality specifications, i.e. geometric and/or aesthetic constraints, directly from the construction packages and reduce work effort in establishing quality control procedures. This model is established to align the BIM environment with quality specifications, focusing on the design product, and enable semantic querying in the domain of steel frame assemblies manufacturing. As described in the previous section, the ontology augments the BIM model by adding steel frame building terms and implicit design features such as the types of connections available, as well as manufacturing and quality related information, including their properties and interrelationships.

The proposed ontology establishes a formal link between the product, its manufacturing process, and quality specifications as illustrated in Figure 4.3 (inverse properties not shown). Each knowledge domain is modeled individually and linked accordingly based on expert knowledge. First, a model for construction products based on the BIM schema is necessary and finding the correct design feature that enables the link between product design, manufacturing, and quality is key. Next, manufacturing operations are modeled from the design feature selected, the product element intersections of steel frame assemblies. Finally, quality knowledge is represented and linked to both previous models. These models are explored in more detail in the following subsections.

4.3.1 Construction Product Ontology

The ontology model presented in this subsection builds upon an already available ontology model for light-weight structures, namely wood frames, found in the literature [75]. This model reported an approach for quantity take-off of construction products

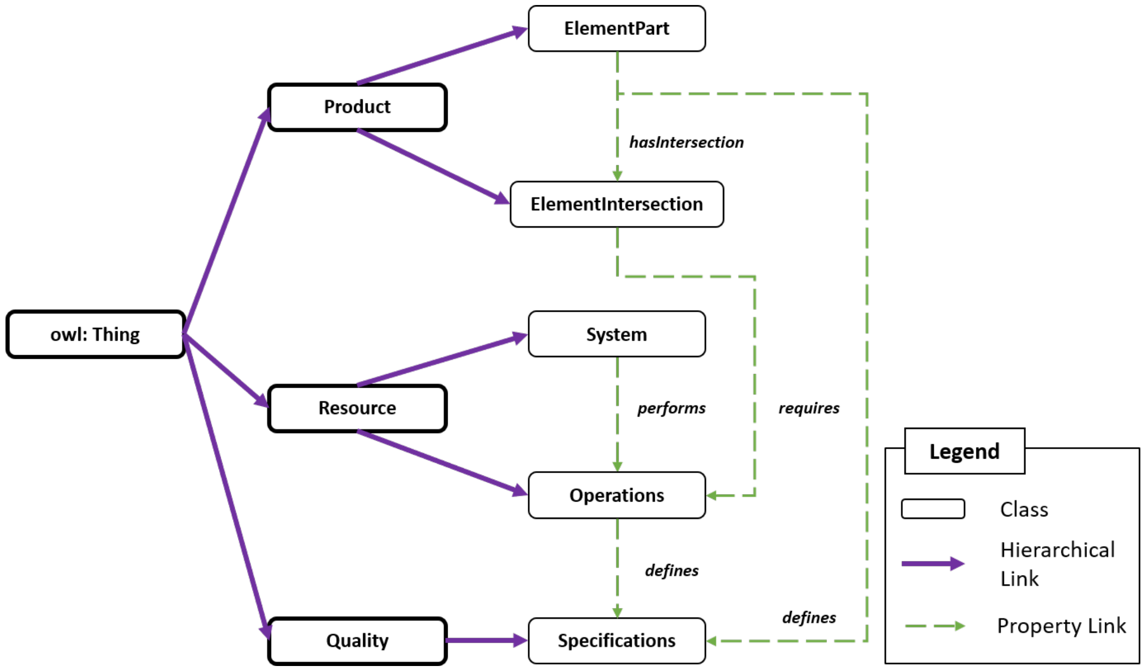


Figure 4.3: General overview of the proposed ontology model for quality assessment of construction manufactured products.

based on BIM models. On its the first step, BIM elements and its relevant information are retrieved and the authors create a model that is able to detail relationships between semantic domains in common construction vocabulary. For that, the authors defined 'Element Parts' such as 'Stud', 'Plate', or 'Cripple'. Similarly, the proposed construction product ontology replicates the structure presented by Liu et al. but focusing on steel frame assemblies. For this study, four 'ElementPart' components of steel frames are defined: 'Stud', 'Track', 'Header', and 'Blocking'. For each class, several sub-classes can be defined to provide further classification of frame elements. For example, studs can be differentiated into 'Regular', 'Jack', 'King', or 'Cripple' studs. As such, all frame components can be uniquely identified and given unique semantic domains.

Then, as observed in Figure 4.3, the 'ElementIntersection' of steel frame needs to be modeled. Intersections are defined as the physical space where two (or more) 'Element Part' components overlap. Although previous authors identified intersections as important elements of construction products, the modeling provided targeted wall intersections leaving sub-component intersections such as stud-to-stud intersections unimportant. This ontology proposes a model for the intersections between element sub-components as key to link design with manufacturing operations. By identifying the types of connections existing between frame elements, a link can be established between each 'Element Part' extracted from the BIM model of the designed frame and its corresponding 'ElementIntersection' as designed. For steel frame assemblies, five types of 'ElementIntersection' are found: 'Perpendicular' (or T-connection), 'Angled', 'Double-Angled', 'Lateral, and 'Crossing'. An illustration of each type of intersection can be found in Figure 4.4, being the 'Perpendicular' connection the most common in steel frame assemblies.

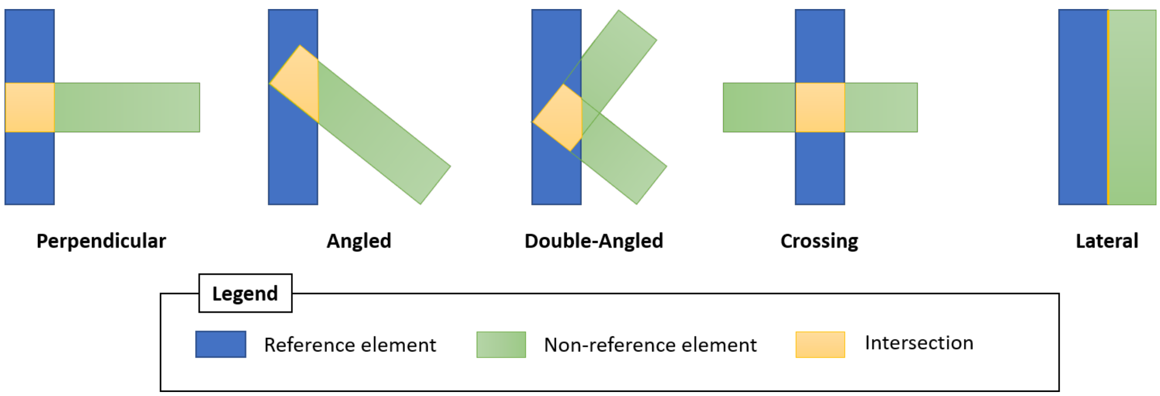


Figure 4.4: Illustration of the interactions between steel frame members.

In steel frame assemblies, each intersection is related to certain combination of sub-components and specially to which one is considered as the reference element in the connection. The reference is selected based on the element that supports the connection, as it would be done during manual assembly and usually are the load-bearing elements of the frame. Table 4.1 lists the compositions of sub-elements that define the intersections aforementioned.

As such, each sub-component of the frame assembly is characterized by the intersections that link them to other members. Using the property 'hasIntersection', each individual of type 'ElementPart' is linked to as many types of 'ElementIntersection' as is designed in the BIM model. In this regard, the proposed product ontology enhances

Table 4.1: List of elements that define each 'ElementIntersection' for steel frame assemblies.

Element Intersection	**Reference Element**	**Non-reference Element**
Perpendicular	ElementPart.Track or ElementPart.Header or ElementPart.Stud	ElementPart.Stud or ElementPart.Bracing .Horizontal
Angled	ElementPart.Stud .Regular	ElementPart.Bracing .Diagonal
Double-Angled	ElementPart.Stud .Regular	2×ElementPart.Bracing .Diagonal
Crossing	ElementPart.Stud	ElementPart.Bracing .Horizontal
Lateral	ElementPart.Stud	ElementPart.Stud

the interrelationships among elements by explicitly defining them and specifying the nature of the relationships among the domain term interrelationships. Ontology in turn can create new information by reasoning/inferring about the explicit information. More specifically, ontology reasoning can not only confirm and check “known knowns”, but also shed light on some “known unknowns”. For example, 'connects' is the inverse property of 'hasIntersection' in the proposed ontology. When a 'ElementPart' has a explicit 'ElementIntersection' as extracted from the BIM information, the ontology reasoning infers its inverse relationship and deduces the fact that the 'ElementIntersection' connects certain members of the type 'ElementPart'. The inferred fact is then saved explicitly in the ontology, which boosts the efficiency of information extraction. In summary, the modified construction product ontology based on Liu et al. model [75] is illustrated in Figure 4.5.

Note that other types of intersections may exist in current practice, for example, special connections for building corners in exterior walls. Those connections are not modeled as they represent connections between different frame assemblies which are not relevant in the studied manufacture process of single frame assemblies. However,

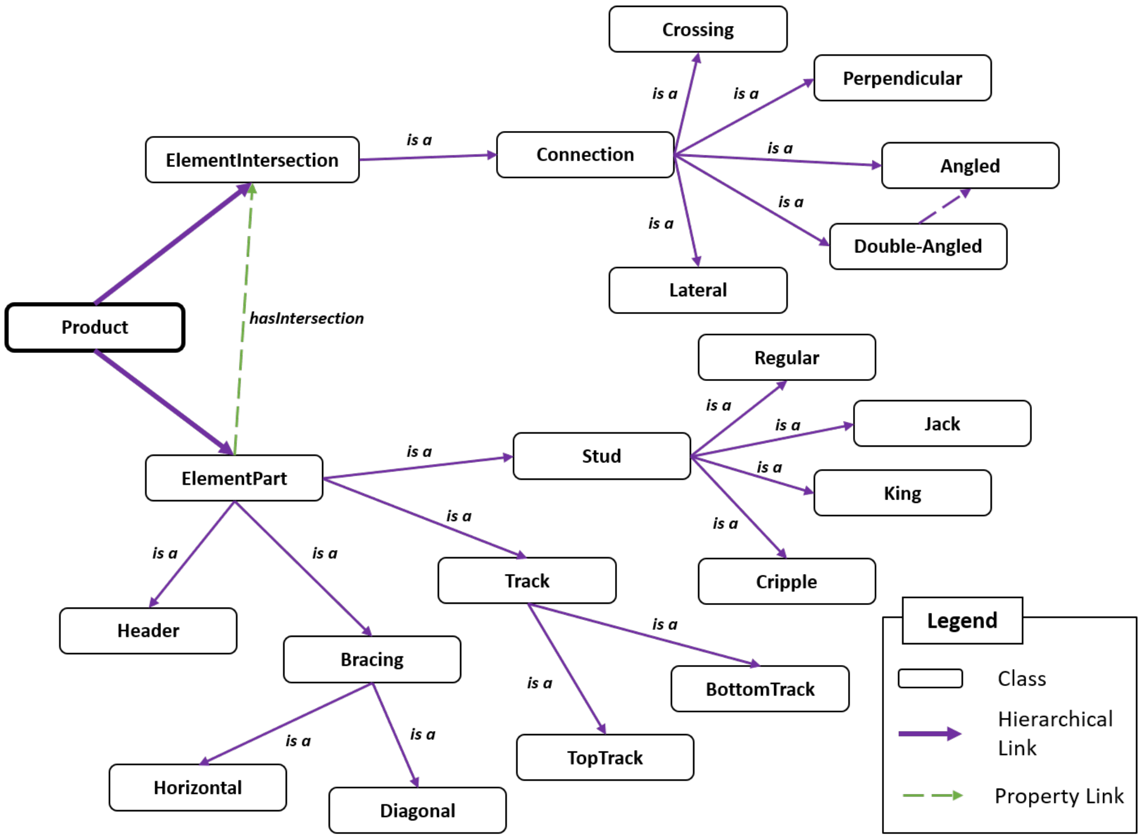


Figure 4.5: Overview of the proposed construction product ontology model.

a single frame assembly analysis of design features, as performed, may limit the knowledge modeling and establishment of connections between design, manufacturing, and quality in the future. Anyhow, the used manufacturing environment modeled in the following subsection cannot manufacture such exterior walls, thus for the study presented the ontology model proposed is sufficient.

4.3.2 Manufacturing Ontology

In typical manufacturing processes, knowledge modeling has successfully enabled decision making systems to be defined for such purposes. A proposal named MASON (MAnufacturing's Semantic ONtology) by Lemaignan et al. created a common semantic net in the manufacturing environment using ontologies for general purposes [78]. This approach successfully related product specifications with manufacturing resources and operations. MASON set the foundation to link manufactured products to its environment. In this subsection, a steel framing manufacturing ontology is proposed by adapting the generic structure reported by Lemaignan et al.

MASON described a manufacturing environment as a ”set of several systems that carry out manufacturing operations”. As such, the construction resources used for the assembly process of steel frames can be identified as ’Systems’ or ’Operations’. For example, for steel frame assemblies, a possible manufacturing setup is that a screw fastening manipulator (system) screw fastens (operation) steel members to create a permanent connection (as shown in Figure 4.6). Thus, an inherent relationship exists between the manufacturing systems available, the operations that can be performed using those systems, and the location where those operations are needed for the correct assembly of a product. This described relationship is the basis of the manufacturing ontology model herein proposed for steel framing machinery.

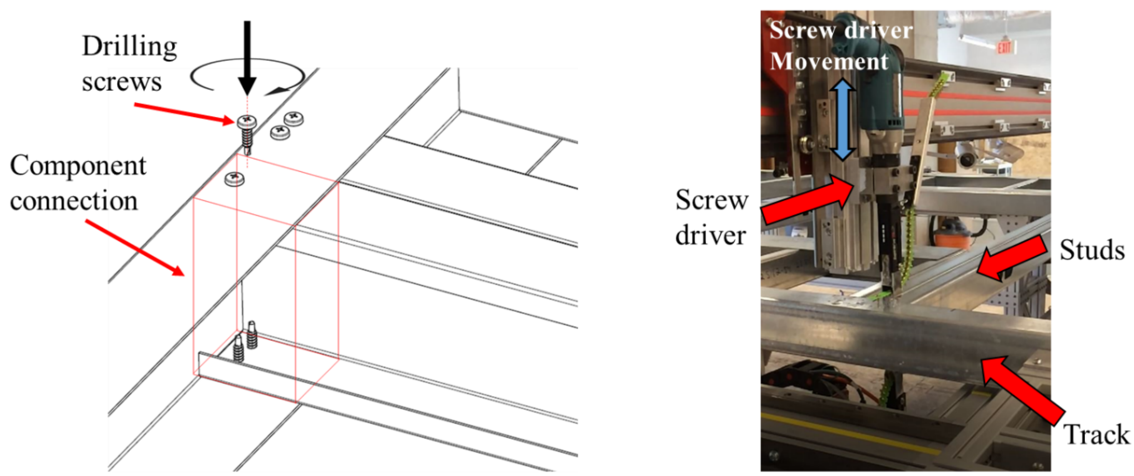


Figure 4.6: Overview of the systems used and operations carried out for automated steel frame assemblies. Left: schema of screw fastening operations on a track-stud connection. Right: screw fastening system in the machine environment.

Then, as observed, systems and operations surrounding the manufacturing process of steel frame assemblies need to be modeled. The ’System’ class defined represents, as systems, the manufacturing capabilities of the machine environment selected. In generic terms, the machine used in this study is reduced, from a manufacturing perspective, to the smaller agents responsible of the manufacturing operations: the

'Squaring System' responsible of aligning the location of the frame connection with the screw manipulator and the 'Screw Fastening System' which carries a screw driver capable of screw fasten steel members together. As the current machinery available is really unique, the presented manufacturing model is quite simple. However, as new machines appear and novel systems and operations are capable of assembling steel frames, further systems and operations have to be introduced. For example, the 'Operation' class not only may include the current operation used, namely 'Screw Fastening', but also other potential operations capable of permanently join steel elements, such as 'Clinching', 'Welding', or 'Drilling'.

Then, each 'System' is characterized by the operation it can perform. Using the property 'performs', each individual system of the machine is linked to one or several operations it can perform automatically. Similarly, each 'ElementIntersection' requires a permanent connection obtained at its location through a manufacturing 'Operation'. A 'requires' property of 'ElementIntersection' establishes the link between designed steel frame assemblies and the available manufacturing operations in machine environments. For example, a 'Double-Angled' connection requires a 'Operation' in the overlapping area between the three steel members; however, an exception is made for 'Crossing' connections as they do not require any manufacturing operation (pressure fit). Additionally, as seen for the previous ontology model proposed, inverse relationships are deduced for both properties: 'performedBy' for 'performs' and 'requiredBy' for 'requires'. Remind that those inferred facts establish a stronger relationship between knowledge domains and a more efficient information extraction. An illustration of the steel frame assemblies manufacturing ontology model proposed is shown in Figure 4.7.

4.3.3 Quality Ontology

Finally, the quality ontology model presented plays a two-fold role: 1) formalizes the modeling of quality specifications of pre-designed construction products; and 2) establishes a clear link between product design, manufacturing processes, and quality

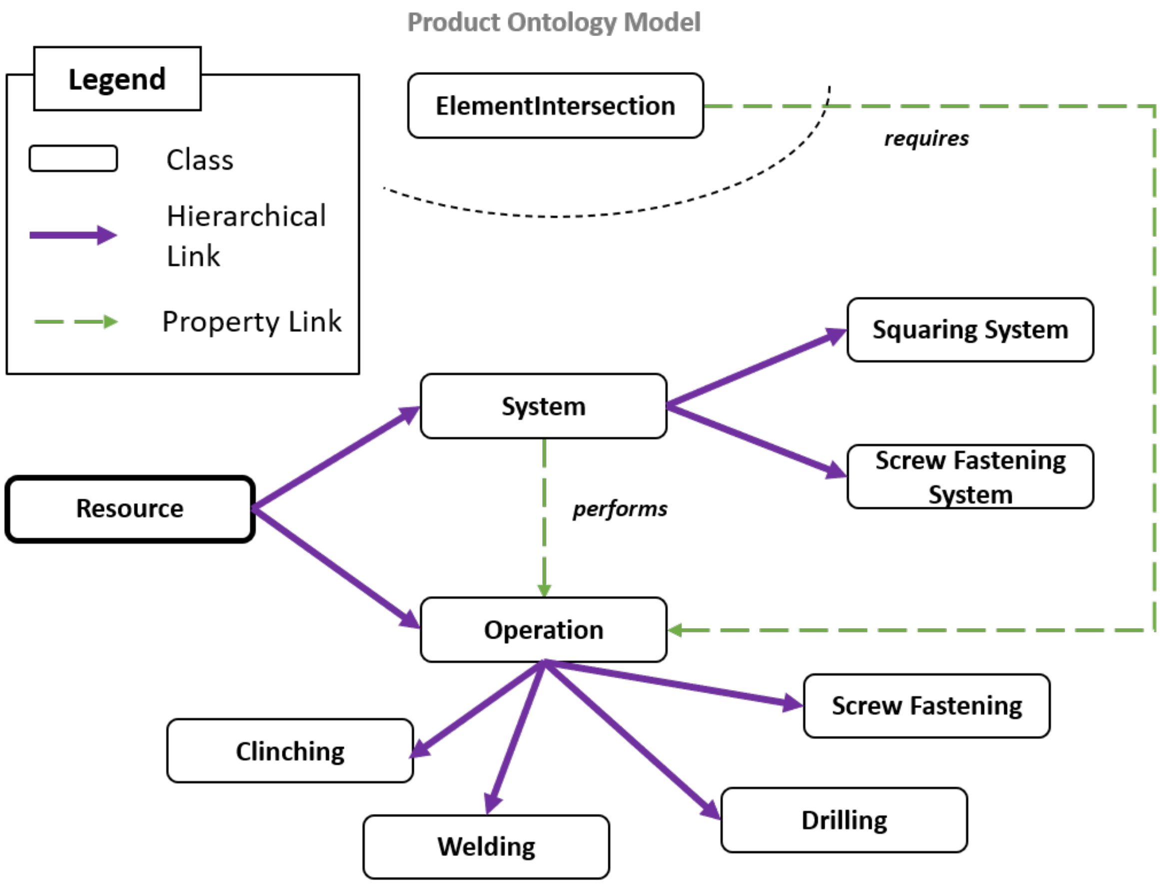


Figure 4.7: Overview of the proposed manufacturing ontology model.

specifications. All the information modeled herein regarding quality control and assurance of steel frame assemblies has been directly obtained from international, national, provincial, and local standards, regulations, or codes. In this study, it is assumed that Canada, Alberta, and Edmonton are the target regions for national, provincial, and local regulations respectively.

For construction manufactured products, quality specifications are grouped into three different classes that define potential defects in the product: 'Geometrical', 'Physical', and 'Aesthetic'. First, 'Geometrical' specifications group all the constraints and maximum deviations defined in regulations related to the geometrical end-shape of the product, i.e. maximum deviation in stud positioning. Then, 'Physical' specifications relate to the physical properties of the materials that support the connections' integrity manufactured during the assembly process. Finally, 'Aesthetic' groups all the identifiable superficial non-conforming defects, such as scratches, tears, and so forth, which is in most cases specific to each company. All those constraints are then linked to an 'ElementIntersection' and/or 'Operation'. Through the property 'defines' (and its inverse 'definedby'), the link between quality with manufacturing and product design is established. An illustration of the quality ontology model proposed is shown in Figure 4.8.

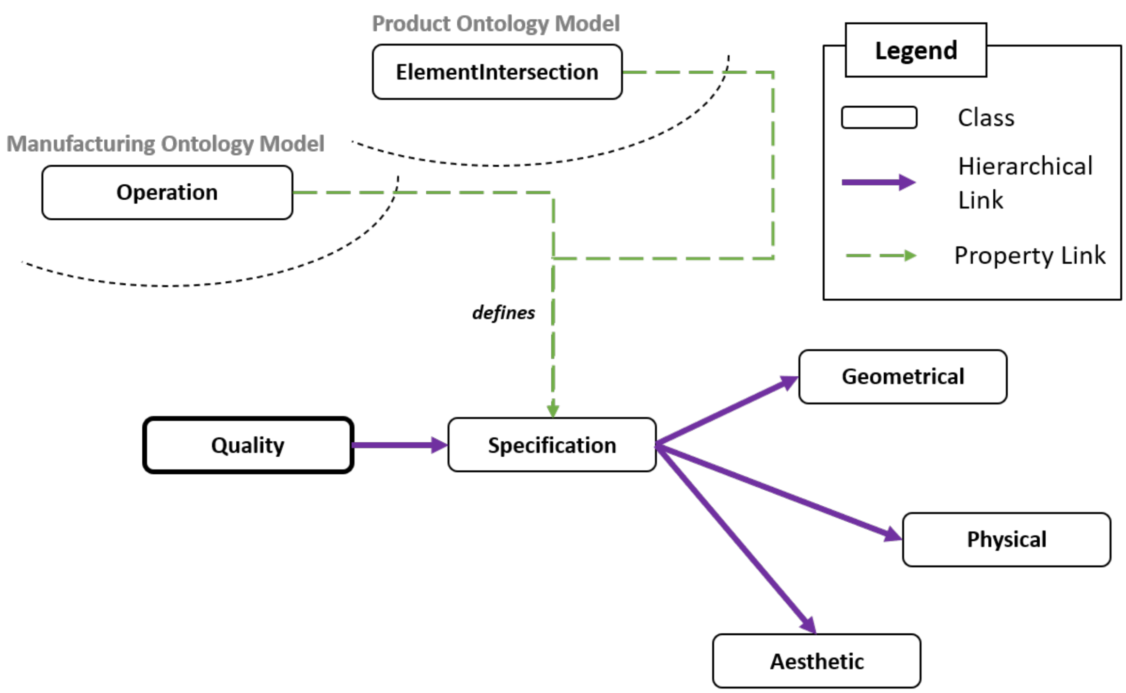


Figure 4.8: Overview of the proposed quality ontology model.

Although the illustration above is generic for all construction products, some assumptions are taken to populate the quality model for steel frame assemblies. In regard to manufacturing operations, only the available option in the current machine environment is considered, namely 'Screw Fastening'. A list of the identified specifications for steel frame assemblies is provided in Table 4.2.

As reported, most construction regulations limit the geometric and physical defects a conforming steel frame assembly may have, whereas aesthetic requirements are not even considered. Quality requirements in can be automatically linked to specific types of connections. On the one hand, geometric constraints are defined in relation

Table 4.2: List of steel frame assembly quality specifications.

Source	**Identifier**	**Specification Sub-class**	**Required by 'Element.Intersection'**
ASTM C1007-11a	Element Misalignment	Geometrical	Connection.Perpendicular and Connection.Angled and Connection.Double-Angled
	Lateral Displacement	Geometrical	Connection.Perpendicular and Connection.Angled and Connection.Double-Angled and Connection.Lateral
	Frame Squareness	Geometrical	Connection.Perpendicular
CSA S136-07/S1-10	Connection Angle	Geometrical	Connection.Perpendicular and Connection.Angled and Connection.Double-Angled and Connection.Crossing
	Screw Fastener Type	Physical	Connection.Perpendicular and Connection.Angled and Connection.Double-Angled and Connection.Lateral
	Fastening Depth	Physical	Connection.Perpendicular and Connection.Angled and Connection.Double-Angled and Connection.Lateral

to the product design, hence heavily linked to the product ontology. For example, Figure 4.9 represents the 'Element Misalignment' and 'Lateral Displacement' defects for a perpendicular connection between steel frame members. On the other hand, physical specifications are linked to the manufacturing operation performed. In this case, only screw fastening related constraints are reported, however, in situations where other operations may be used, additional quality regulations and, consequently, specifications need to be introduced in the model.

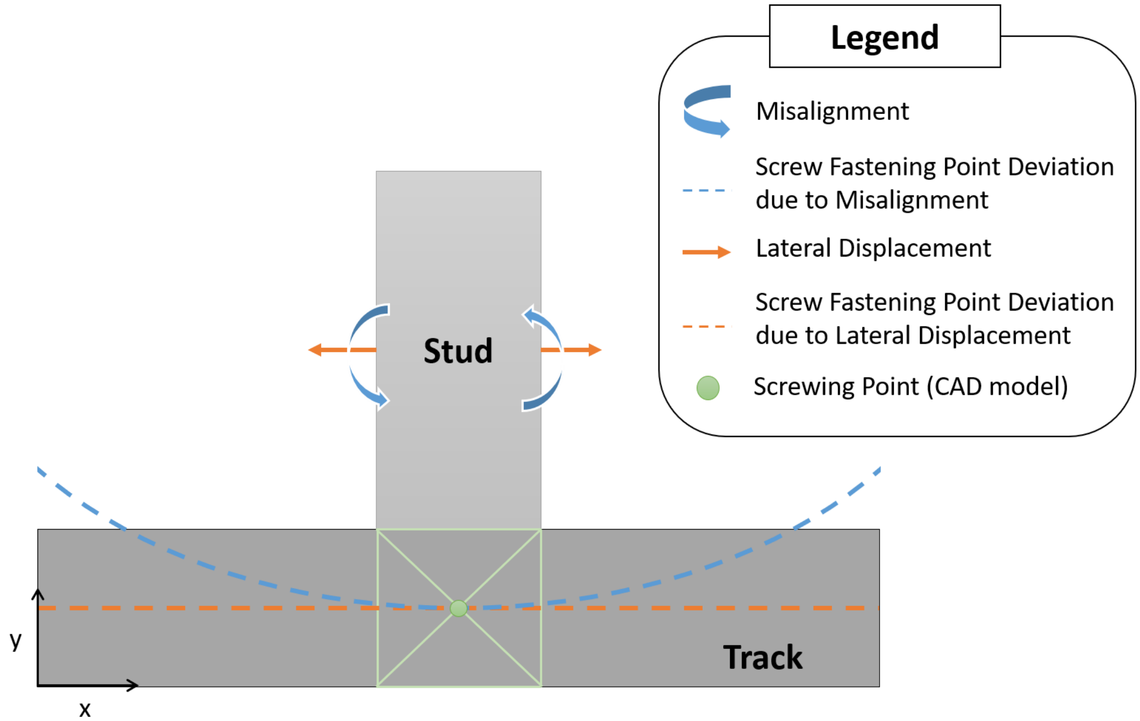


Figure 4.9: Example of geometric quality specifications over a stud-track perpendicular connection.

4.4 Validation & Limitations

This section provides a use case for the ontology model defined in the previous section, aiming to validate the information flow and knowledge modeling proposed. A single steel frame assembly in designed in Autodesk Revit / FrameX with as many different modeled components as possible, i.e. different types of studs, bracings, etc. As such, the frame used in this case can visualize as much as possible the extent of the ontology modeling performed. A 3-dimensional view of the frame and each sub-component identified is shown in Figure 4.10 and a list of the frame sub-components as per the BIM Schema is found in Table 4.3.

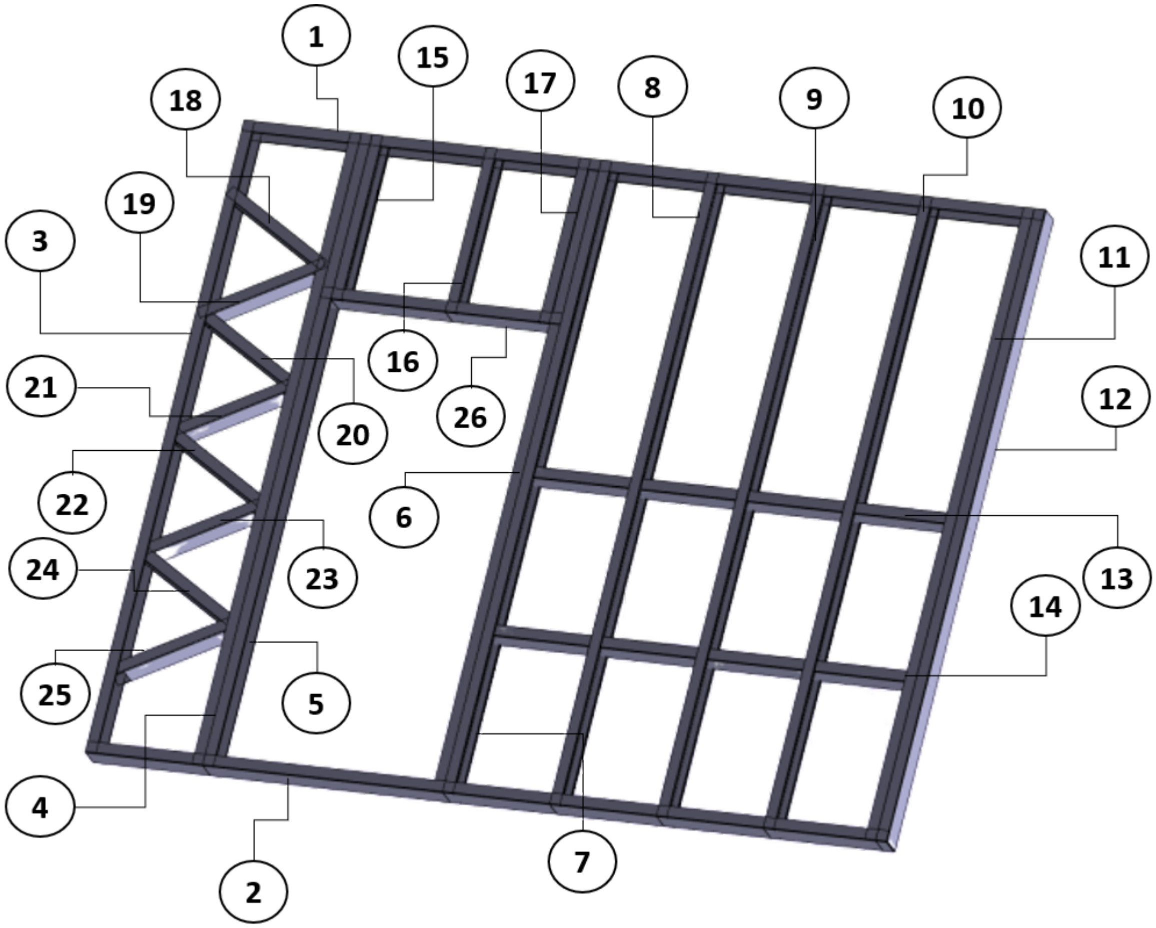


Figure 4.10: Steel frame assembly model and identifiable element parts.

Table 4.3: List of the steel frame assembly element parts.

BIM Element ID	Description	Ontology Model Individual	Ontology Element ID
1	Frame Top Track	ElementPart.Track.TopTrack	TTT_1
2	Frame Bottom Track	ElementPart.Track.BottomTrack	TBT_1
3	Frame Stud	ElementPart.Stud.Regular	SR_1
4	Frame King Stud	ElementPart.Stud.King	SK_1
5	Frame Jack Stud	ElementPart.Stud.Jack	SJ_1

(Table continues on next page...)

BIM Element ID	Description	Ontology Model Individual	Ontology Element ID
6	Frame Jack Stud	ElementPart.Stud.Jack	SJ_2
7	Frame King Stud	ElementPart.Stud.King	SK_2
8	Frame Stud	ElementPart.Stud.Regular	SR_2
9	Frame Stud	ElementPart.Stud.Regular	SR_3
10	Frame Stud	ElementPart.Stud.Regular	SR_4
11	Frame Stud	ElementPart.Stud.Regular	SR_5
12	Frame Stud	ElementPart.Stud.Regular	SR_6
13	Frame Horizontal Bracing	ElementPart.Bracing.Horizontal	BH_1
14	Frame Horizontal Bracing	ElementPart.Bracing.Horizontal	BH_2
15	Frame Cripple Stud	ElementPart.Stud.Cripple	SC_1
16	Frame Cripple Stud	ElementPart.Stud.Cripple	SC_2
17	Frame Cripple Stud	ElementPart.Stud.Cripple	SC_3
18	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_1
19	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_2
20	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_3
21	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_4
22	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_5

(Table continues on next page...)

BIM Element ID	Description	Ontology Model Individual	Ontology Element ID
23	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_6
24	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_7
25	Frame Diagonal Bracing	ElementPart.Bracing.Diagonal	BD_8
26	Frame Header	ElementPart.Header	H_1

For each element of the steel frame designed, its data is extracted from the BIM model in order to populate the ontology model. Through the dotNetRDF extension of the Revit API, functions such as RDFGraph.Assert() allow to automatically write BIM data onto the ontology file (.owl) and generate ontology individuals of specific classes. As observed, all the elements of the steel frame are given a unique element identifier. From there, once the ontology model contains individuals, the ontology reasoner can be executed so that the rest of the model is populated following the axioms, properties, and relationships explicitly defined.

First, the reasoner identifies the connections that exist between elements within the steel frame. As stated, those connections identify the areas where manufacturing is required in the overlapping locations between steel frame sub-components, as well as specifying the location for quality inspection. A list of all the connections created by the ontology reasoner can be found in Table 4.4.

Table 4.4: List of the steel frame assembly connections inferred by the frame element parts.

Ontology Connection	Reference Element	Non-reference Element	Ontology ID
Perpendicular	TTT_1	SR_1	CP_1
		SR_2	CP_2
		SR_3	CP_3
		SR_4	CP_4
		SR_5	CP_5
		SR_6	CP_6
		SK_1	CP_7
		SK_2	CP_8
		SJ_1	CP_9
		SJ_2	CP_10
		SC_1	CP_11
		SC_2	CP_12
		SC_3	CP_13
	TBT_1	SR_1	CP_14
		SR_2	CP_15
		SR_3	CP_16
		SR_4	CP_17
		SR_5	CP_18
		SR_6	CP_19
		SK_1	CP_20
		SK_2	CP_21
		SJ_1	CP_22
		SJ_2	CP_23
	H_1	SJ_1	CP_24
		SJ_2	CP_25
		SC_1	CP_26
		SC_2	CP_27
		SC_3	CP_28
	SK_2	BH_1	CP_29

(Table continues on next page...)

Ontology Connection	**Reference Element**	**Non-reference Element**	**Ontology ID**
Perpendicular	SK_2	BH_1	CP_30
	SR_5	BH_1	CP_31
		BH_1	CP_32
Angled	SR_3	BD_1	CA_1
		BD_8	CA_2
Double-Angled	SR_3	BD_2 and BD_3	CDA_1
		BD_4 and BD_5	CDA_2
		BD_6 and BD_7	CDA_3
	SK_1	BD_1 and BD_2	CDA_4
		BD_3 and BD_4	CDA_5
		BD_5 and BD_6	CDA_6
		BD_7 and BD_8	CDA_7
Crossing	SR_2	BH_1	CC_1
		BH_2	CC_2
	SR_3	BH_1	CC_3
		BH_2	CC_4
	SR_4	BH_1	CC_5
		BH_2	CC_6
Lateral	SK_1	SJ_1	CL_1
	SJ_1	SC_1	CL_2
	SC_3	SJ_2	CL_3
	SJ_2	SK_2	CL_4
	SR_5	SR_6	CL_5

In total, the ontology model generates 52 connections throughout the frame by linking location and geometric information: 32 instances of 'Perpendicular' connection, 2 instances of 'Angled' connection, 7 instances of 'Double-Angled' connection, 6 instances of 'Crossing' connection, and 5 instances of 'Lateral' connection. For the steel frame studied, all the connections are correctly identified and modeled accordingly.

The knowledge of the distribution and quantity of 'Connection' types is necessary to understand the manufacturing and quality requirements of the designed frame. For the case of steel frame assemblies, such connections can be performed by either 'Screw Fastening', 'Drilling', 'Clinching', or 'Welding' operations. The selection is purely based on the manufacturing capacity of the shop floor as there is no actual difference in the final functionality or design of the steel frame assembly. However, such selection does alter the specifications to be used in the quality control procedures of the product, i.e. different specifications are needed if welding or screw fastening operations are the manufacturing choice.

For the remaining of this section, the example provided is tailored to the manufacturing environment available: the steel framing machine in the Modular Construction Lab at the University of Alberta. Such machine is capable of automated top and bottom screw fastening operations. These manufacturing constraints suppose: 1) identified 'Lateral' connections, which require lateral screw fastening, are ignored; and, 2) manufacturing solutions in the model, other than 'Screw Fastening', are disabled from the ontology reasoner. As all the connections are performed using the same method, the quality specifications depend solely on the 'Connection' class as shown in Table 4.2. Thus, introducing appropriate queries, quality 'Specification' and all the information modeled under that class can be accessed from the BIM model. A sample query with its resulting information extracted from the ontology model is shown in Figure 4.11.

The query presented aims to showcase the capacity of the augmented BIM ontology model to transfer and visualize quality information regarding steel frames in a BIM environment. This example illustrates a query that lists all the 'Geometrical' quality specifications of any 'Connection' type CA ('Angled' connection), assuming 'Screw Fastening' operations only as discussed, and provides a 3-dimensional visualization that highlights the 'Angled' connections located in the frame. The results of the query matches the list of quality specifications in this case as listed in Table 4.2, showcasing

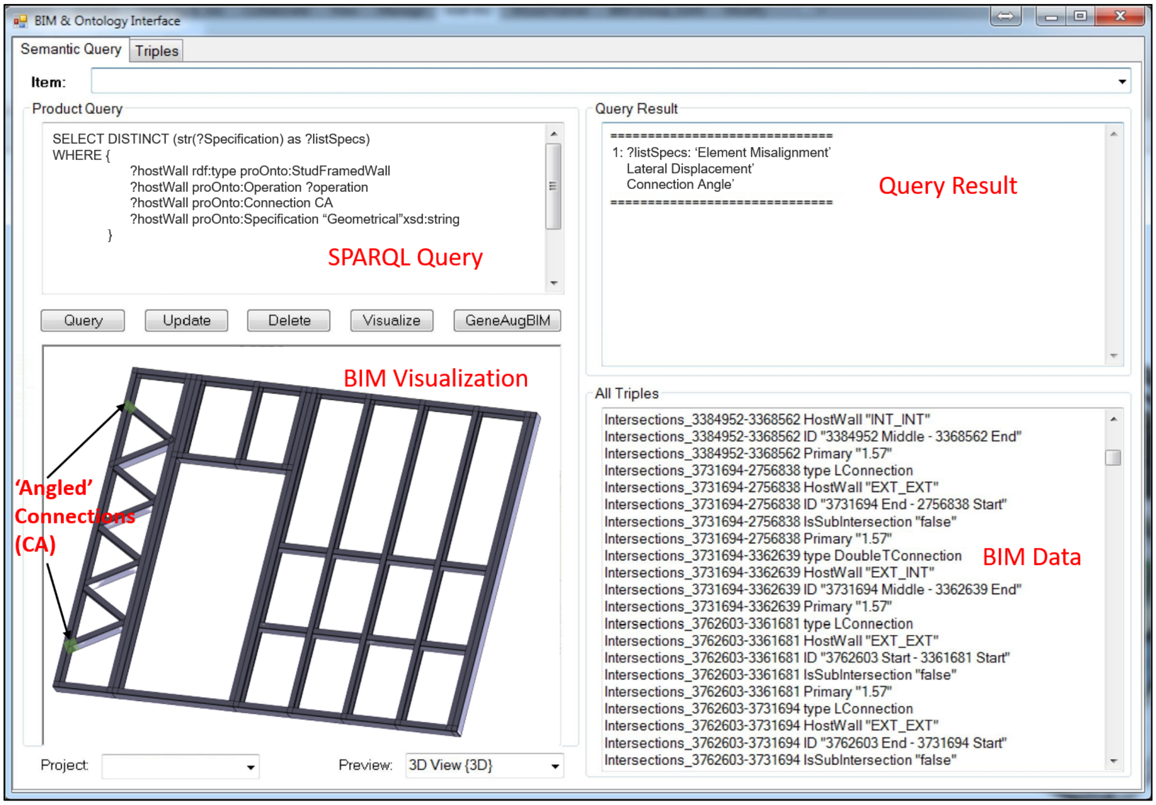


Figure 4.11: Example of semantic query through Revit add-on.

that the BIM data extraction and ontology model proposed are working as intended.

In summary, this chapter presents a knowledge model capable of establishing a link between quality specifications of steel frame assemblies and its design features, via manufacturing operations. The ontology model proposed is able to support identifying the areas that require quality control procedures and listing the features that need inspection in an automatic fashion. This data is specially interesting to plan the posterior inspection procedures at different levels: in general, a list with the all the required features to inspect per frame can be obtained, which helps defining the necessary output of the algorithms; but also it can be obtained per connection, supporting a dynamic smart inspection system that would adapt its outputs to the type of connection inspected. In the following chapter (Chapter 5), the design and development of vision-based algorithms that can provide quality information, inter alia the identified quality specifications linked to the BIM model, is presented.

Chapter 5

Vision-based Inspection Systems for Steel Frame Manufacturing

5.1 Overview

In current steel framing machines and also in the selected machine, the assembly of the light-gauge steel panels and the screw-fastening automatic operations are unsupervised, therefore the quality of the final product can be compromised. As previously mentioned, operator errors, machine accuracy failures, and supplies' deficiencies are not considered in the BIM, therefore not accounted for in the current manufacturing process of the steel frame assembly. With the ontology-enhanced BIM model developed in Chapter 4, quality information can be obtained and inspection targets can be defined so that the required features are measured. As such, the development of smart visual systems would provide an accurate inspection of the actual state of the construction product at different points in time during the manufacturing process and the quality of the manufacturing process itself. In the presented study, based on the specifications required, three inspection systems are included in the machine environment: 1) pre-manufacturing inspection system, that generates information regarding the quality of the manual assembly process; 2) online inspection system, which oversees the quality during screw-fastening operations; and 3) post-manufacturing inspection system, which confirms the conformance/non-conformance of the machine operations.

All the inspection systems proposed are visual in nature: visual sensors, namely cameras, and image processing algorithms are used to generate the quality-oriented data. In the steel framing machine used, several cameras are installed for this purpose. First, a wide-angle camera is positioned on top of the loading area of the machine for the pre-manufacturing inspection. Then, short-range cameras are installed on each one of the screw-fastening carriages, four in total, for the online and post-manufacturing inspection systems. An overview of the proposed systems installed on the steel framing machine is outlined in Figure 5.1.

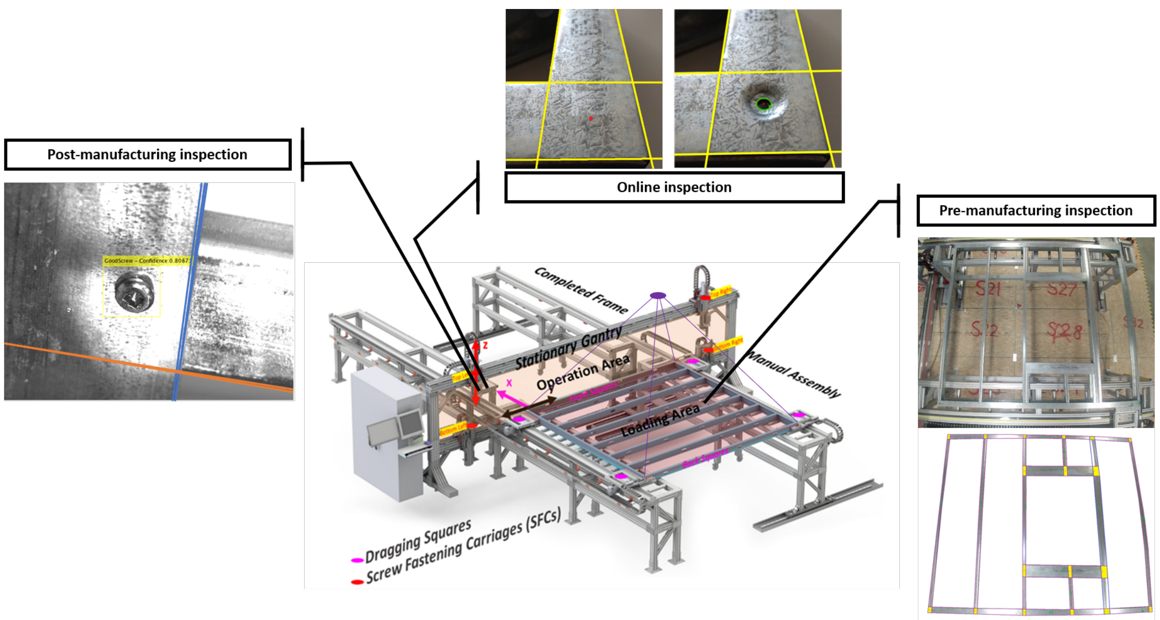


Figure 5.1: Overview of the steel framing machine with the developed inspection systems.

The following sections provide deep insight on the proposed inspection systems for steel frame assemblies, from the models to the algorithms involved.

5.2 Pre-Manufacturing Inspection System

The system presented aims to automatically validate the manually assembled frame components in the loading zone of the steel framing machine prototype (SFMP) using 2D images from the scene. The proposed vision-based algorithm is developed and implemented in Python programming language (computation tool) integrated with a camera system. The Python (version 3.6.4) programming language was chosen due to of its ability to generate, modify and structure data intuitively as well as simulate and apply computer vision algorithms through widely available libraries.

5.2.1 Frame Pre-Inspection Algorithm

In the proposed inspection system, the frame pre-inspection algorithm aims to extract the relevant information for the manufacturing process from a 2D image of the frame assembly that ultimately captures the quantity and location of all input materials of the process. The input materials are the components of each frame assembly, namely light gauge steel studs. The input image can be obtained from the loading zone of the machine or from the top view of a 3D CAD virtual environment. The completion of the frame inspection outputs the relevant information of each stud in the assembly: the stud's intersection, the stud's metrics and the stud's relative position in the frame assembly. Thus, for every steel frame assembly, a real-time pre-verification can be obtained.

Regarding image processing techniques, the Hough Transform has been previously used to detect vertical studs in wall assemblies [179]. The proposed frame inspection algorithm is a novel Hough transform-based algorithm to detect and identify frame components. It works with either real images from the machine environment or images from the frame CAD model. The algorithm works in three sequential stages: line detection, intersection detection and stud detection. The flowchart of framing inspection is illustrated in Figure 5.2. It must be noted that all the following stud dimensions and locations are in pixels. To obtain metric results, standard camera calibration is expected [193].

Whereas CAD models might have artificial transparent or clear backgrounds, real environments contain backgrounds that are proven to be extremely noisy for computer vision algorithms due to changing lighting conditions, vibrations on the camera and possible partial occlusions. To obtain a clearer result from the Hough Transform, the

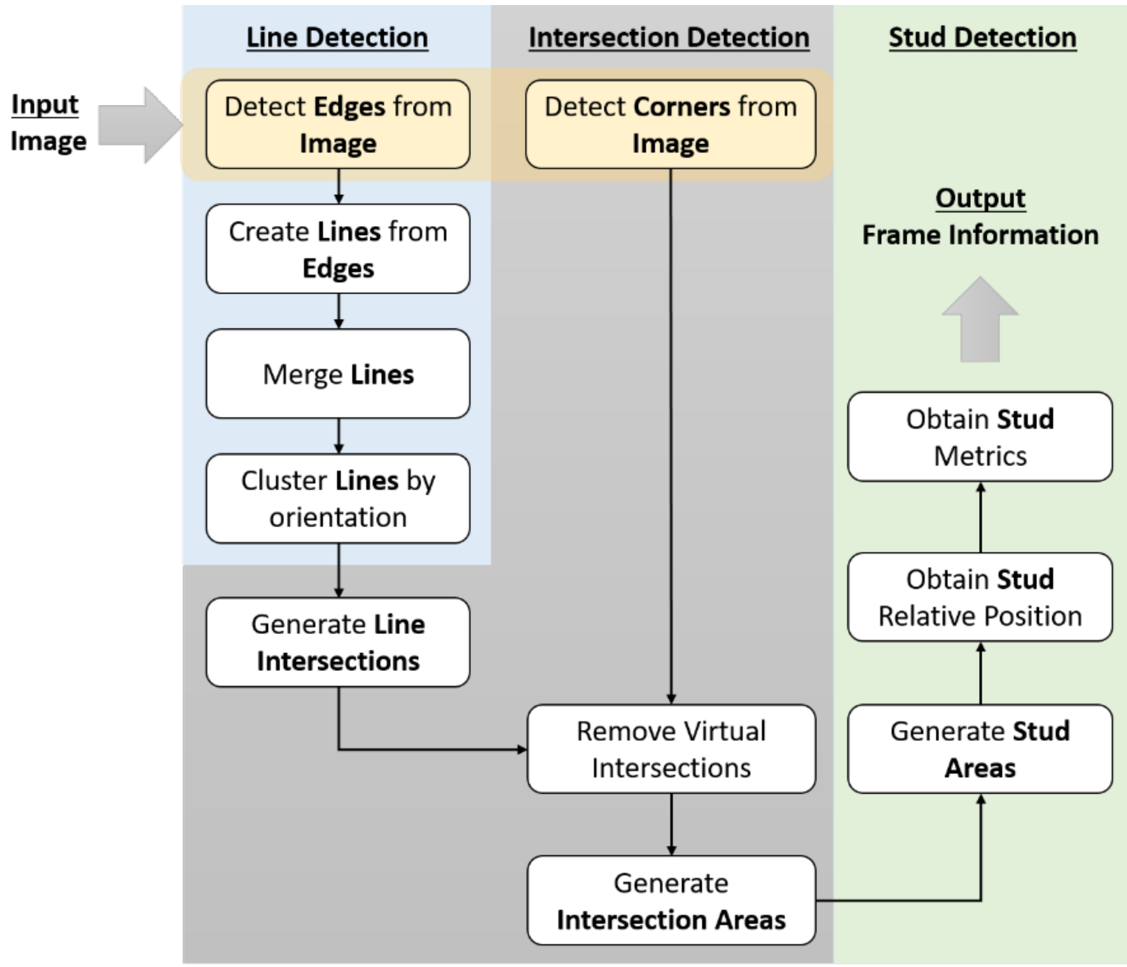


Figure 5.2: Flowchart of the pre-manufacturing frame inspection.

real images must be preprocessed to eliminate the background image and isolate the frame assembly satisfying Equation 5.1. To ensure that the camera is stationary, the structure that holds the camera on its correct position was separated from the general structure of the SFMP. Using such setup, the background can be eliminated using well-known techniques such as the frame-difference approach [194].

$$D(x, y, \Delta t) = \mid I(x, y, t) - I(x, y, T) \mid, (x, y) \in \Re^3 \tag{5.1}$$

where, $I(x, y, t)$ and $I(x, y, T)$ are the real images obtained at the real time (t) and the moment in which the template was obtained (T). $D(x, y, \Delta t)$ is the resultant frame-difference image. Therefore, obtaining a template image with the static background of the loading area beforehand is necessary. In indoor industrial environments, keeping the template updated is a key factor for the efficiency of the algorithm as the background tends to constantly change with time. Updating the background template should be added to the machine calibration routine and its updating schedule should be coded within the machine logic each time the machine changes its settings, such as any lateral adjustment of the table. Considering all of this, (Δt) must satisfy the following:

$$\forall \Delta t, \begin{cases} \Delta t = t - T \\ 0 \leq \Delta t \leq T_{max} \end{cases} \tag{5.2}$$

where (T_{max}) is the maximum recommended elapsed time since the last template update and is dependent on the activity surrounding the loading area of the steel framing machine. At first, transforming the image into gray-scale is required to apply the well-known Canny edge detector. Then, the Hough Transform is applied to transform the detected edges into a set of two parameters (ρ, θ) that define the detected line in polar coordinates as stated in Equation 5.3.

$$L(\rho, \theta) := \begin{cases} \rho = \sqrt{x^2 + y^2} \\ \theta = \tan^{-1} \frac{y}{x} \end{cases} \quad , (x, y) \in D \tag{5.3}$$

where $L(\rho, \theta)$ is the set of lines detected by the Hough transform in polar coordinates and (x, y) are the pixel coordinates of the undistorted image. This set represents then, as lines, the edges reflected by the Canny algorithm, as illustrated in Figure 5.3.

The detected lines that define frame edges, however, should belong to a unique stud or track. Thus, two unique clusters are generated using k-means clustering around the value of (θ) of each line to differentiate between vertical and horizontal lines, (V_l) and (H_l) respectively. Each cluster would then define to which stud or track each subset of lines belongs to. For example, based on the orientation of the camera selected, vertical lines would belong to either tracks or headers in window components, and horizontal lines would belong to studs or bracings. Both subsets are complementary and are defined satisfying the following system of equations:

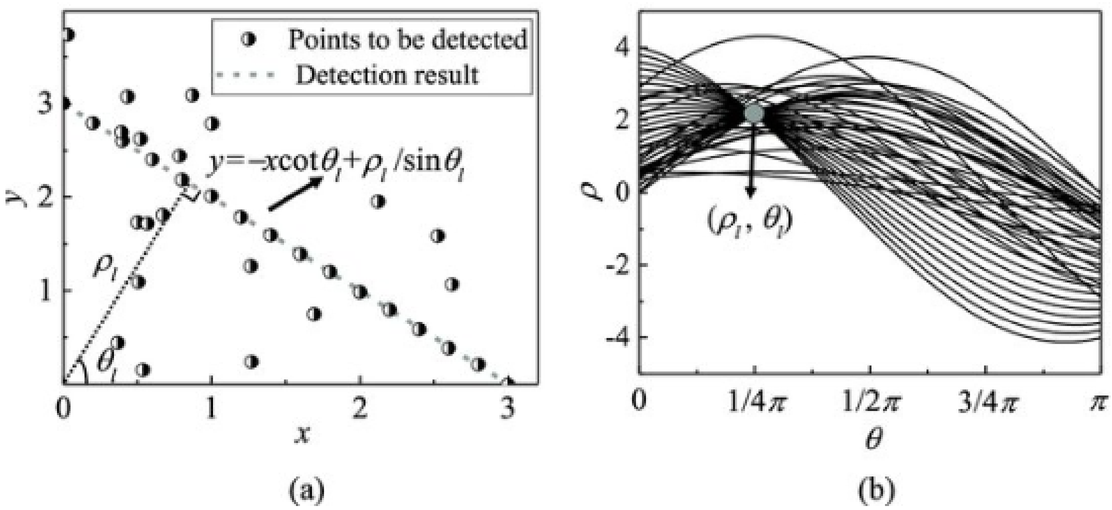


Figure 5.3: Example of line detection by Hough Transform, after [195].

$$\begin{cases} V_l \subseteq L, V_l(\rho,\theta) := \{(\rho,\theta) \in L \mid \theta \approx \frac{\pi}{2} \pm k\pi, k = 1,2,...\} \\ H_l \subseteq L, H_l(\rho,\theta) := \{(\rho,\theta) \in L \mid \theta \approx 0 \pm k\pi, k = 1,2,...\} \\ V_l \cap H_l = \emptyset \end{cases} \tag{5.4}$$

Once the lines have been clustered, the intersections between each vertical and horizontal line can be found following Equation 5.5, thus computing the coordinates for all the intersection points, (N_l). The system of equations can be solved to obtain all the (x, y) pair of coordinates for each pair of lines.

$$N_l(x,y) := \begin{cases} x\cos\theta_1 + y\sin\theta_1 = \rho_1 \\ x\cos\theta_2 + y\sin\theta_2 = \rho_2 \end{cases} ,(\rho_1,\theta_1) \in V_l, (\rho_2,\theta_2) \in H_l \tag{5.5}$$

Therefore, finding the intersections of the frame is reduced to solve the set of systems of equations for each possible pair of vertical and horizontal lines on the form of $AX = B$ as defined in Equation 5.6. An example of results for the line detection, line clustering, and intersection point estimation are shown in Figure 5.4.

$$A = \begin{bmatrix} \cos\theta_1 & \sin\theta_1 \\ \cos\theta_2 & \sin\theta_2 \end{bmatrix}, B = \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix}, X = \begin{bmatrix} x \\ y \end{bmatrix} \in N_l \tag{5.6}$$

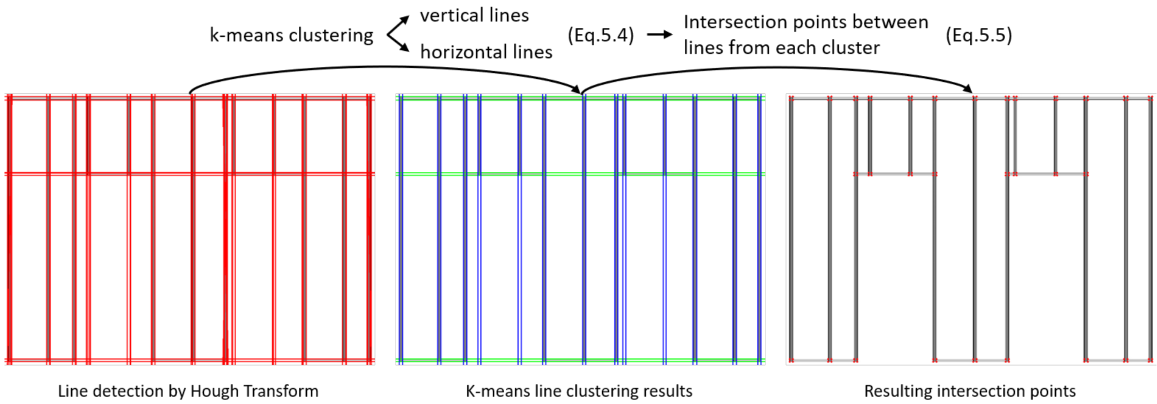


Figure 5.4: Line detection, clustering and intersection points results on a light-gauge steel frame modeled in Revit.

However, each detected line is projected over the whole 2D space. For short studs, its detected edge lines create virtual intersections on the longer studs, usually in window or door components. Those virtual intersections need to be removed in order to accurately define the frame assembly. As such, we need to be able to identify a feature of any real intersection area that can differentiate both. The proposed solution is to use the Harris corner algorithm to detect the corners of the whole frame, (x_c, y_c), and filter the intersection points that are further than a specific threshold from the corner points. The threshold is a user-defined parameter that gives the maximum width, (w_{max}), of any stud that can be used as input material for the SFMP. The filtered intersection points, (N_{fl}), satisfy the conditions set in Equation 5.7. A graphical representation of the virtual intersection removal is also shown in Figure 5.5.

$$\forall k, N_{fl}^{(k)}(x,y) = \partial_k N_l^{(k)}(x,y)$$
$$\partial_k := \begin{cases} 1 & \text{if } x - x_c \leq w_{max} \text{ or } y - y_c \leq w_{max} \\ 0 & \text{otherwise} \end{cases} \tag{5.7}$$

Once the intersection points are fully defined and possible errors filtered out, an iterative process is followed to generate the intersection areas. An intersection area, (N_{area}), is defined as a rectangular area that represents the superposition of two studs, generated from four different intersection points. It is assumed that each intersection

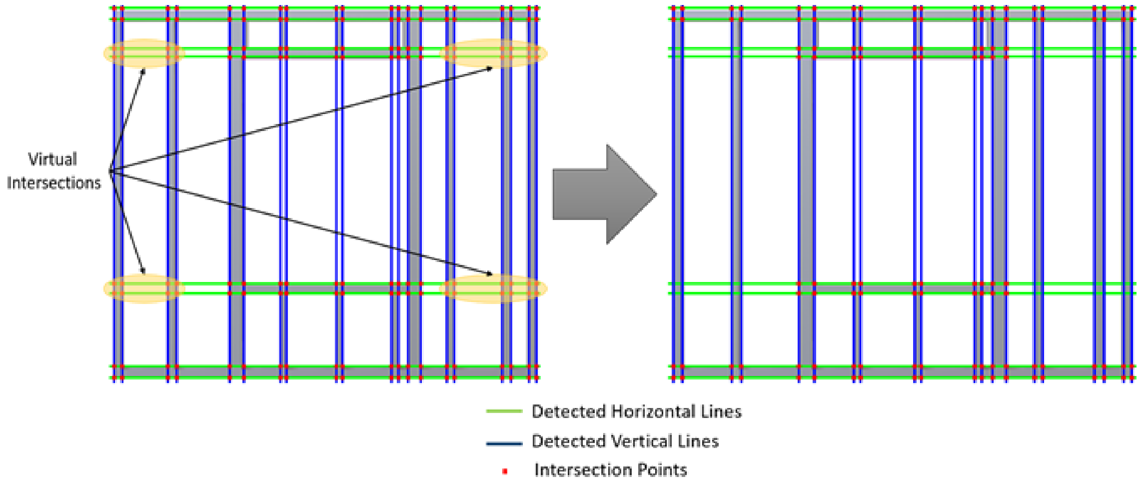


Figure 5.5: Example of virtual intersections removal for a steel frame with a window component.

point belongs to a unique intersection area. Then for each intersection area, its defining intersection points are obtained as follows:

$$\begin{aligned} N_{area} :&= \{(x_1, y_1), ..., (x_4, y_4)\}, (x_1, y_1), ..., (x_4, y_4) \in N_l \\ \forall j, k &\in 1, ..., \frac{N}{4}, j \neq k, N^j_{area} \cap N^k_{area} = \emptyset \end{aligned} \tag{5.8}$$

where (N) is the number of intersection points found in the frame, and each pair of coordinates for the intersection area are defined as follows:

$$\begin{aligned} (x_1, y_1) &= \{(x, y) \mid \min(sgn(x)sgn(y)\sqrt{x^2 + y^2})\} \\ (x_2, y_2) &= \{(x, y) \mid \min(sgn(x - x_1)sgn(y - y_1)\sqrt{(x - x_1)^2 + (y - y_1)^2})\} \\ (x_3, y_3) &= \{(x, y) \mid \min(sgn(x - x_1)sgn(y - y_1)\sqrt{(x - x_1)^2 + (y - y_1)^2}) \\ &\qquad \wedge (x, y) \neq (x_1, y_1)\} \\ (x_4, y_4) &= \{(x, y) \mid \min(sgn(x - x_1)sgn(y - y_1)\sqrt{(x - x_1)^2 + (y - y_1)^2}) \\ &\qquad \wedge (x, y) \neq (x_2, y_2) \wedge (x, y) \neq (x_3, y_3)\} \end{aligned} \tag{5.9}$$

A simplified pseudo-code and graphical representation (see Figure 5.6) of the generation of intersection areas can be found below.

1. Sort the intersection points in ascending distance to the origin of the frame;

2. Pick the first intersection point from the list that is not part of an intersection area;

3. Calculate the distance to the remaining intersection points from the selected point;

4. Sort the points by ascending distance;

5. Pick the first three points and create an intersection area;

6. Repeat from step 2 until all intersection points have been visited.

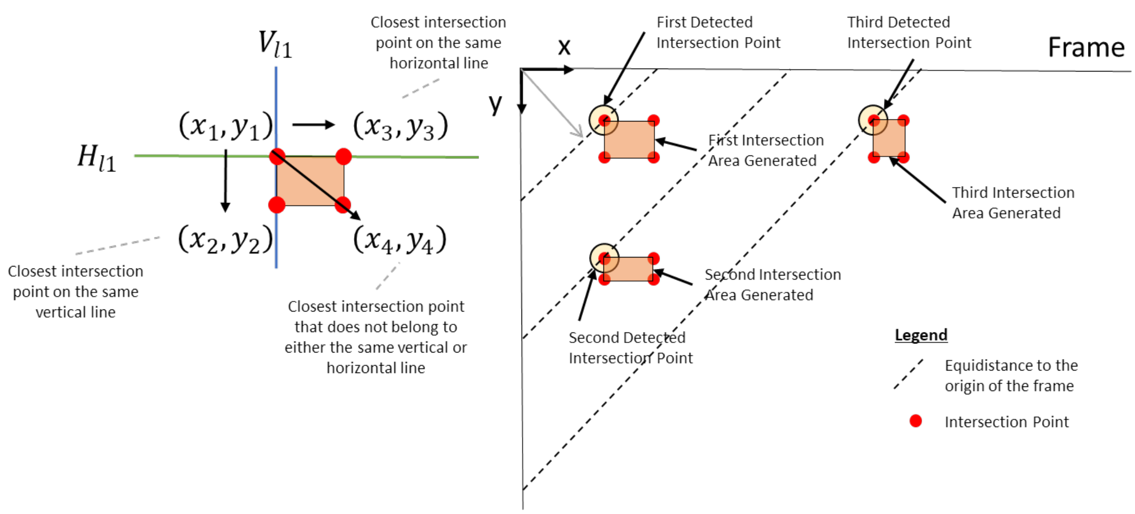


Figure 5.6: Overview of the intersection area generation algorithm.

Similarly, stud areas should be generated following an iterative process using the intersection areas recently defined. A stud area, (S_{area}), is defined as a rectangular area that represents a stud. Acknowledging that each stud starts and finishes on an intersection area due to the frame structure, the stud area would be generated between both intersection areas, both included. It is assumed that a unique couple of intersection areas can only generate one stud area, but an intersection area can be part of several stud areas. Then, for each stud area, its defining intersection points are obtained as follows:

$$\forall j,k \in \{1,...,R\}, j \neq k, S_{area} = \{(x_1,y_1),...,(x_4,y_4)\},$$
$$(x_1,y_1),(x_3,y_3) \in N^j_{area} \wedge (x_2,y_2),(x_4,y_4) \in N^k_{area} \tag{5.10}$$

where (N^j_{area}) is a random intersection area, (N^k_{area}) is an intersection area that shares a vertical or horizontal line with (N^j_{area}), and (R) is the number of detected studs in the frame. An illustration of the stud generation algorithm is found in Figure 5.7.

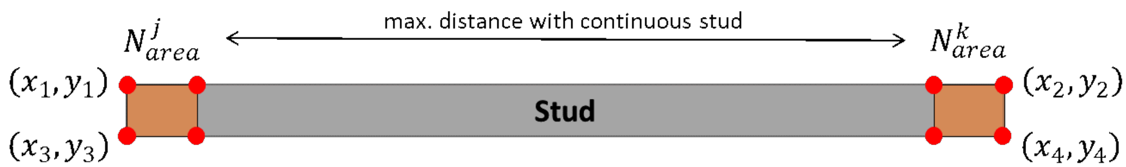


Figure 5.7: Stud area generation algorithm overview.

Acknowledging that each stud starts and finishes on an intersection area due to the frame structure, the stud area would be generated between both intersection areas, both included. Note that, stud identification does not rely on predefined stud width values and, as such, any detected stud can be in reality the junction of several studs. However, the presence of a real stud between intersection areas might not be assured in window or door components (as seen in Figure 5.8).

Thus, it is paramount to verify the stud continuity after reaching an intersection area to fully define different studs that are aligned vertically or horizontally and avoid defining studs on empty areas. Assuming that by definition stud intersections cannot be generated in empty areas, stud continuity is considered when no important image gradient is observed anywhere between both intersection areas. A stud area is considered continuous when the pixels inside the area satisfy Equation 5.11. Let (D_p) the difference image between both intersections and (∂_p) the binary variable that defines the continuity of the stud in an area. Then:

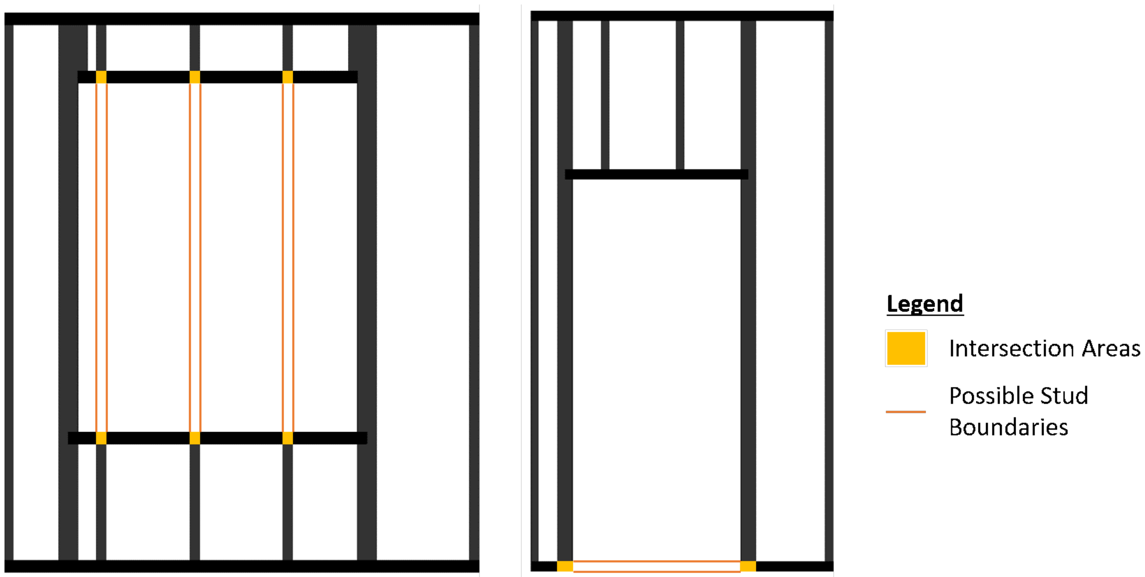


Figure 5.8: Stud discontinuity between aligned intersection areas for window or door components.

$$\nabla D_p(x,y) = \begin{bmatrix} \frac{\partial D_p}{\partial x} \\ \frac{\partial D_p}{\partial y} \end{bmatrix}$$
$$\partial_p = \begin{cases} 0 & \text{if } \sqrt{\frac{\partial D_p}{\partial x}^2 + \frac{\partial D_p}{\partial y}^2} \geq T \\ 1 & \text{otherwise} \end{cases} \tag{5.11}$$

where (T) is the maximum image gradient possible with stud continuity. In ideal conditions, $T \approx 0$, however the value of this threshold must be set considering the lighting conditions. This step may give false stud areas if the threshold value is comparable to the maximum gray-scale gradient value ($T \approx 255\sqrt{2}$). Thus, low lighting conditions on the loading area are recommended as steel has a high light reflectance value. Finally, the stud metrics, such as stud width, (ws), and stud length, (ls), can be directly calculated from the combination of intersection points of each stud area as per Equation 5.12.

$$\forall S_{area}, \begin{cases} w_s = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \\ l_s = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \end{cases} \tag{5.12}$$

Thus, the pseudo-code for the proposed algorithm to generate the stud areas is as follows:

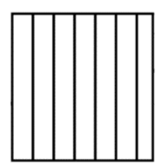
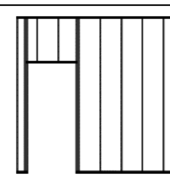
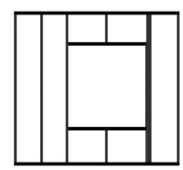
1. Select first/next intersection area and pick the first intersection point of the intersection area and store it as the first point of the stud area P1: (x_1, y_1);
2. Make a list with the intersection points that belong to the same vertical line;
3. Calculate the distance between P1 and the selected points. If all values are positive, pick the furthest one that ensures stud continuity and store it as the second point in the stud area P2: (x_2, y_2); if any value is negative, the stud area being defined is not a full stud, skip to step 8;
4. Check if the second intersection point of the first selected intersection area is in the list: if yes, pick the third one; if not, pick the second one. Store the selected point as the third point of the stud area P3: (x_3, y_3);
5. Select the intersection area of the intersection point found in step 3 and store the fourth intersection point as the fourth point in the stud area P4: (x_4, y_4);
6. Store as stud width the distance between P1 and P3 (or P2 and P4) of the stud area array;
7. Store as stud length the distance between P1 and P2 (or P3 and P4) of the stud area array;
8. Make another list with the intersection points that belong to the same horizontal line;
9. Follow steps 3 to 7 with the new list;
10. Repeat from step 1 until all intersection areas have been checked.

To summarize, the proposed frame inspection algorithm identifies four different structures in any frame assembly from the Hough Transform results: edge lines, intersection points, intersection areas, and stud areas.

5.2.2 Results & Validation

This section illustrates the effects of various panel configurations on the results obtained by the aforementioned inspection system. To represent the main components found in design and drafting of steel frame assemblies, this study presents three different virtual scenarios obtained from two commonly used CAD software (SolidWorks and Autodesk Revit): one frame with only vertical studs, one frame with a door component, and one frame with a window component. Relevant information obtained from the BIM for each one of the case studies is shown in Table 5.1.

Table 5.1: Summary of frame assemblies information (case studies).

Frame Design		**Case 1**	**Case 2**	**Case 3**
Shop Drawing				
Frame Dimensions [mm] *width (z) = 92		Length (x) = 2448; Height (y) = 2439	Length (x) = 3048; Height (y) = 2439	Length (x) = 2448; Height (y) = 2439
Stud Quantity	Single	10	12	10
	Multiple	0	2	1
	Total	10	16	12
Screw-fastening Operations (per layer)	Left	8	10	10
	Right	8	16	10
	Total	16	26	20

These design cases based on a prefabricated home plan are studied to validate the applicability of the proposed framework. The inspected product accuracy on the stud count and screw-fastening operations (intersection areas) are compared with the information obtained from the 3D-BIM models. Further, the algorithm time performance is discussed in Table 5.2. The case studies are analyzed using a standard computer with Intel Core i7-6700 CPU with 16 GB RAM.

Table 5.2: Time performance for the pre-manufacturing inspection system on each case study.

	Case 1	**Case 2**	**Case 3**
Time Performance (mean $\pm$ std.dev. of 7 runs, 100 loops each)	3.54 s $\pm$ 25.4 ms	3.61 s $\pm$ 28.4 ms	3.49 s $\pm$ 37.8 ms

As observed, there is not much difference between the time performance of the algorithm for each case study. In fact, such difference could be the consequence of fluctuations of work in the computer processor due to other background running programs. It would be fair to assume that the complexity of the frame assembly does not impact the processing time of the algorithm.

Figure 5.9 shows the results obtained by the pre-manufacturing inspection system. As observed, for all frame assemblies, the number of studs detected and intersection areas created match the frame information provided in Table 5.1.

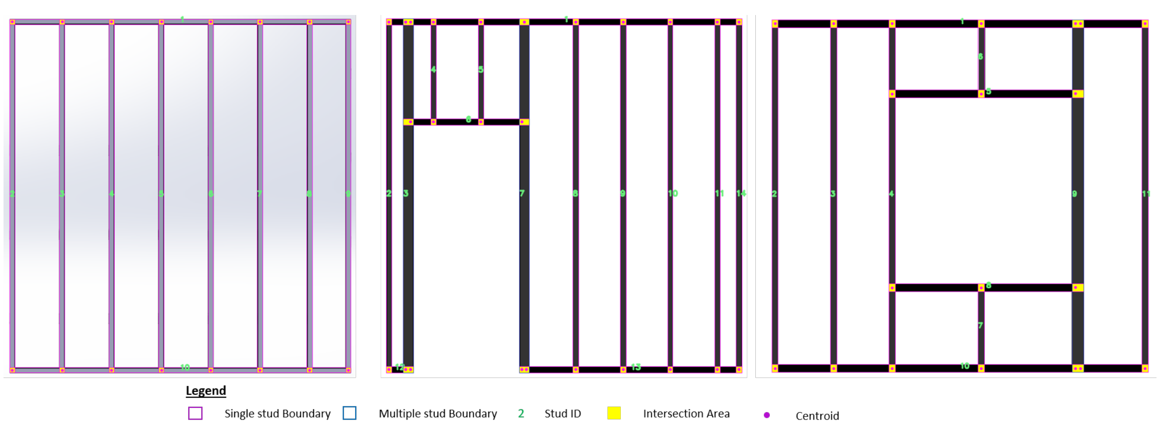


Figure 5.9: Case study results from the pre-manufacturing inspection system on virtual scenarios.

At last, a comparison between the results obtained with a simulated scenario and its corresponding real scenario is presented. Figure 5.10 showcases the results obtained from both scenarios. Note that the real scenario original image has some perspective as the camera mount was not perfectly positioned to obtain a clear top view of the loading zone, however, it shows a more probable scenario and proves that perspective does not alter the results obtained. Nevertheless, the measurements obtained need to be corrected subject to camera angle and positioning via calibration beforehand.

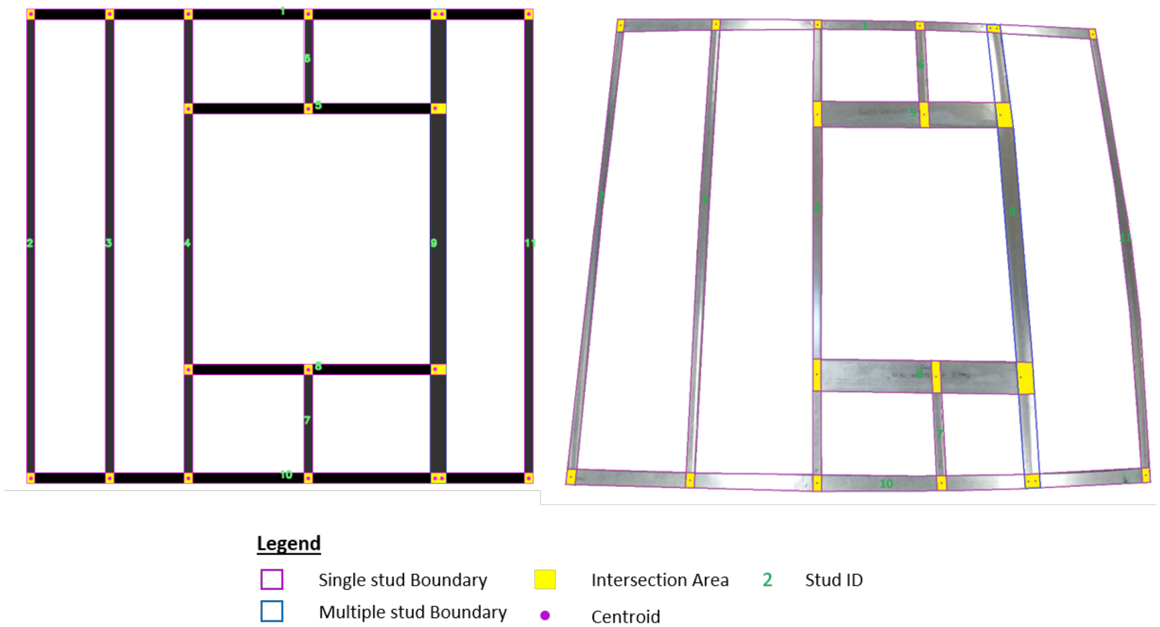


Figure 5.10: Case study 3 results from virtual (left) and real (right) scenarios.

As observed, the real window component available for testing does not match exactly with the 3D-BIM information. As both window components have the same amount of studs and intersection areas, for comparison purposes solely both models will be assumed similar. Given the presented results, the amount of studs detected and intersection areas is identical. As each manual assembly is different and no ground truth can be set on the real scenario, no metric comparison and accuracy analysis are made between both models. For all the cases just mentioned, the inspection system presented offers a clear insight on each individual component of the frame by measuring the defining features of each stud. This available information confirms that the current frame assembly standing on the loading zone of the SFMP matches with the scheduled frame coming from the BIM information. With this methodology, industry manufacturers would benefit from an extra layer of security at the beginning of their production line against operator errors in the selection or positioning of studs and/or supplies' deficiencies, as well as having machinery that take into consideration the status of the input materials in their manufacturing process. This last point will enable steel framing machinery to collect data in real-time and operate and take decisions based on a virtual scenario created from a single image. Both principles, real-time data generation and virtualization, are key components of Industry 4.0.

5.2.3 Discussion and Limitations

Eliminating the effects of artificial lighting in industrial environments and obtaining the correct stud metrics from the rectangle fitting is no simple task after the background differentiation. When encountering high intensity lighting, the light-gauge steel easily reflects the light to the camera. When running the inspection system, the reflection may in some cases affect the end results, especially when the light is reflected from the edges of a stud. Empirical results showed that this inspection system would define such studs incorrectly. Further, the slightest vibrations that alter the position of the camera during either of the image shots generate blurry edges in the resulting frame, therefore, inaccurate metrics are obtained. For industrial utilization purposes, the vision-system has to be placed in an isolated environment, i.e. place the camera in an isolated structure or design a motionless mount for the camera (gimbal), to allow the system to operate correctly and obtain results that can match the specifications of the industry standards. Otherwise, vibrations coming from the machine environment or other sources may affect the image pre-processing and alter the metric results.

Moreover, some limitations are encountered in some wall panel designs when dealing with multiple studs of different lengths, which may occur when complex panel components are used. The edges of the stud with lesser length would be initially detected, except the one in between both studs. As such, the detected geometry for the possible multiple stud is not rectangular. As the algorithm is optimized to deal with rectangular forms, the stud of lesser length would be treated as noise and therefore not detected. The results obtained for such panels from the frame inspection algorithm are often incorrect.

The proposed framework allows for fast inspection, identification, and location of frame components for steel frame assemblies within a few seconds on real and virtual scenarios. While the estimated functional features seem located in the correct position, future work could include an accuracy analysis comparing the obtained results to the actual system [196]. This study might give further insight on the practical industrial application and required precision of the functional features generated by the proposed system.

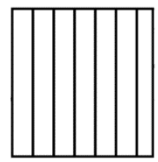
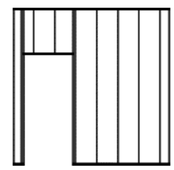
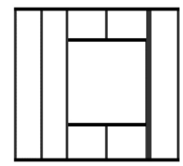
Whereas the applicability of such framework is necessary in completely autonomous systems, in semi-automated systems, where machine and operator work together, the cost-effectiveness of the proposed solution can be questioned. As of today, panelized construction is far from being a fully automated manufacturing process. Taking that into consideration, a cycle time analysis on the manufacturing process is performed and shown in Table 5.3. The duration shown for assembly, misplacement correction, and substitution delays were obtained empirically in the machine environment. A similar approach could be used for other framing machines to justify quality assessment procedures from a cost perspective.

5.3 Online Inspection System

5.3.1 Model Description

The purpose of this online inspection system is to validate the quality of the light-gauge steel frame during the screw-fastening operations in the steel framing machine prototype environment. The workflow of the proposed system commences with visual data acquired independently by different cameras. One camera is installed on each screw-fastening carriage, as illustrated in Figure 5.11.

Table 5.3: Cycle time analysis for quality assessment of steel frame assemblies manufacturing considering pre-inspection results.

Frame Design		**Case 1**	**Case 2**	**Case 3**
Shop Drawing				
Manufacturing Time [min:sec]	Manual Assembly	2:00	3:00	2:30
	Screw Fastening	1:03	1:48	1:39
	Total Time	3:03	4:48	4:09
Manufacturing Time + Inspection (no errors) [min:sec]		3:07 (+2.19%)	4:52 (+1.39%)	4:13 (+1.61%)
Manufacturing Time + Inspection (1 error) [min:sec]	Manual Misplacement Correction	3:40 (+20.22%)	5:25 (+12.85%)	4:46 (+14.86%)
	Manual Substitution	4:40 (+53.00%)	6.25 (+33.68%)	5:46 (+38.96%)

The online inspection system is integrated within the sequential screw-fastening logic and control of the machine. This system is triggered by each scheduled screw-fastening operation, as planned by the CAM (computer-aided manufacturing) software [196]. The images are then processed to obtain the relevant quality information regarding screw-fastening operations, estimating the squareness of the stud-track connection and the adequate location of the screw-fastening operation itself. If needed, corrective motions of the screw-fastening carriage are finally performed to ascertain quality during the operation.

The strategy presented does not require complex coordinate frame transformations because the distance and angle between the camera and the frame is fixed. Thus, the camera would capture the intersection area (as defined in the previous chapter) as

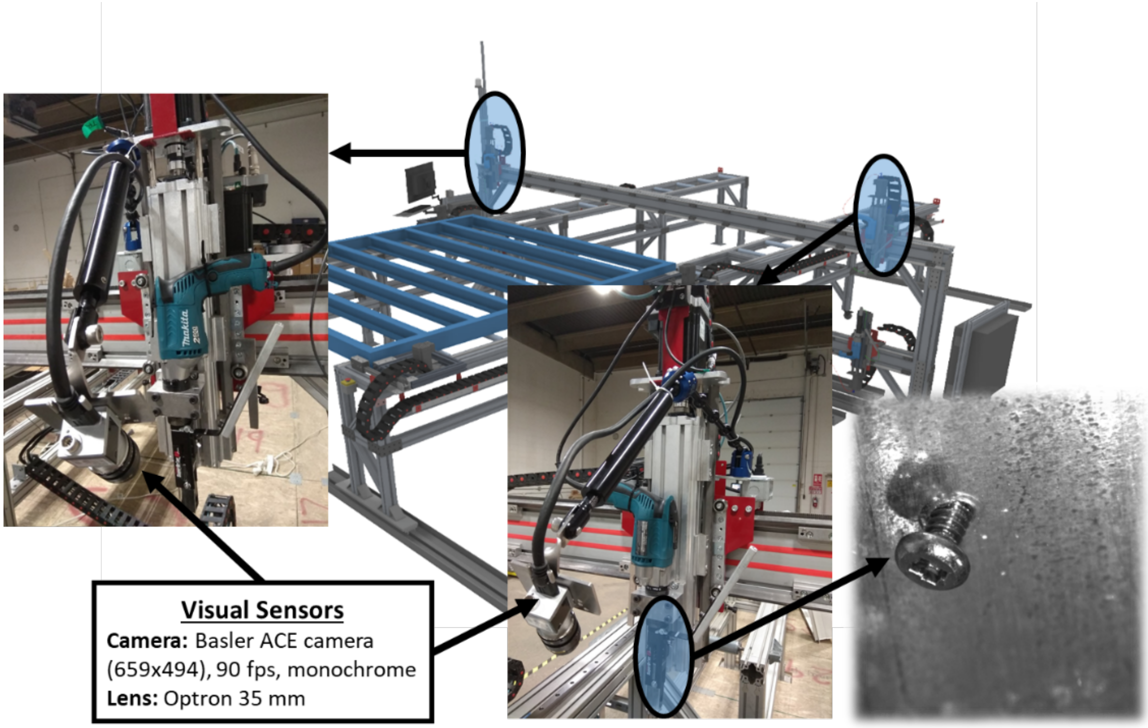


Figure 5.11: Overview of the location of visual sensors installed for online inspection of screw-fastening operations.

the panel gets processed. Using the pinhole model for the camera, the relationship between the global coordinates and the camera coordinates are shown below:

$$\mathbf{m} = \mathbf{A}[\mathbf{R}|\mathbf{t}]\mathbf{M}, \text{ with } \mathbf{A} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \tag{5.13}$$

where ($\mathbf{m}$) is the homogeneous 2-dimensional image projection and ($\mathbf{M}$) is the homogeneous 3-dimensional coordinates; ($\mathbf{A}$) is the camera intrinsic matrix with (u_0,v_0) being the coordinates of the principal point, (α) and (β) the scale factors in the image on the u and v axes respectively and (γ) the parameter describing the skew of both image axes; and ($\mathbf{R}$) and ($\mathbf{t}$) are the rotation and translation matrices respectively, called the extrinsic parameters of the system. The proposed model schematic is shown in Figure 5.12.

As such, with the proposed configuration, the extrinsic parameters are fixed. The matrix containing the rotation and translation transformations necessary for the

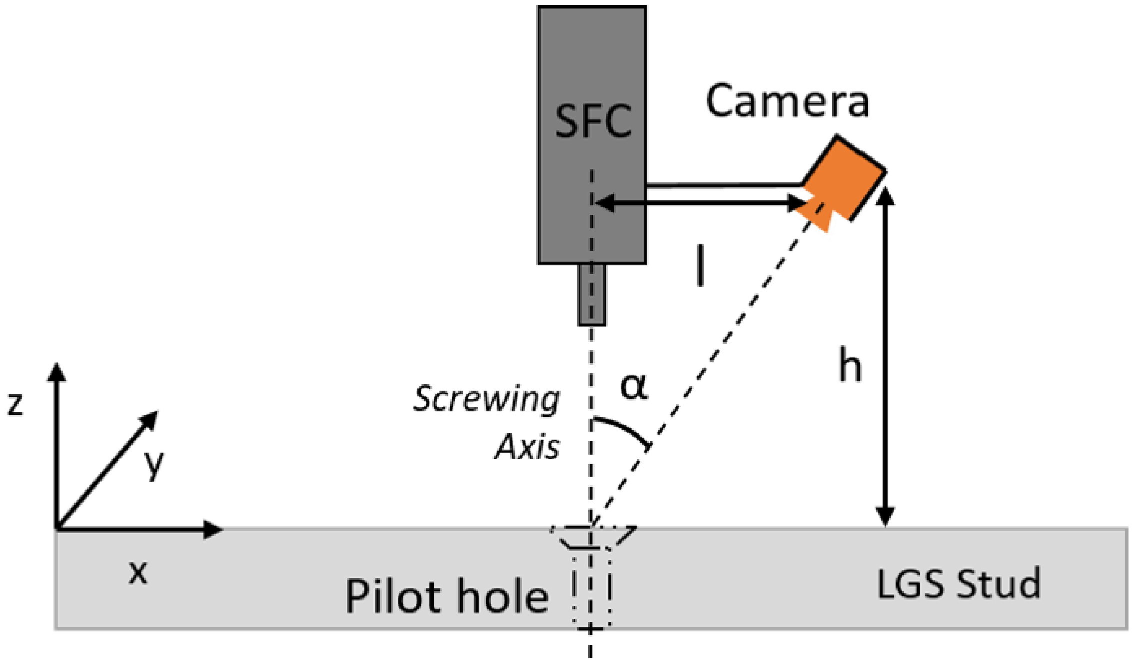


Figure 5.12: Proposed online inspection model schematic.

proposed model is given then by Equation 5.14. For the setup used in this study, $\alpha = 39.5°$, $h = 550$ millimeters, and $l = 350$ millimeters.

$$[\mathbf{R}|\mathbf{t}] = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 & l \\ \sin\alpha & \cos\alpha & 0 & 0 \\ 0 & 0 & 1 & h \end{bmatrix} \tag{5.14}$$

5.3.2 Squareness Estimation Algorithm

The approach proposed in the present research for estimating the squareness of a given frame component connection, i.e. stud-to-track connection, is based on the use of the Hough transform. Squareness in the context of the present research is defined as the angle between the steel components that are being connected through the screw-fastening operation. It should be noted that detecting exclusively the edges of the visible studs can be a challenging task, since the steel members used in light-gauge steel construction are highly reflective and often contain numerous superficial marks or dents. Hence, a large number of noisy edges are to be expected. In this context, the proposed algorithm to estimate the squareness of steel stud connections works in a sequential process that is described in detail below.

First, as this algorithm will be dealing with geometric calculations to estimate the squareness of the connection, standard camera calibration is required to mitigate the impact of lens distortion on the final measurements [193]. Next, a mask is created from the undistorted image using the automated threshold Canny edge detector [197]. This approach is widely known to be capable of optimizing the edge generation over relevant features of an image and of reducing background noise. Then, the Hough transform is applied to define the detected lines from the initial edges as a set of two parameters (ρ, θ), as stated in Equation 5.3 and illustrated in Figure 5.13.

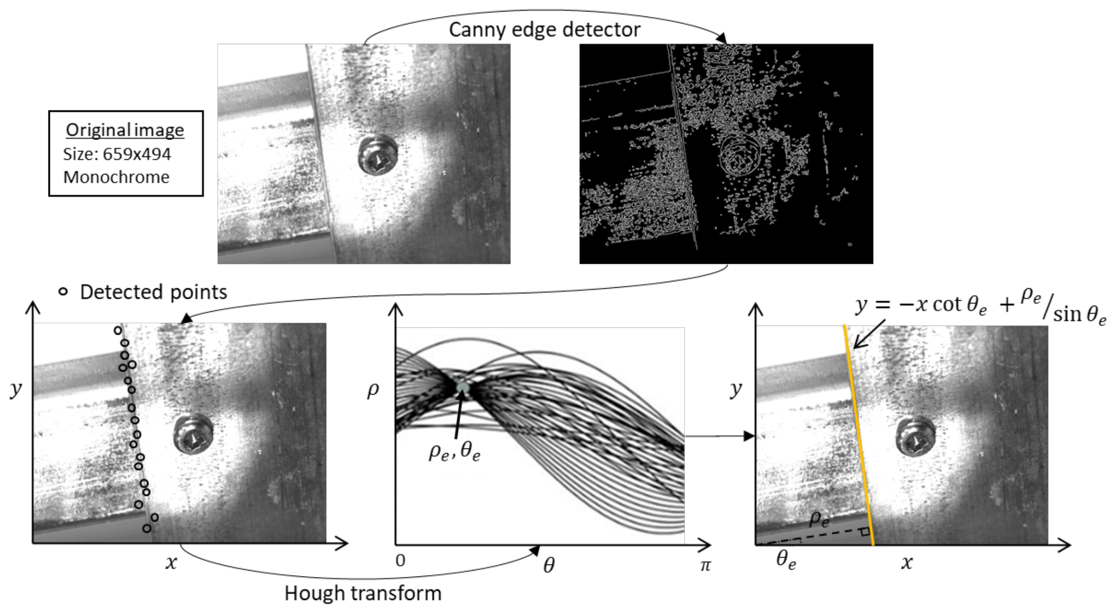


Figure 5.13: Example of the detection process of a line on a light-gauge steel track-stud connection.

This set represents then, as lines, the edges reflected by the Canny algorithm. The detected edges, however, must belong to a unique steel member. Thus, two unique clusters are generated using k-means clustering around the value of (θ) of each line to differentiate between the vertical and horizontal lines, (V_l) and (H_l), respectively. Each cluster then defines the steel member to which each subset of lines belongs. For example, vertical lines would belong to either tracks or headers in window components, and horizontal lines would belong to studs or bracings. Both subsets are complementary and are defined satisfying the system of equations presented in Equation 5.4.

Once both sets are defined, and assuming that none of them is an empty subset, the squareness is estimated to be the angle between the lines on each subset. Typically, both subsets contain a few lines, as the Hough transform generates several lines for each stud edge. In the present research, the squareness of the connection, ($\perp$), in the image, is estimated using Equation 5.15. However, it should be noted that a more complex statistical approach may yield better results if a larger number of lines are detected.

$$\perp = \left| \frac{1}{m} \sum_{i=1}^{m} \theta_h - \frac{1}{n} \sum_{i=1}^{n} \theta_v \right| \tag{5.15}$$

where (m) and (n) are the numbers of lines in the horizontal and vertical line clusters, respectively. An illustration of the squareness estimation result on a post-manufactured stud-track connection is shown in Figure 5.14.

The squareness algorithm results and further discussion on the performance of this proposed solution can be found in Section 5.4.

5.3.3 Screw Fastening Location Estimation Algorithm

The proposed screw fastening location estimation algorithm builds upon the initial steps of the squareness estimation algorithm aforementioned (see previous subsection). This decision is made solely to reduce computational time and optimize resource usage, which is really limited in real-time online systems. This algorithm starts by taking the result of the edge detector and cluster the edges in vertical and horizontal lines (see Equation 5.4). For this study, two scenarios are presented: either the steel frame components have been pre-drilled or not. Due to its ease of assembly, pre-drilled pilot holes are commonly used in industry, but it requires extra machinery and space that

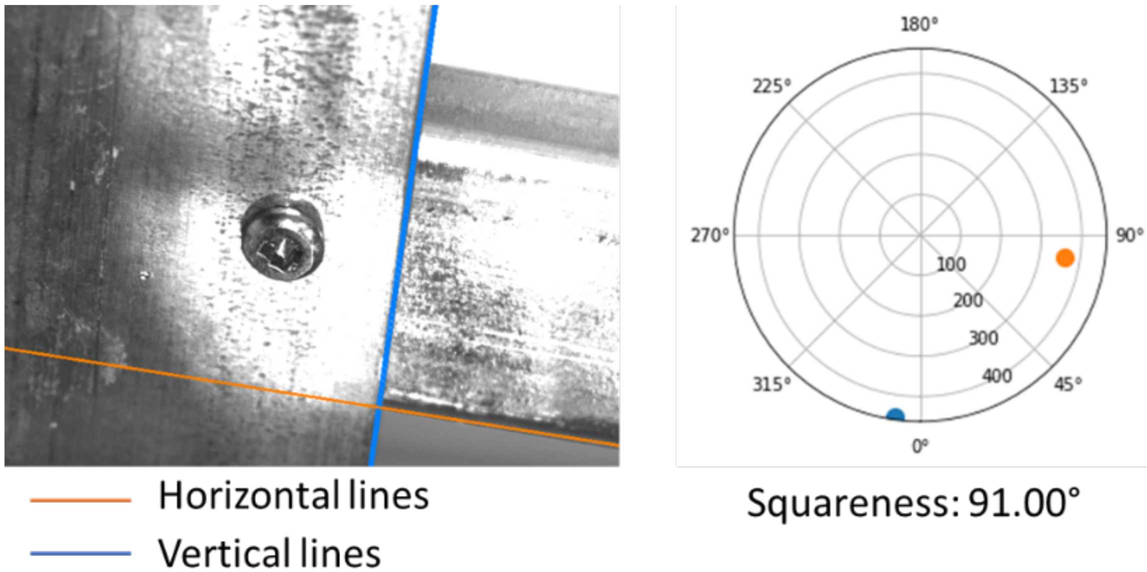


Figure 5.14: Example of squareness estimation results for a light-gauge steel track-stud connection.

is not always available. To support a flexible manufacturing process, the proposed inspection system will assure screw-fastening quality in both scenarios. Initially, the aim is to identify the pre-drilled pilot hole in the upcoming steel frame connection in the boundary area that contains the connection between steel members (or intersection area as defined in Section 5.2). An illustration of the boundary obtained by the detected edges can be found in Figure 5.15. In the case that no pilot hole is found by the aforementioned algorithm, the inspection system assumes that 'raw' steel is used for the inspected frame. The flowchart in Figure 5.16 showcases how the inspection system determines what are the appropriate algorithms to use in each case. This is key to obtain a real-time overall system performance.

Pre-drilled Pilot Hole Detection Algorithm

To detect the pilot hole, four steps are needed to process the image. Step (1): The image is first converted to gray-scale to reduce its memory allocation, thus reducing computational requirements, and then the well-known Canny edge detector is applied. Step (2): Relevant contours are then defined from the resulting binary image as Suzuki

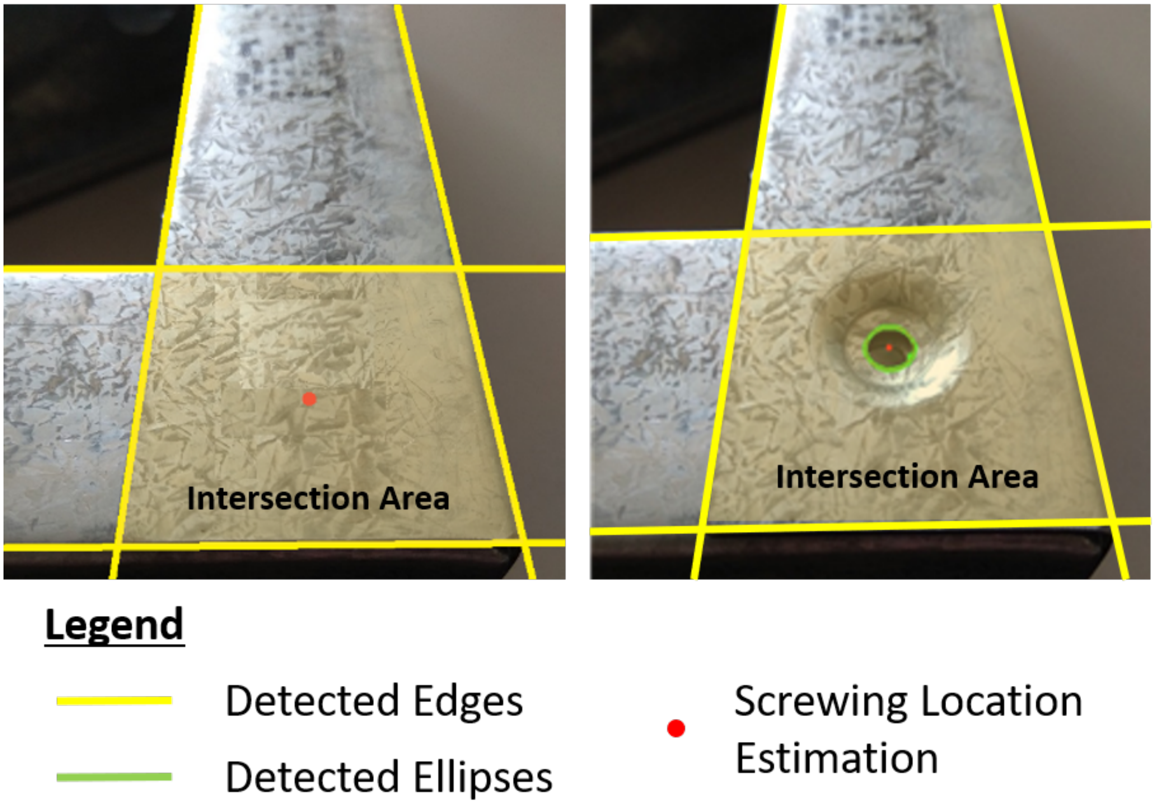


Figure 5.15: Example of online inspection results on screw fastening of light-gauge steel components. Left: 'raw' steel. Right: pre-drilled studs.

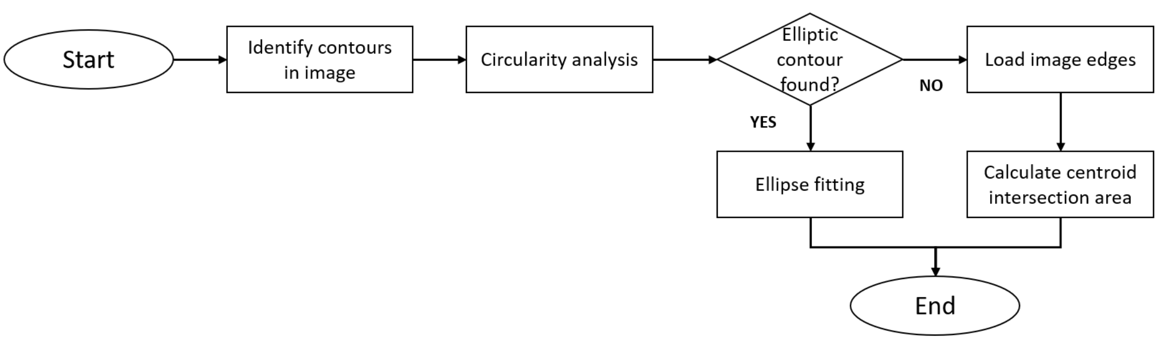


Figure 5.16: Online inspection procedure flowchart.

and Abe described on their first algorithm [198]. As the order of magnitude of the pilot hole is well known, this step allows for the reduction of most of the unwanted edges obtained by the Canny edge detector, which can be quite numerous as shown in Figure 5.17, by restricting the area of each contour to avoid detecting contours that are too large or too small. Step (3): The detected contours are checked for a "circular" shape. The circularity of a contour, (ϕ), is defined in Equation 5.16.

$$\phi = \frac{P_c^2}{4\pi A_c} \tag{5.16}$$

where (P_c) and (A_c) are the perimeter and the area of a contour respectively. The contour will be considered elliptical enough for this problem if the value of the circularity of a contour is between 0.8 and 1.2. Step (4): For the remaining contours, an ellipse fitting algorithm is used to define the center of the pilot hole that will be noted $[u, v]^T$. The ellipse is defined using the algebraic distance with quadratic constraint algorithm (B2AC) [25]. For a family of curves ($C(\mathbf{a})$), the algorithm searches the value of ($\mathbf{a}$) that minimizes the error function shown in Equation 5.17.

$$\epsilon^2 = \sum_{i=1}^{n} \delta(C(\mathbf{a}, \mathbf{x}) \tag{5.17}$$

where $\delta(C(\mathbf{a}, \mathbf{x}))$ represents the distance metric from a point ($\mathbf{x}$) of the contour to the curve. An example of the results obtained at each step can be found in Figure 5.17.

To prove its efficiency and accuracy, our method is compared against three methods for fast ellipse detection, namely the methods of Xie and Ji [199], its randomized version of Basca et al. [200], and the most recent algorithm of Fornacieri et al. [201]. These methods have been selected due to their diffusion, declared efficiency, and availability of source code. Since some methods do not provide a pre-processing step, to guarantee the fairness of the comparison, all methods start from the same edge mask. All the methods have been tested on the same dimpled LGS panel with 6 studs. The results of the visual detection of the pre-drilled pilot holes on the panel are depicted in Table 5.4 for each different method in terms of accuracy and computational time. Computational time is the average elapsed time over 10 runs with 1000 loops each and has been computed on a PC with 16 GB of RAM and an Intel Core i7-6700 processor. The measurement error is the average absolute value of the error between

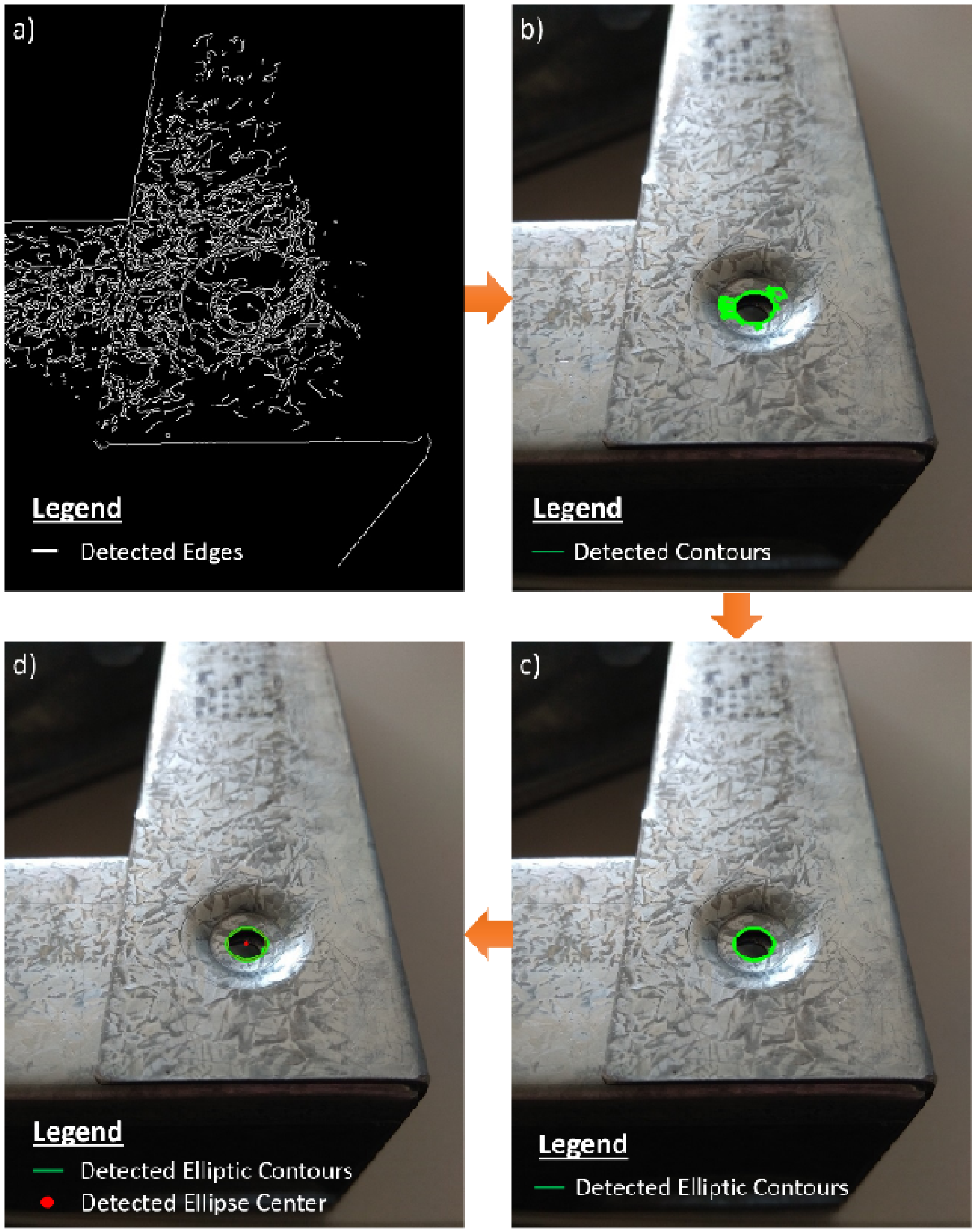


Figure 5.17: Results obtained for pre-drilled pilot hole detection in a dimpled LGS stud: (a) edge detection; (b) filtered contour detection; (c) 'circular' contour detection; and (d) ellipse fitting and screwing point estimation.

the real center and the estimated center of the pilot hole. The real center is measured with a mechanical caliber (0.02 mm precision). For each measurement, Figure 5.18 shows the accuracy box-plots per visual detection method.

Table 5.4: Accuracy and computational time results for the detection of pre-drilled pilot holes.

Method	Computational Time (mean ± std.dev.)	Average Measurement Error
Proposed Method	286.64 ± 42.39 ms	3.14 mm
Xie and Ji [199]	395612.87 ± 41632.27 ms	1.68 mm
Basca et al. [200]	32684.97 ± 8463.02 ms	25.38 mm
Fornacieri et al. [201]	71.21 ± 12.37 ms	7.36 mm

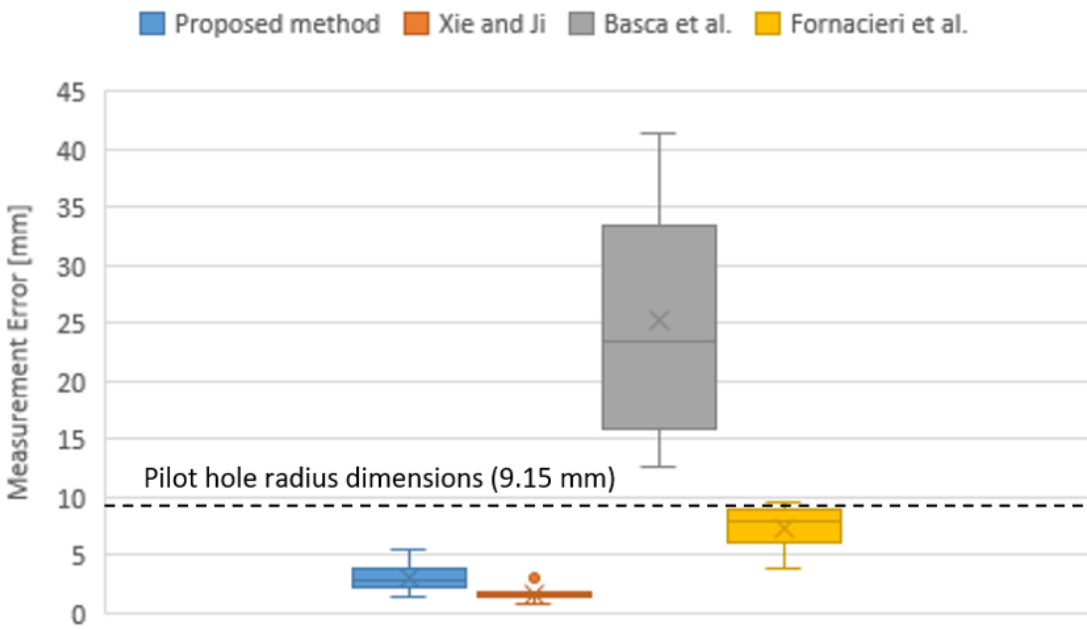


Figure 5.18: Accuracy box plot results per visual detection methodology.

As expected, the exhaustive search method of Xie and Ji guarantees good average accuracy at the cost of a very high computational time. Its randomized version (Basca et al.) is much faster but loses in accuracy. The point selection optimization in Fornacieri et al. method gives a considerably faster computational time but sacrifices some accuracy. Our method is computationally more demanding than the previous one but offers a slightly better accuracy.

Due to the problem constraints, the algorithm for pilot hole detection should be running in real-time and accurately determine the screwing location within the pilot hole diameter. From a computational perspective, a real-time operation is considered when no significant delay on the overall performance of the system is introduced. In this case, the deadline is set around one second. As a result, both Fornacieri's algorithm and our proposed method proved that they can perform under real-time constraints. From an accuracy perspective, only Basca et al. does not meet the minimum requirements of detecting the pilot hole center within the pilot hole dimensions. Such minimum requirements are necessary to ensure that the ellipse detection algorithm is accurate enough to define the screwing operation within the boundary of the pre-drilled pilot hole. When all things are considered, either our method or Fornacieri's method can be used for real-time detection of pre-drilled pilot holes.

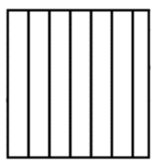
Centroid Estimation

For 'raw' steel assemblies, the correct location for the screw fastener is defined as the center of the area in which the track and stud steel members overlap. Considering the computational effort made during the squareness algorithm to determine the edges of the studs, this algorithm uses the already available information to ease the calculations, and reduce computational time. From the already clustered edge lines detected, an intersection area can be built as it was defined in the pre-inspection system (see Section 5.2). As such, the coordinates of the centroid of the intersection area are estimated following Equation 5.18.

$$\forall (x,y) \in N_{area}, \begin{cases} X_V = \frac{1}{4}\sum_{i=1}^{4} x_i \\ Y_V = \frac{1}{4}\sum_{i=1}^{4} y_i \end{cases} \tag{5.18}$$

To validate the proposed approach, a single light-gauge frame is manufactured whilst the inspection system is running. Images are collected and the screw fastening location for each stud-track connection is estimated using Equation 5.18. Table 5.5 summarizes the results obtained using the inspection system. Computational time is the average elapsed time over 10 runs with 1000 loops each and has been computed on a PC with 16 GB of RAM and an Intel Core i7-6700 processor. The measurement error is the average absolute value of the error between the real location and the estimated centroid of the intersection area. The real location is measured with a mechanical caliber (0.02 mm precision).

Table 5.5: Accuracy and computational time results for the location estimation of screw fastening operations with 'raw' steel.

Frame Design	**Computational Time per Operation** (mean ± std.dev.)	**Average Measurement Error**
	115.37 ± 25.17 ms	3.44 mm

In the case of 'raw' steel, no standard or specification determines the correct location for the screw fastening operation. As such, to determine if the proposed algorithm is accurate enough to perform such operations safely and providing good quality, certain geometric restrictions are proposed: the screw fastening location should occur at a certain distance from the edges of the track and the stud to maintain the connection strength and structural integrity. For this study, the correct location for screw fastening operations considers a 10% safety factor as is illustrated in Figure 5.19.

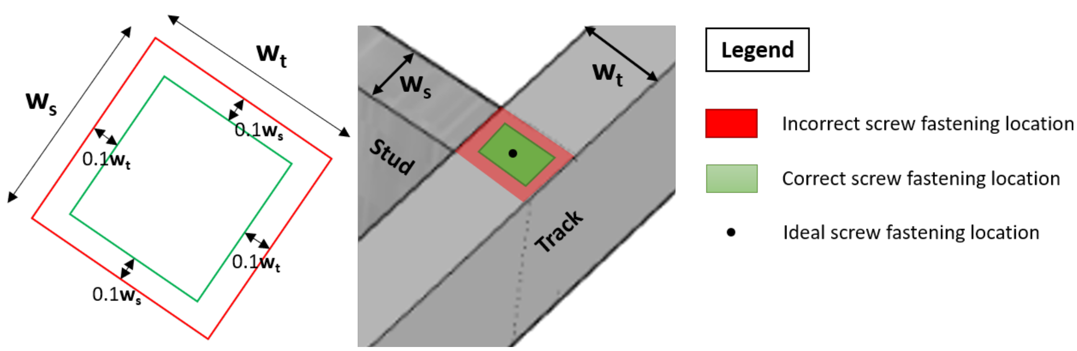


Figure 5.19: Illustration of geometrical restrictions on screw fastening locations for steel stud-track connections.

Taking the smaller web sizes for studs, $\min(w_s) = 2' - 1/2" = 63.5$ mm (250S), and tracks, $\min(w_t) = 3' - 1/2" = 88.9$ mm (350T), the minimum precision for a conforming screw fastening operation is 25.4 mm and 35.56 mm respectively. As such, the average measurement error for the estimated location is sufficient to ensure safe and conforming screw fastening operations.

5.3.4 Adaptive Screw Fastening Operations

From the initial set of coordinates obtained from the CAD shop drawings, the correction approach aims to address possible errors in the position of the screw manipulator. For each screw fastening operation, three sets of coordinates are available: the original position set by the CAD model, $[X_{CAD}, Y_{CAD}]$, one set obtained from the proposed inspection, $[X_V, Y_V]$, and one set obtained from the motor encoders in the dragging squares and screw fastening carriage respectively, $[X_F, Y_F]$, that represent the real-time position of the screw manipulator relative to the position of the steel frame. Assuming the minimum performance necessary of the vision-based algorithm discussed in the previous subsection, the screw manipulator needs to be aligned with the estimated location to ensure a safe and accurate screw operation. The screw fastening operation, under these circumstances, needs to always satisfy Equation 5.19, where (d) is the maximum error admissible for the operation. For steel frames with pre-drilled pilot holes, (d) is given by the diameter of the pilot hole, otherwise, the screw fastening operation may miss the pilot hole, hit the steel stud, and possibly cause damage to the frame and the screw manipulator.

$$(X_V - X_F)^2 + (Y_V - Y_F)^2 \leq \frac{d^2}{4} \tag{5.19}$$

Currently, the initial step for any screw fastening operation is to set the position of the screw manipulator satisfying $X_F = X_{CAD}$ and $Y_F = Y_{CAD}$. Then, machine vision gives its estimate on the real position. If Equation 5.19 is not satisfied, then motors engage on an extra corrective motion until $X_F = X_V$ and $Y_F = Y_V$. Finally, the algorithm runs again to check if the corrected position satisfies Equation 5.19. If that is not the case, the correction approach would restart with the most recent results of the machine vision algorithm. A flowchart representing the corrective approach steps can be found in Figure 5.20.

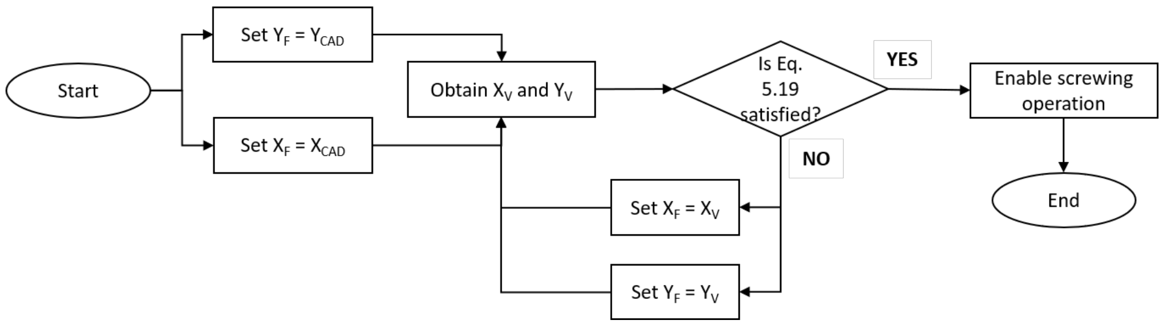


Figure 5.20: Complete screwing operation procedure flowchart.

5.4 Post-Manufacturing Inspection System

This section aims to provide insight of the proposed solution for post-manufacturing inspection of light-gauge steel frame assemblies, that is, after the screw fastening operation has occurred. For this system, a visual approach is used following the model presented in Section 5.3. Two main metrics are automatically determined using the algorithms presented in this section: (1) final squareness of the steel connection; and, (2) quality assessment of the screw fastening operation. The first algorithm is already presented in Section 5.3, as squareness estimation is required before and after the screw fastening operation. Nonetheless, this section provides the analysis and discussion over the use of the proposed squareness algorithm in a real scenario.

5.4.1 Automatic Screw Fastening Quality Assessment

Optical inspection is vital to ensuring that manufactured end-products satisfy the given specifications, and, in the case of manufactured construction components, are safe to use. While intensive industrial defect detection methods, such as feature selection, can provide comprehensive results, such solutions remain limited to the characteristics and features of the final product. Thus, if a new feature is introduced in the product, for example a change in the self-driving screw fastener, a new set of problems may arise [202]. In contrast to manually engineered image processing solutions, supervised learning approaches such as deep learning techniques may be used to overcome the inherent limitations of the practice of manually redefining features for each new inspection problem in a reactive manner.

The present study investigates the use of a Region-based Convolutional Neural Network (R-CNN) [203] to provide automatic inspection of screw-fastening operations. By taking images and object proposals from select searches as inputs, R-CNNs use convolutional neural networks (CNNs) to extract features, and then locate and classify objects based on the initial search parameters. This approach significantly improves the accuracy of object detection in comparison to previous CNN-based methods, such as sliding windows. The proposed approach has been previously used, for example, to detect surface defects on steel and concrete structures, i.e., corrosion or cracks [204]. The following paragraphs describe in detail the data-set used to train the R-CNN, its architecture, and the training/validation results.

First, to develop a database containing results of screw-fastening operations in light-gauge steel members, 239 images (with a resolution of 659×454 pixels) are collected using the system defined in Figure 5.11. Images are captured for different steel members and lighting conditions. To annotate the labels of the inspection results and the coordinates of their corresponding bounding boxes in images, the software environment, MATLAB, is used to manually specify them. During the annotation process, each image is assigned a single label. Two labels are used to determine the conformity of the screw-fastening operation. Labeling is determined, it should be noted, based on the need for rework after the operation is finished, as stated in the Canadian specifications for the design of cold-formed steel structural members (CSA S136-07/S1-10). For example, if the screw is loose enough to require tightening, or if the screw is missing or tilted, the operation fails the quality inspection and is assumed to be non-conforming. If no need for rework is identified, the screw-fastening operation requires no further action and is considered acceptable. Given that the images are obtained using an automatic screw manipulator, the data-set is initially biased towards ‘conforming screw-fastening operations. In fact, of the 239 images obtained, only 21 images show screw-fastening operations that would require rework in order to be considered acceptable. Therefore, data augmentation techniques are applied to generate more images of poor screw-fastening operations in order to balance the data-set. In this case, horizontal flipping and random rotation are used to generate new images. Finally, the augmented data-set contains 228 and 160 images of correct and failed screw-fastening operations, respectively. An example of images from the data-set is shown in Figure 5.21.

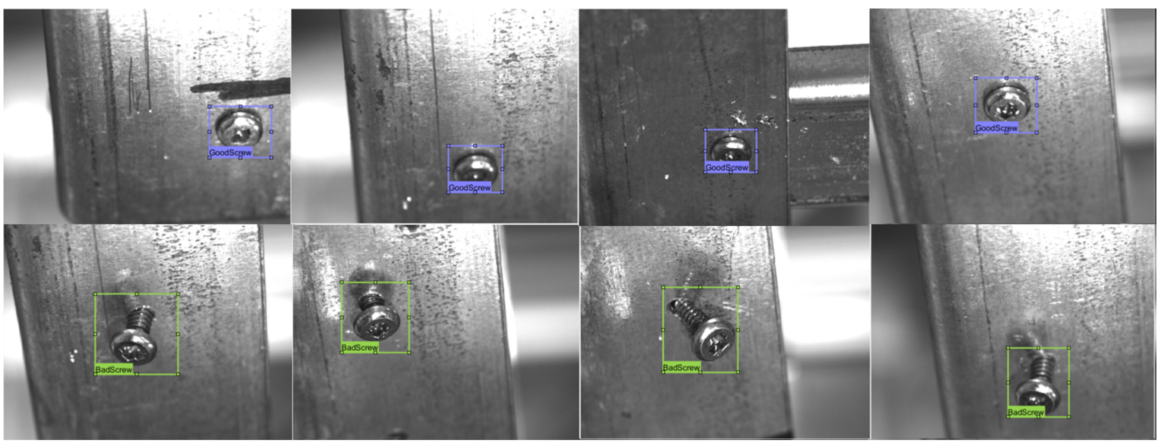


Figure 5.21: Sample images with corresponding bounding boxes and labels.

Figure 5.22 presents the R-CNN architecture used in this study for screw detection and classification. The R-CNN designed for use in this study is based on the pre-trained ResNet-50 [205]. (Transfer learning, it should be noted, has proven to be effective in reducing training time and computational demand and in providing accurate results, even with small data-sets [206].) By skipping connections within the network, ResNet enhances the detection of smaller objects in images, such as the screws for this study. To adapt it to the context of this study, the last three layers of the ResNet-50 are substituted by a fully connected layer, a SoftMax layer, and a classification layer, themselves connected by average pooling. These layers are retrained for the purpose of screw detection and classification.

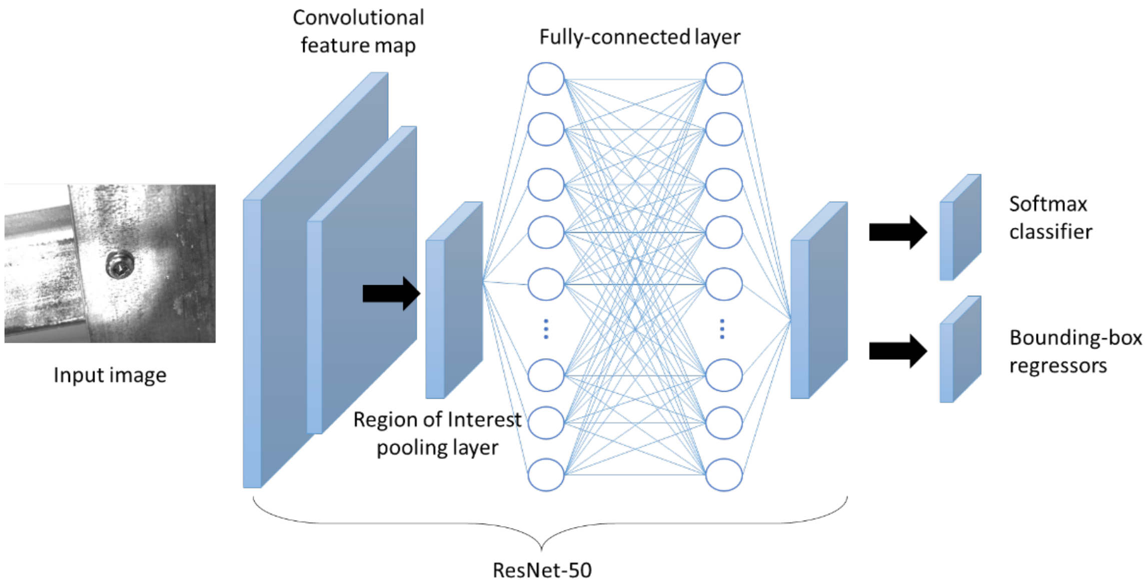


Figure 5.22: The schematic architecture of the R-CNN used.

To generate a training and validation data-set, images are randomly selected from the labeled images such that each of the two label types—correct and failed screw-fastening operations—represent at least 30% of the images contained in the validation set. The remaining images not selected are used for training the R-CNN. Both training and validation are performed using the open-source R-CNN library available within MATLAB2019b. The neural network is trained using stochastic gradient descent, with a momentum of 0.9, an initial learning rate of 10^{-4}, and a batch size of 32. The accuracy and loss function during both training and validation are recorded, as presented in Figure 5.23. After approximately 10 epochs, the accuracy of the network reaches over 93% for both the training and validation data.

5.4.2 Results and Discussion

This section aims to validate the proposed system in a real scenario. First, the experimental setup is explicitly defined. Then, the results obtained from the inspection system are presented. Finally, the results and limitations of the system are discussed

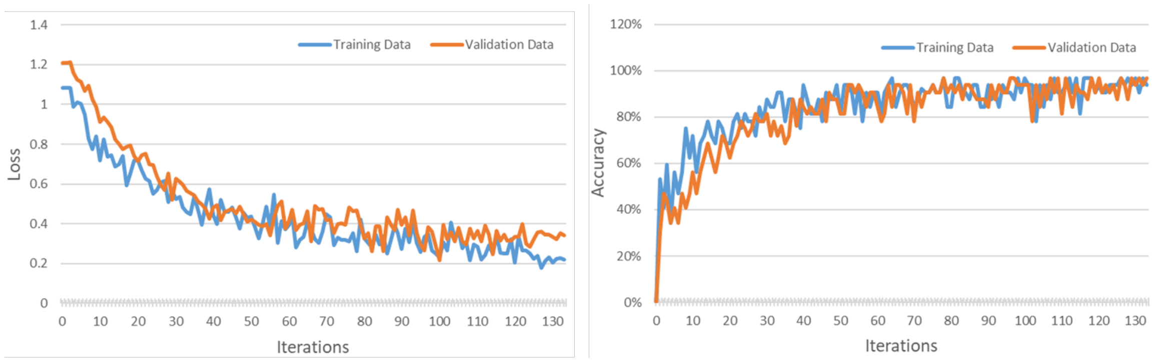


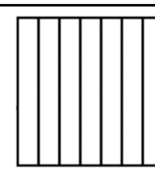
Figure 5.23: Training and validation results.

in depth.

Experimental Setup

To test the trained inspection systems, an experiment is set up to provide results in a machine environment. The purpose of this experiment is to ensure the accuracy of the proposed systems, as well as the real-time performance of the inspection systems. A panel frame is prepared to be used as a case study for this experiment. The relevant information pertaining to the panel can be found in Table 5.6.

Table 5.6: Summary of panel information.

Frame Design		
Frame Dimensions (mm) *Width(z) = 92		Length(x) = 2448 Height(y) = 2439
Stud Quantity		10
Screw-Fastening Operations	Left	8
	Right	8
	Total	16

To obtain relevant data for each possible scenario that the inspection systems can encounter, the frame is manually assembled three times: (1) automatically fastened correctly; (2) manually fastened incorrectly, and (3) not fastened at all. Scenarios 1 and 2 are needed in order to test the recall (true positives and false negatives), while scenario 3 determines the algorithm's specificity (false positives and true negatives). For each assembly, all the steel connections are inspected. An example of the same connection for each of the scenarios is presented in Figure 10.

Scenario 1 Scenario 2 Scenario 3

Figure 5.24: Sample of testing data (images) for each scenario on the same panel location.

Each scenario is tested using the same inspection process and the steel framing machine prototype. For each connection, squareness is estimated before and after the screw-fastening operation to check the impact on squareness, and each screw-fastening connection is inspected individually. For the designed panel (see Table 5.6), the inspection system performs 32 squareness inspections and 16 screw-fastening inspections per scenario, except for scenario 3 where the second round of squareness inspection is ignored as there is no screw-fastening operation being executed. A total of 80 squareness inspections and 48 screw-fastening inspections are performed to test the performance of the algorithms presented.

Real-time Performance

The time performance of both algorithms is discussed in this subsection. Using an Intel Core i7-6700 CPU with 16 GB RAM, the time performance results are presented in Table 5.7. From a computational perspective, both algorithms should be running in real-time to avoid unnecessary delays to production. However, the manufacturing process does need to pause for the inspection system to capture the appropriate image of the connection before and after the screw-fastening operation. Once the image is captured, the framing process can proceed and the image processing presented in this study can be carried out in parallel. Nonetheless, the authors consider that, by the time the frame is finished, the inspection results of the whole panel should be available, so the quality control process is accelerated, thereby avoiding unnecessary delays to the downstream manufacturing processes.

Table 5.7: Time performance for both algorithms in the post-manufacturing inspection system.

	Squareness Estimation	**Screw-fastening Detection & Quality Assessment**
Time Performance (mean ± std. dev. of 7 runs, 100 loops each)	0.72 ± 14.4 ms	4.87 ± 68.4 ms

For the steel framing machine prototype, in the current process for light-gauge steel framing, a synchronous double screw-fastening operation occurs every 20 to 25 seconds (depending on the distance between operations). Within that time frame, four squareness estimations and two screw-fastening detections are performed, requiring a computational time of approximately 12 seconds. Therefore, the time performance of both algorithms is sufficient for them to be run in real-time systems, and no delays are introduced by implementing the inspection system proposed. It should be noted that, in the present study, both algorithms are CPU-powered, and improved performance can be expected by enabling and optimizing GPU, especially for the R-CNN detection.

Squareness Estimation Results

The results obtained for each scenario using the squareness estimation algorithm are presented in Tables 5.8, 5.9, and 5.10. The ground truth ('real') results are obtained, by manual measurement, seconds before and after the screw-fastening operation (SFO) occurs without any further motion from the machine or changes to the frame. The measurements are obtained using a protractor with 0.1 degrees of accuracy, assuming that no deviation occurs on the steel member in close proximity to the connection of concern.

Table 5.8: List of the results obtained in Scenario 1 by the squareness estimation algorithm on the studied panel.

No. SFO	**Before SFO [deg]**			**After SFO [deg]**		
	Real	Estimation	Error	Real	Estimation	Error
1	92.3	91.61	-0.69	91.1	93.17	2.07
2	95.1	96.28	1.18	94.5	96.92	2.42
3	97.3	98.49	1.19	95.3	94.79	-0.51
4	88.9	89.61	0.71	84.5	82.10	-2.40
5	88.2	88.05	-0.15	87.1	86.56	-0.54
6	90.7	89.74	-0.96	86.0	85.90	-0.10
7	84.9	88.64	3.74	82.3	81.45	-0.85
8	90.3	91.55	1.25	88.0	86.72	-1.28
9	96.1	97.55	1.45	93.5	91.70	-1.80
10	86.1	85.33	-0.77	85.1	86.96	1.86
11	88.5	88.47	-0.03	88.6	89.81	1.21
12	90.9	90.27	-0.63	92.3	92.25	-0.05
13	85.7	84.32	-1.38	85.2	84.29	-0.91
14	94.0	93.37	-0.63	92.8	94.75	1.95
15	95.7	96.98	1.28	98.7	97.65	-1.05
16	88.2	86.95	1.25	90.4	92.36	1.96

Based on the squareness results obtained, the performance of the algorithm can be statistically analyzed. Table 5.11 shows the performance analysis of the algorithm for each of the scenarios. For all the scenarios, the mean error, variance, and root mean square error (RMSE) are calculated. As observed, the algorithm can estimate the squareness of a light-gauge steel member connection with a margin of error of less than two degrees.

Table 5.9: List of the results obtained in Scenario 2 by the squareness estimation algorithm on the studied panel.

No. SFO	**Before SFO [deg]**			**After SFO [deg]**		
	Real	Estimation	Error	Real	Estimation	Error
1	89.0	87.80	-1.20	94.2	92.33	-1.87
2	97.4	98.73	1.33	87.4	88.89	1.49
3	95.4	94.67	-0.73	84.2	86.94	2.74
4	99.7	95.83	-3.87	85.7	83.62	-2.08
5	88.2	88.63	0.43	88.1	85.07	-3.03
6	82.1	81.58	0.52	85.2	87.06	1.86
7	87.7	89.54	1.84	89.2	86.36	2.84
8	84.2	86.96	2.76	91.8	93.66	1.86
9	86.8	89.59	2.79	87.6	89.73	2.13
10	90.4	92.37	1.97	96.6	93.29	-3.31
11	87.4	90.92	3.52	87.7	88.61	0.91
12	93.4	91.34	-2.06	83.2	84.29	1.09
13	86.6	86.09	-0.54	83.3	85.41	2.11
14	85.6	85.52	-0.08	92.6	91.87	-0.73
15	88.2	86.87	-1.33	87.0	90.45	-3.45
16	96.9	95.20	-1.70	96.6	98.74	2.14

Screw Fastening Quality Assessment Results

The results of the screw-fastening inspections on the test data-set are recorded in Table 5.12. The confusion matrix provided below shows the prediction results of the R-CNN against the actual label of the image. Although the R-CNN is trained as a 2-class output network, the third class in the matrix showcases the images obtained from scenario 3 (missing screws).

As observed, the inspection algorithm proposed for quantifying the quality of screw-fastening operations has an overall accuracy of 91.67%. For each class, *correct SFO* detection has a precision of 100%, a recall of 93.75%, and a specificity of 100%; *failed SFO* detection has a precision of 80%, a recall of 100%, and a specificity of 87.5%;

Table 5.10: List of the results obtained in Scenario 3 by the squareness estimation algorithm on the studied panel.

No. SFO	**Before SFO [deg]**		
	Real	Estimation	Error
1	92.5	93.98	1.48
2	86.7	85.82	-0.88
3	91.6	87.45	-4.15
4	94.4	94.69	0.29
5	86.8	82.18	-4.62
6	86.1	88.14	2.04
7	91.4	89.07	-2.33
8	84.8	84.76	-0.04
9	89.7	88.72	-1.18
10	85.3	81.28	-4.02
11	88.8	88.13	-0.77
12	96.8	93.28	-3.52
13	94.0	94.74	0.74
14	94.6	97.27	2.67
15	90.1	90.42	0.32
16	90.8	89.72	-1.08

Table 5.11: Performance statistics of the squareness estimation algorithm.

Case		**Mean Error [deg]**	**Variance [deg^2]**	**RMSE [deg]**
Scenario 1	**Before SFO**	1.08	0.678	1.345
	After SFO	1.44	1.072	1.772
Scenario 2	**Before SFO**	1.66	1.285	1.990
	After SFO	2.10	0.6635	2.246
Scenario 3		1.86	2.298	2.372
Overall Performance		1.63	1.28	1.98

and missing screw detection (*no SFO*) has a precision of 100%, a recall of 81.25%, and a specificity of 100%. The results of the screw-fastening inspection on the test

Table 5.12: Confusion matrix for screw-fastening inspection test data.

	n = 48	**Predicted Class**		
		Correct SFO	Failed SFO	No SFO
Actual Class	Correct SFO	15	1	0
	Failed SFO	0	16	0
	No SFO	0	3	13

data shown in Figure 5.24 are illustrated in Figure 5.25.

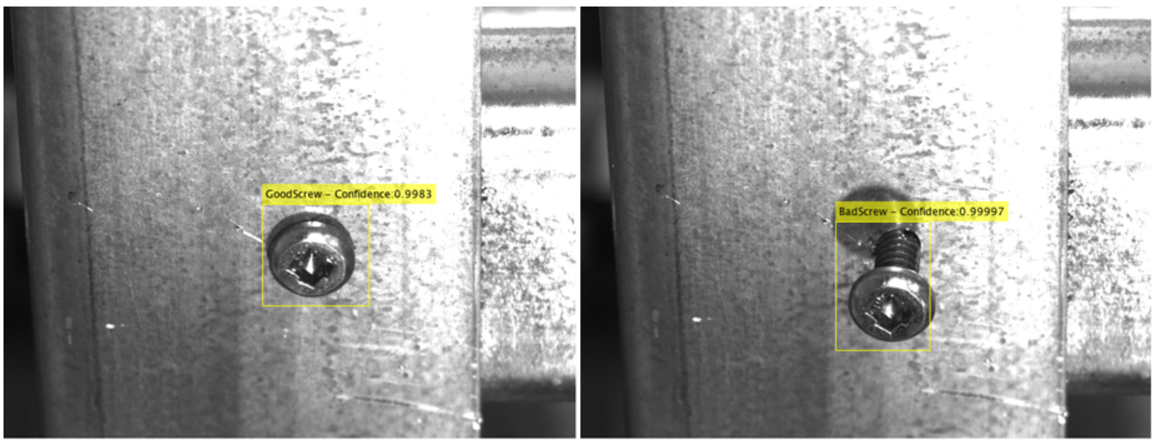


Figure 5.25: Example of correct screw-fastening inspection results in images from the testing data-set.

Given the importance of quality control in production lines, it is paramount to minimize the number of false positives of conforming procedures to avoid unexpected quality issues in subsequent processes. In the proposed inspection system, the precision and specificity of the 'good' SFO are maximized for this purpose. Although the screw-fastening inspection outputs satisfactory results, the confusion matrix is built on a small data-set, and the performance metrics need to be understood with this in mind. The inspection system will need to be installed in a continuous production line where its performance can be monitored throughout a large number of light-gauge steel connections.

To summarize, the proposed online inspection system generates quality-oriented data accurately during the process of manufacturing light-gauge steel frame assemblies.

The proposed system is able to assess, in real-time, the quality of the screw-fastening operations and the final quality of the light-gauge steel panel, one stud at a time. By the time the panel has been fully assembled, the results of the inspection process and final quality assessment are available. However, some limitations are encountered in the present study, as the proposed system does not address the real-time effect of the inspection results during the manufacturing process. As an example, if a screw-fastening operation has been flagged as incorrect due to the screw being missed, the corrective action would be to repeat the screw-fastening operation by overriding the current order of operations, rather than relying on the operator to manually correct the detected deficiencies in the frame. However, such an approach requires a deeper integration of the visual sensors into the machine environment and significant modifications to the machine logic. A similar situation could be flagged if a non-conforming screw fastening operation is detected, but the changes to machinery so that automatic actions may address the issue are beyond the scope of this thesis. In the future, such undertakings will be pursued.

Chapter 6

Cyber-Physical System for Quality Control & Assessment of Steel Frame Assemblies

6.1 Overview

This section defines in detail each one of the levels in the 5C architecture of CPS for the purpose of automated quality control of steel frame assemblies manufacturing. Starting from the lowest level, the following subsections illustrate the hardware and software elements, the data acquired or used and its potential use cases for the proposed case study, and the interactions between the cyber and physical world on each level. Standard 5C architecture defines the interaction between the physical and digital worlds at the lowest and highest levels. However, considering the purpose of this CPS, providing feedback information in extra layers increases its effectiveness. For example, introducing an interaction at the data conversion level enables providing real-time feedback to the manufacturing system, or both higher levels may exchange information to adhere to user input and supervise quality control operations.

Figure 6.1 illustrates the proposed extended interactions between the CPS architecture and the physical world. The system presented is centered around a machine or production line (manufacturing system), from its input materials all the way to the end product. Starting at the *Smart Connection Level*, raw visual data is acquired at

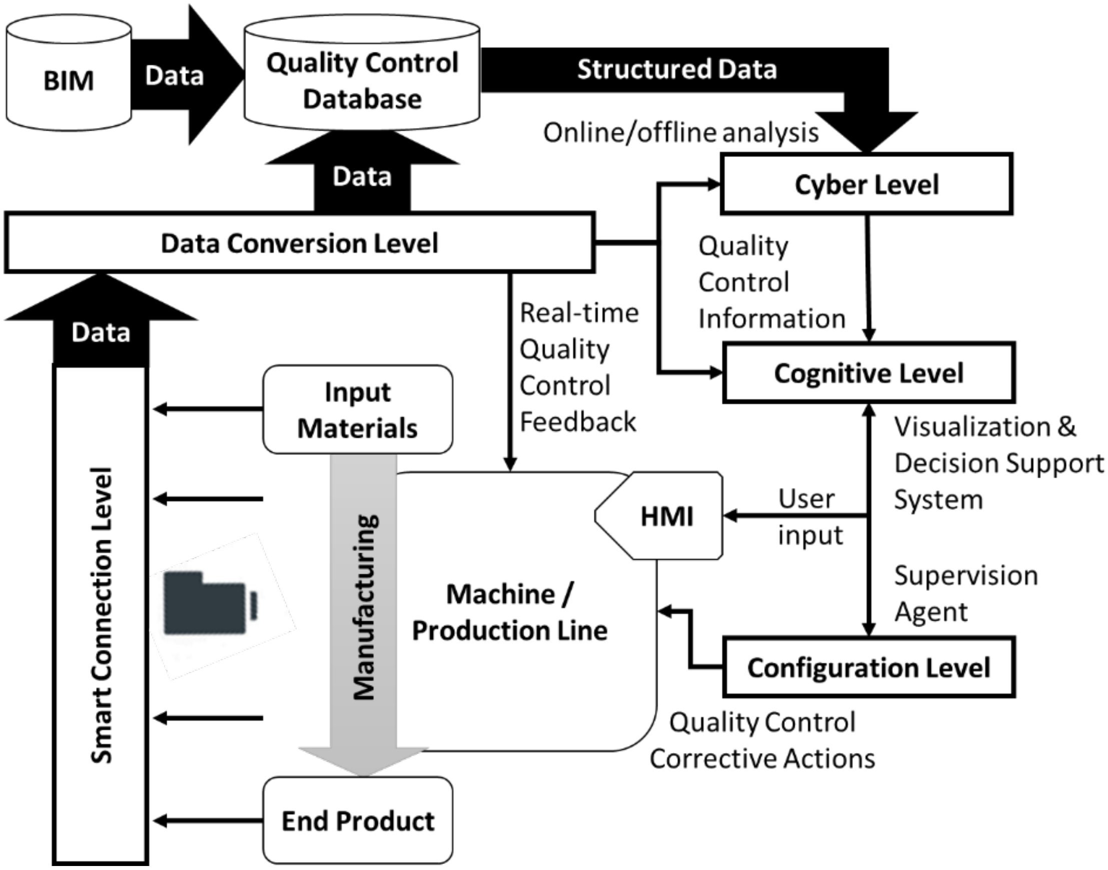


Figure 6.1: CPS integration within a BIM-based manufacturing process.

the precise moments in which the construction product, in this case an light-gauge steel frame, enters the machine environment or undergoes an irreversible (within the same machine environment) manufacturing process. Such data is then sent to the *Data Conversion Level* to be processed by several machine vision algorithms to extract the relevant quality-oriented information. Such information may be used, then, to provide real-time quality feedback to the machine operator. All the data is stored then in a database, along with necessary BIM data. The *Cyber Level* provides offline analysis of the structured data, with potential online applications. Then, inspection results are visualized in the *Cognitive Level* through the human-machine interface, that enables human intervention in the quality control process while the inspection results support decision making regarding the conformity of construction products. Finally, the *Configuration Level* outputs corrective actions and supervises the inspection results based on operator feedback.

6.2 Case Study: Steel Framing Machine

Recently, responding to the industry's need for prefabricated light-gauge steel panels, the manufacturing process was successfully automated [207]. A unique steel framing machine was designed and prototyped at full-scale at the University of Alberta in order to support the Canadian OSC industry. The most relevant parts and systems of the machine are highlighted in Figure 6.2.

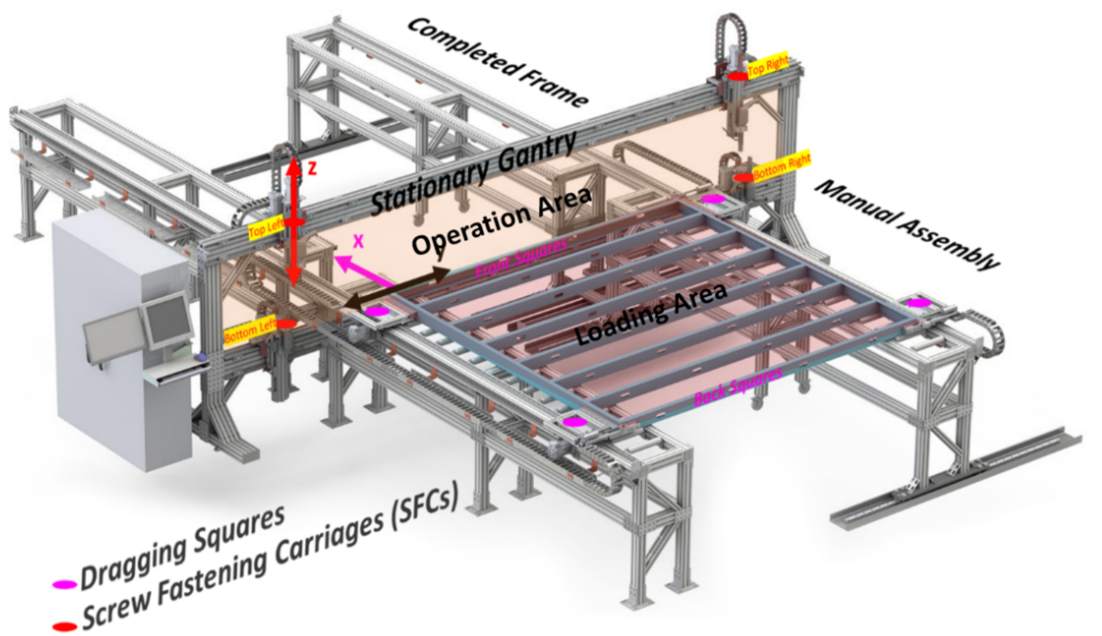


Figure 6.2: Steel framing machine model schematics.

The prototype consists of a semi-automated light-gauge steel (LGS) framing machine that uses data from the building information model to safely and automatically manufacture LGS frame assemblies. The manufacturing of the frame assembly is a sequential process as follows. First, operators manually place all the frame elements in the loading area (manual assembly phase), then mechanical actuators located in the dragging squares (see Figure 6.2) ensure the squareness of the frame (squaring phase). The dragging system consist of four electromagnetic squares, positioned along the corners of the steel frame, thereby allowing for proper squaring and synchronized motion of the LGS panels. Finally, the soft-connected frame is dragged using front and back dragging apparatus through a stationary gantry consisting of four automatic screw fastening carriages. Each motion of the dragging system ensures that the frame is positioned such that self-drilling screws can be added as required according to the shop drawings. After the completion of the frame, the wall panel is manually inspected and offloaded to the next stage of the wall panel construction.

The aforementioned prototype represents the capacities of the Industry 3.0 (third industrial revolution) paradigm in terms of automation in construction. A manual assembly process, such as the screwing operations required to manufacture LGS frames, is replaced by servo-actuated screw manipulators driven by a programmable logic controller. This supposes a interesting opportunity to test the capabilities of Industry 4.0 principles when applied to construction machinery and in a digital environment led by BIM data structures. Furthermore, the manual assembly of LGS panels and their screw-fastening process are unsupervised, thus the quality of product can be compromised. As automated quality inspection is a pending matter for most construction manufacturing processes, the introduction of digital tools such as machine vision or machine learning may provide a robust framework from which practitioners can work towards reducing defects in OSC production lines while mitigating its downside effects. Thus, for example, giving LGS frame manufacturers control over the quality of their processes and adjusting their best practices accordingly. Following the aforementioned guidelines to introduce CPS to current manufacturing systems, an overview of the CPS integration in the studied machine is presented in Figure 6.3.

6.3 Smart Connection Level

The *Smart Connection Level* serves as the data acquisition layer for the cyber-physical system to be implemented. In this study, the inspection process is a vision-based system as presented in Chapter 5. Hence, visual sensors are placed at strategic locations

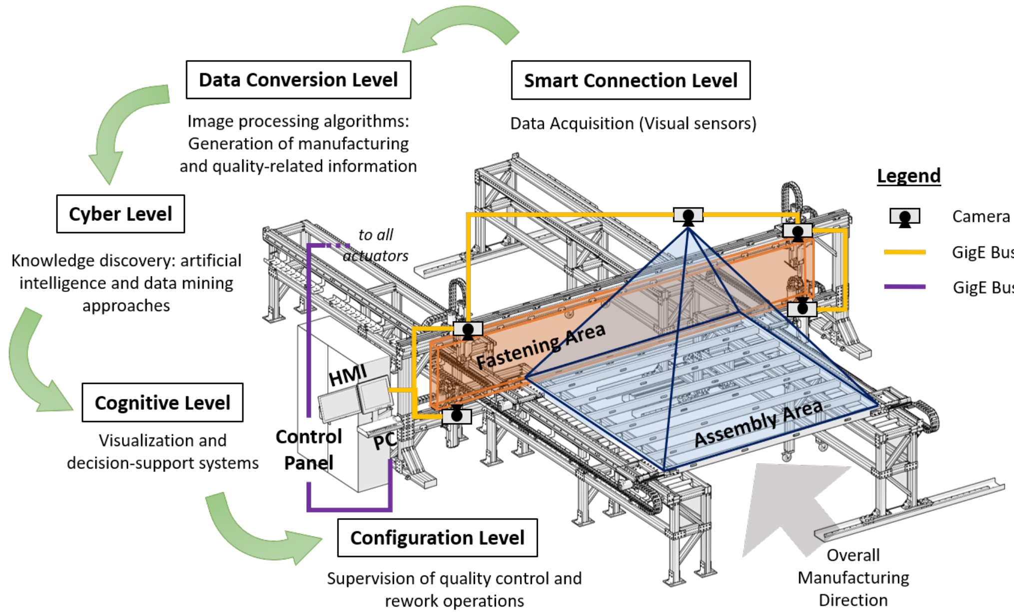


Figure 6.3: Overview of the proposed CPS for quality control of steel frame assemblies manufacturing process.

based on the needs for inspection during the manufacturing process. These locations are decided based on the requirements of construction specifications and regulations regarding the quality of steel frame assemblies. In this study, two areas have been identified: the loading area where the manual assembly of the steel frame occurs (labeled 'Assembly' area) and the area under the gantry where the manufacturing operations happen (labeled 'Fastening' area).

Quality control, in this study, is defined as the establishment of evidence, i.e. measurements, that satisfies and validates minimum requirements as predetermined in specifications or quality attributes. Construction specifications, in most cases, define minimum requirements and regulations that need to be inspected to determine confirming products. Quality control requirements can be extracted from specifications and the BIM model of the product when relevant manufacturing information is given (see Chapter 4). For the proposed case study, Table 6.1 provides a list of elements to be inspected as given in construction specifications by the Canadian Standards Association (CSA) and the American Society for Testing and Materials (ASTM) or by expert knowledge (N/A).

Table 6.1: List of relevant inspection information and corresponding specifications.

Inspection Target	**Area of Inspection**	**Occurrences per Frame**	**Relevant Specification**
Frame Element Location	Assembly	m	ASTM C1007-11a
Frame Element Width	Assembly	m	ASTM C1007-11a
Frame Element Length	Assembly	m	ASTM C1007-11a
Frame Squareness	Assembly	1	ASTM C1007-11a
Connection Angle	Fastening	$2n$	CSA S136-07/S1-10
Screw Fastening Operation Location	Fastening	$2n$	N/A
Screw Fastening Operation Quality	Fastening	n	CSA S136-07/S1-10

Note that (m) and (n) represent the number of frame elements and screw-fastening operations required respectively for the manufacture of any steel frame assembly. The *Frame Element Location* defines the maximum displacement errors, in spacing and alignment, for the placement of frame elements. The *Frame Element Width* and *Frame Element Length* determine the maximum deviation in width and length respectively from the element original description (BIM). The *Frame Squareness* defines the maximum squareness error for the overall frame. The *Connection Angle* defines the maximum angle deviation for connections between frame elements. Finally, the *Screw Fastening Operation Location* and *Screw Fastening Operation Quality* describe the correct location and aesthetic requirements respectively of a conforming screw fastening operation. As showcased in Chapter 5, the inspection systems provide the necessary data for quality assessment of steel frame assemblies.

As a summary, a total of five cameras are placed in the steel framing machine:

one camera to inspect the whole assembly area (field of view: 10×8 ft., resolution: 3840×2160) and one camera on each screw fastening carriage to inspect each screw fastening area (field of view: 6×4 in., resolution: 659×494), as shown in Figure 6.4. The camera in the assembly area provides imaging of the whole assembly area after the manual assembly is finished and the cameras in the fastening area feature a close image of the screw fastening operation/location. The cameras are responsible for creating a digital input from which the current status of the construction product and its digital representation can be built. Based on the manufacturing process and machine operations, each camera system is externally triggered to capture the appropriate image at specific points in time. The specific instants are defined by the sequential logic process in the programmable logic controller (PLC) of the machine. Two binary signals are transmitted to the visual controller that proceeds to initialize the image capturing routine. Details on those signals and all the connectivity signals used are given in Table 6.2.

Table 6.2: List of trigger signals communicating between visual sensors, controller, and main computer.

Location	**Signal**	**Type**	**Description**
Programmable Logic Controller	rqAsmbIns	Binary	Request assembly area inspection data
	rqFastnIns	Binary	Request fastening area inspection data
	insStat	Binary	Displays the inspection status at the main computer
Main Computer	rqAsmbIns	Binary	Synchronous copy of ’rqAsmbIns’
	rqFastnIns	Binary	Synchronous copy of ’rqFastnIns’

The pre-allocated binary signals on the main controller are updated when logic requires inspection data to continue with the manufacturing process. The associated computer, which deals with heavy image processing algorithms and control of the visual sensors, reads the values of such binary variables on the computer by synchronously pinging the memory direction in the controller (via Ethernet/IP protocol). If any binary variable switches to '1', the computer interprets that the controller is waiting for inspection results. Then, images are grabbed from the cameras as necessary. The camera context and handlers are hard coded as visual controllers, which are built from the Python library *Pypylon* and connect to the cameras via Ethernet/IP protocol. Once the requested images are taken, the computer updates the value of the 'insStat' variable in the PLC using OPCServer access. Although time-inefficient (2-4 seconds compared to 30 ms response in the Ethernet/IP communications), this approach enables the computer to modify automatically variables allocated in specific memory directions in the PLC. This method reduces drastically the amount of computational power and memory storage required at the PLC, which is really limited, and reduces the memory strain in the main computer compared to continuous acquisition from the visual systems (video acquisition versus triggered frame acquisition).

A timeline with the steps for steel frame assemblies manufacturing, the specific moments in which cameras are triggered, and sample images are presented in Figure 6.4. In summary, images are taken in two key moments during the manufacturing process: 1) after the frame has been fully assembled and secured by the machine squaring system, the camera in the assembly area captures the result of the assembly process; and, 2) the cameras on each screw fastening carriage capture images just before and after for each location where a screw fastening operation occurs. The time between inspection events depends on the product size, the complexity of the manual assembly process, and the tool-path selected.

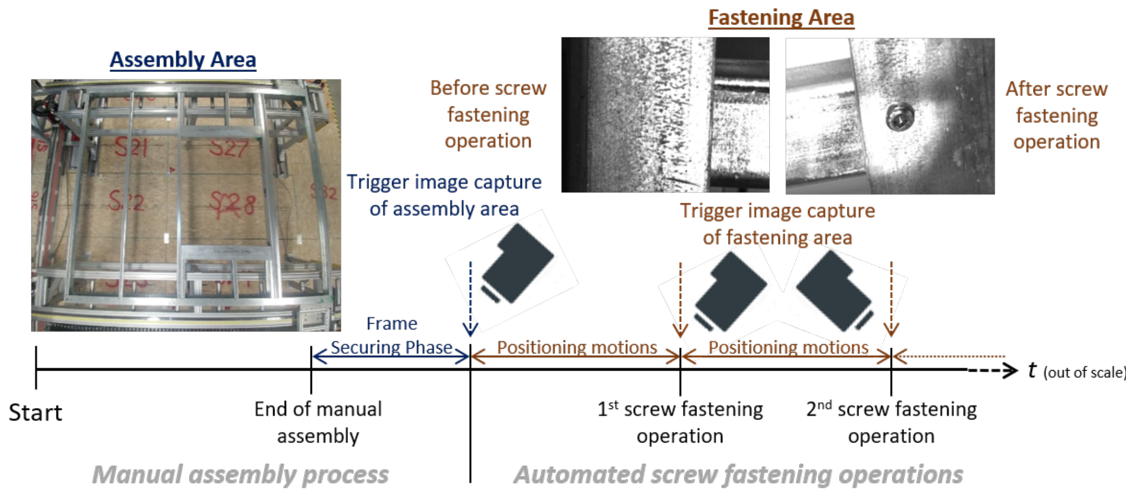


Figure 6.4: Overview of the steel frame assemblies manufacturing timeline with the integrated inspection systems.

6.4 Data Conversion Level

The *Data Conversion Level* procures manufacturing and quality-oriented data using image processing algorithms. The generated data is required to be able to procure an estimation on the quality of the currently manufactured steel frame assembly. As BIM data is considered the "ground truth" for all dimensional measurements, the image processing algorithms offer estimations to provide a situational analysis based on one-to-one comparisons. Table 6.3 provides a summary on the data generated by each image processing algorithm, their relevant reported metrics, such as the root mean square error (RMSE) of each measurement as reported in Chapter 5, and their equivalent BIM data obtained from the Autodesk Revit API. An illustration of the measurements made by the inspection systems proposed is shown in Figure 6.5.

As reported, the dimensional measurements obtained using the image processing algorithms are accurate enough for the required manufacturing tolerances in steel frame assemblies by the North American (ASTM C1007-11a) or Canadian (CSA S136-07/S1-10) standards (see Table 6.1). For the frame element location, for example, the ASTM specifies a maximum error of $\frac{1}{2}$ inch (12.7 mm) for 8 feet long studs; or the

Table 6.3: List of manufacturing and quality-oriented data generated from the image processing algorithms.

Inspected Area	Data Generated	RMSE	Equivalent BIM Data
Assembly	Stud Location	5.487 mm	.Stud.Properties. Coordinates
	Stud Spacing	4.293 mm	.Frame.Spacing
	Stud Length	4.876 mm	.Stud.Properties. Length
	Stud Width	3.427 mm	.Stud.Properties. Width
	Frame Squareness	1.297 mm	N/A
Fastening	Screw Fastening Location	3.440 mm	N/A
	Stud Connection Angle	1.98°	N/A

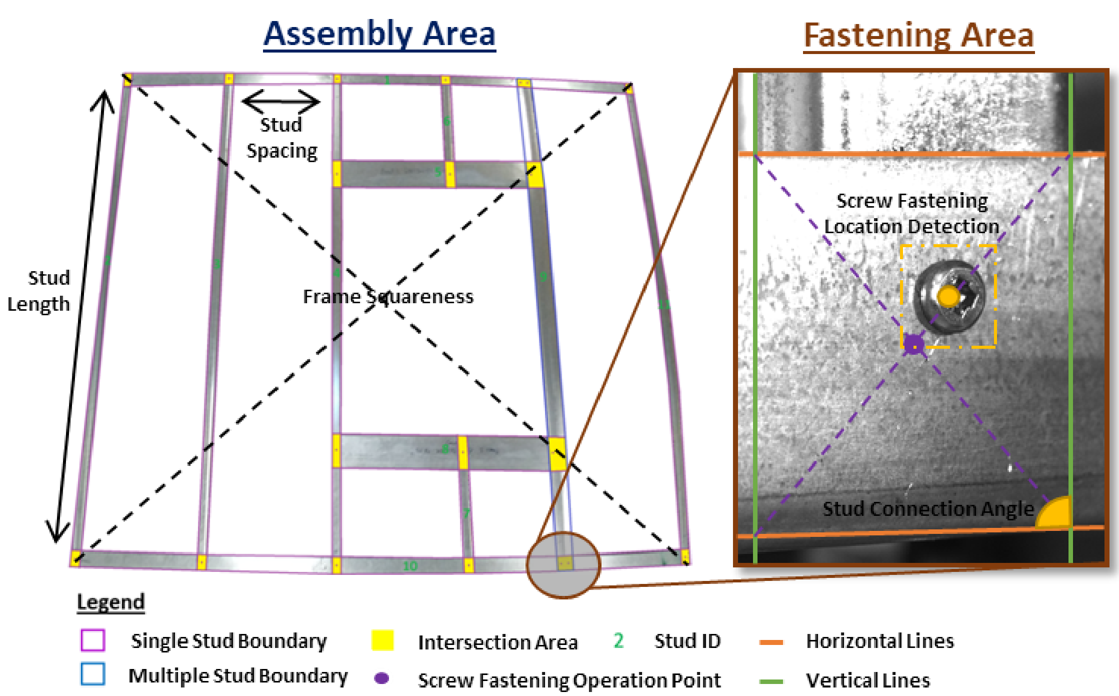


Figure 6.5: Image processing algorithms results for inspection of steel frame assemblies manufacturing.

CSA limits the maximum acceptable deviation angle for steel member connections to around 3.25°. Thus, using these measurements, situational analysis of the results to provide real-time quality control of the steel frame assembly being manufactured is possible. For example, performing a simple rule-based condition, see Equation 6.1, poor quality manufacturing operations are identified and can be corrected appropriately, non-conforming frames are identified, and machine operators may be notified to withdraw the frame from the production line.

$$| d_{act} - d_{measured} | \geq d_{tol} - v^{d}_{err} \tag{6.1}$$

where (d_{act}), ($d_{measured}$), and (d_{tol}) are the actual, measured, and tolerance value respectively for any inspection result (d), and (v^{d}_{err}) is the mean error for the image processing algorithm that determines (d). If the result yields true, the product is non-conforming based on measurement (d). At this point, operators can be notified to withdraw the product from the production line due to quality issues or, if possible, the CPS suggests corrective actions to ensure the quality of the product, for example, online corrective motor motions can be implemented in real-time to accurately perform screw-fastening operations.

To summarize, the proposed inspection algorithms identify different features in any frame assembly: edge lines, intersection points, intersection areas, fastening areas, and stud areas. To extract the relevant information from the proposed system, the different structures are mapped into classes (see Figure 6.6). The storage and accessibility of the information obtained from the algorithms is as vital to the inspection process as the algorithms themselves.

6.5 Cyber Level

The *Cyber Level* is responsible for offline analysis of the data obtained in the *Data Conversion Level* and other data collected from information sources, such as BIM

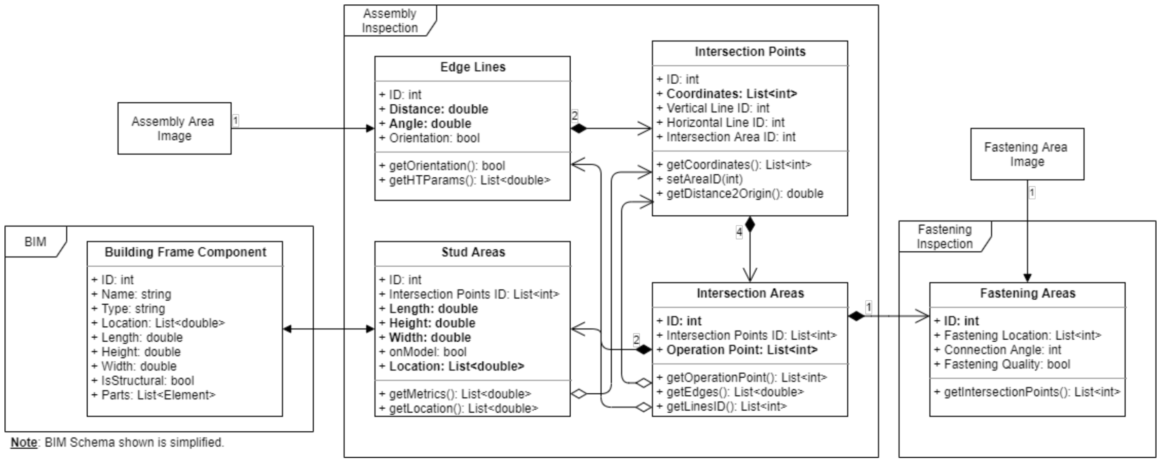


Figure 6.6: UML diagram of system parametric objects.

or the machine environment. For the purpose of this study, a database is created to manage and store the relevant manufacturing and quality-oriented data. This database stores information for each steel frame manufactured in the steel framing machine environment. A summary of the attributes stored in the database can be found in Table 6.4.

Table 6.4: List and description of the quality database attributes.

Source	Attribute	Type	Description
-	Frame	Class	High-level class containing all the frame information: element and connection IDs that are contained in a specific frame, as well as properties (spacing and squareness)
Data Conversion Level - Assembly Area	Raw Image	PNG	Raw image from the assembly area (gray-scale - 1.35 MB average)
	Frame Element	Class	Stores all the information relevant to a specific frame element (ID, length, width, location)
	Width	Double	Defines the measured frame element width

(Table continues on next page...)

Source	Attribute	Type	Description
Data Conversion Level - Assembly Area	Length	Double	Defines the measured frame element length
	Location	Array	Contains the four 2D coordinates in the image reference frame of the frame element
	Spacing	List	Defines the measured frame spacing between frame elements in the same direction
	Squareness	Double	Defines the measured frame squareness
Data Conversion Level - Fastening Area	Raw Image - pre-SFO	PNG	Raw image from the fastening area before the screw fastening operation occurs (gray-scale – 435 kB average)
	Raw Image - post-SFO	PNG	Raw image from the fastening area after the screw fastening operation occurs (gray-scale – 435 kB average)
	Frame Connection	Class	Stores all the information relevant to a specific frame connection (ID, connection angle, location)
	Connection Angle – pre-SFO	Double	Defines the measured angle of a specific connection before the screw fastening operation occurs
	Connection Angle – post-SFO	Double	Defines the measured angle of a specific connection after the screw fastening operation occurs
	Screw Fastening Location – pre-SFO	Array	Contains the 2D coordinates of the estimated screw fastening operation location

(Table continues on next page...)

Source	Attribute	Type	Description
	Screw Fastening Location – post-SFO	Array	Contains the 2D coordinates of the bounding box and centroid that identifies the actual screw fastening operation location
BIM	Frame Properties	Class	Copied and extracted from Revit API Element.Frame.Properties. Contains information relevant to the frame, such as spacing, length, width, etc.
	Element Properties	Class	Copied and extracted from Revit API Element.X.Properties, where X is an IFC construction element, i.e. a stud (Element.Stud.Properties). Contains relevant information, such as location, length, width, etc.
Machine Environment	SFO Conditions	Class	Stores all the information relevant to a specific screw fastening operation (motor speed, SF speed)
	Motor Speed	Double	Contains the speed used to move the screw fastener down during the screw fastening operation
	Screw Fastening Speed	Double	Contains the rpm of the screw fastener during the screw fastening operation

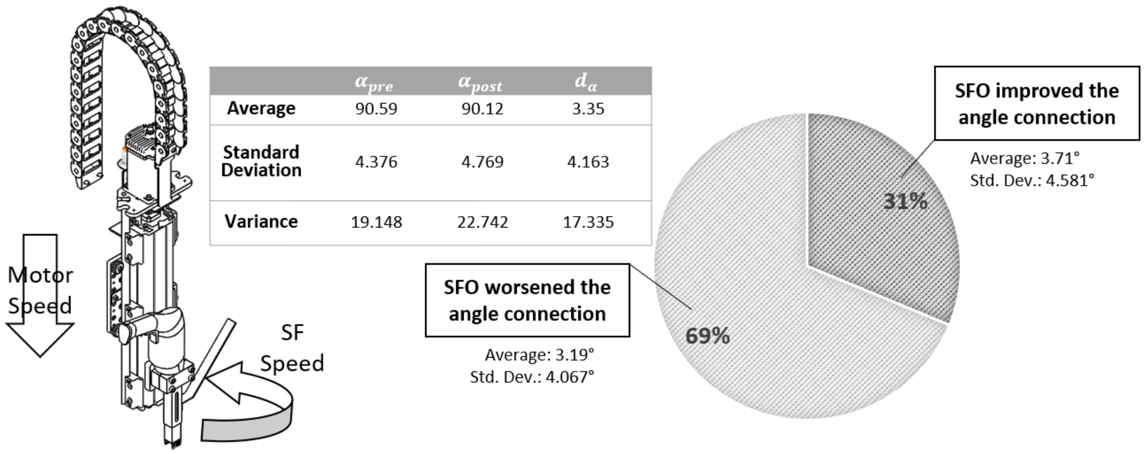
With this database, knowledge discovery in databases (KDD) approaches can be used. KDD is an interdisciplinary science whose goal is to extract useful and actionable knowledge from large data repositories [208], such as the one designed in this study. Mainly, given a set of data, a KDD process aims at finding patterns to classify data or detect anomalies, as well as predict data behavior by creating associations or models. In the last decades, KDD has proven to be an essential element of engineering research and machine learning and data mining are considered as its most recognizable approaches.

Using the data stored, data analytics are enabled, and data-driven decisions can support potential improvements to the steel frame assemblies manufacturing process and continuous improvement of the end quality of steel frame assemblies. In this study, two examples of applications of KDD approaches are presented. First, a data analysis on the effect of screw fastening operations (SFO) on the connection angle is given. Then, a machine learning approach is shown to provide real-time assessment of the quality of SFO. At the time of publication of this study, over 200 entries populate the database. Although only two examples of KDD are given, further research will be reported at a later date as more experimental data is stored and deeper understanding of the manufacturing process and its effect on end quality of steel frame assemblies is gained.

6.5.1 Connection Angle Analysis

In the machine environment used for this study, the screw fastening operations (SFO) rely on the applied pressure of the screw fastener driving mechanism to clamp the frame. This approach was introduced to minimize the complexity of the system and reduce the number of actuators. Such a design-driven decision needs to be analyzed to understand its effect on the manufacturing process of the frame itself as vibrations generated by the rotation of the screwdriver motor are directly transmitted to the frame by contact (see Figure 6.7). These vibrations have a negative impact on the SFO process and the location and orientation of the frame elements. As such, the data obtained helps quantifying the effect of such vibrations and the pressure used during the SFO.

The following data is obtained by setting up a constant motor speed and screw driving rotation (constant SFO conditions) and measuring the connection angle before and after the SFO process. Let (α_{pre}) and (α_{post}) be the measured connection angle pre-SFO and post-SFO respectively, and (d_α) the difference between both measurements. The statistical overview of the data used for this study is presented in Figure 6.7. Note that the connection angle is considered to have improved during the SFO if (α_{post}) is closer to the ideal connection angle (90° for most cases) than (α_{pre}) and vice versa.



	α_{pre}	α_{post}	d_α
Average	90.59	90.12	3.35
Standard Deviation	4.376	4.769	4.163
Variance	19.148	22.742	17.335

Figure 6.7: Connection angle analysis overview.

As observed, SFO has a measurable impact on the connection angle of 3.35° on average, in most cases (69%) worsening the connection. Considering a 95% confidence, most angle connections can be found in the [80-100] degrees interval, which is not an acceptable uncertainty based on current specifications. Hence, a deeper analysis might be justified to study the need for a secondary clamp that secures the frame during the SFO process aiming at stabilizing the connection angle throughout the whole manufacturing process. Furthermore, (α_{pre}) provides insight on the impact of the manual placement of frame elements during the initial assembly process and the frame dragging process. With almost 5° of standard deviation in the angle connection during the manual assembly, a support system might be needed, such as laser projections or placement pins. Both identified issues will be investigated in the near future.

6.5.2 Screw Fastening Operation Quality

Although the data provided by the visual systems is directly used for most quality or manufacturing related issues, the quality of the screw fastening operation itself cannot be directly measured accurately for each individual operation. In fact, quantifying the quality of a SFO from a single image is not a simple task [209] and requires lateral perspective which is not provided by the inspection system. Nonetheless, ensuring the quality of the SFO remains one of the most important tasks of the quality control in the frame assembly manufacturing process. To provide real-time assessment of the quality of SFO, a Region-based Convolutional Neural Network (R-CNN) is trained to classify conforming or non-conforming screw connections. Trained using the images obtained from the fastening area after the SFO, the R-CNN expands the quality control results from the Data Conversion Level. An example of the results of the SFO inspection at each level described so far is illustrated in Figure 6.8 and further details on the R-CNN architecture, results, and limitations can be found in Chapter 5, Section 5.4.

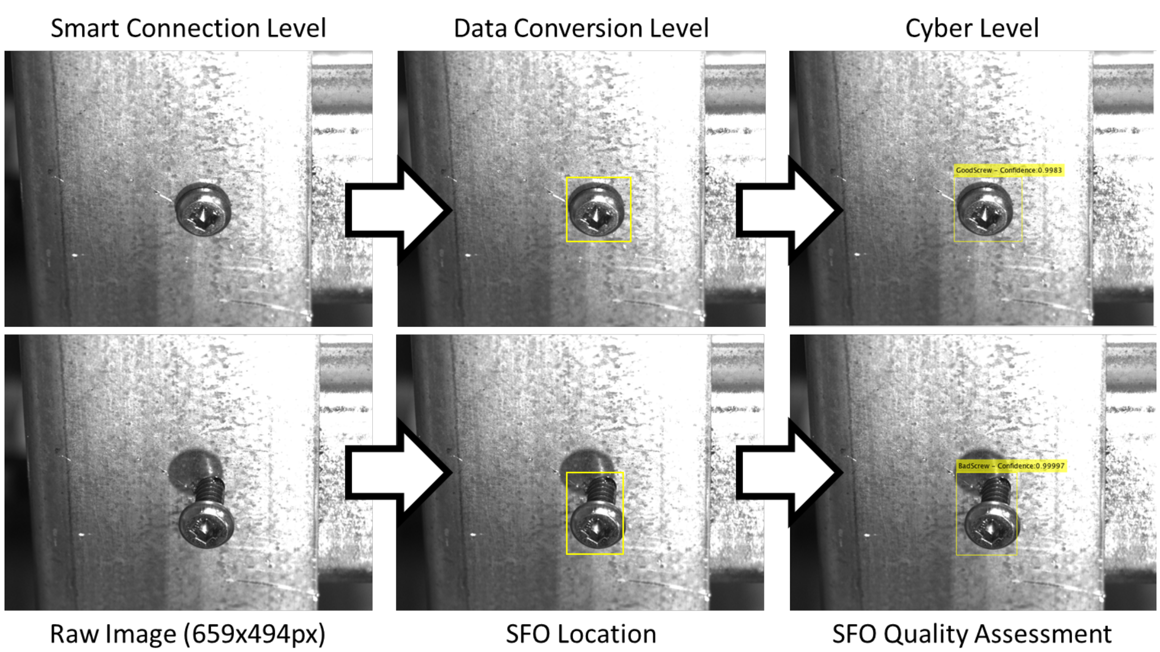


Figure 6.8: Connection angle analysis overview.

As observed, by the Data Conversion Level the information available support identifying the presence and location of the screw fastener after the SFO. However, including historical image data and using a deep learning approach, the quality of the SFO can be assessed in real-time, determining the capacity of cyber approaches to provide an extra layer of functionality regarding quality control.

6.6 Cognitive Level

The *Cognitive Level* provides the interface between the user and the cyber-physical system (CPS). This interface enables human intervention on the inspection process and serves as a critical layer for the inspection results, either to ratify or deprecate them. In summary, this level provides decision support at the user level for quality control. The interface builds upon the BIM information extracted of the panel currently being manufactured: a graphical representation of the frame assembly can be shown as originally modeled in BIM. Information from the database is accessible by the user by clicking on the corresponding frame element, or directly showcased in the interface if it pertains to the whole assembly, such as spacing or frame squareness measurements. Frame elements that need attention are automatically highlighted in red, information is automatically displayed, and non-conforming measurements are shown. Users then decide to either take corrective action or proceed with the process ignoring the inspection results given. If any corrective action is performed, the user notifies the system and the CPS will restart the last inspection routine, either assembly inspection (AI) or fastening inspection (FI). An overview of the user interface for the CPS is illustrated in Figure 6.9.

Based on the system interface available, the machine operator visualizes the quality control decisions taken by the CPS. Thus, the CPS inspection results stored at the database act as a decision support system for the operator in regard to quality control and rework operations for each steel frame assembly. As stated, the two inspection routines require user input for each steel frame assembly. As such, data needs to be

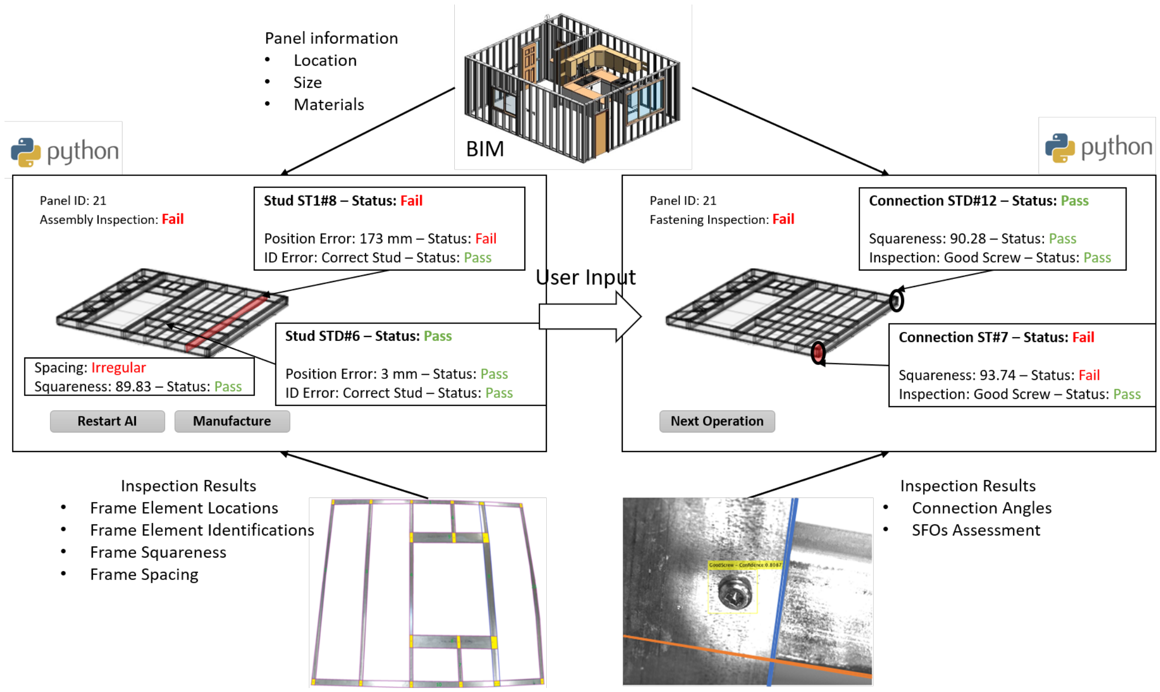


Figure 6.9: Overview of the cyber-physical system interface and information display.

prepared and visualized in an easy and comprehensible way to facilitate correct user input and ensure quality of steel frame assemblies. The support system embedded into the human-machine interface created is showcased in the flowchart shown in Figure 6.10. For each inspection routine, either assembly inspection (AI) or fastening inspection (FI), the data are contrasted one by one with ground truth results (BIM) or tolerances from specifications, and in case of any defect detected warnings and alerts with potential corrective actions are displayed. Finally, the system awaits user action and awaits for its feedback based on what the user wants as following action: restart the inspection, introduce data manually to override inspection results in the database, or keep going with the remaining manufacturing operations. All of these interactions are further explained in the following subsections.

6.6.1 Assembly Inspection Decision Support System

For each frame assembly, the BIM model offers an IFC-compliant bill of materials (BoM), which lists all the components needed to manufacture such frame, as seen

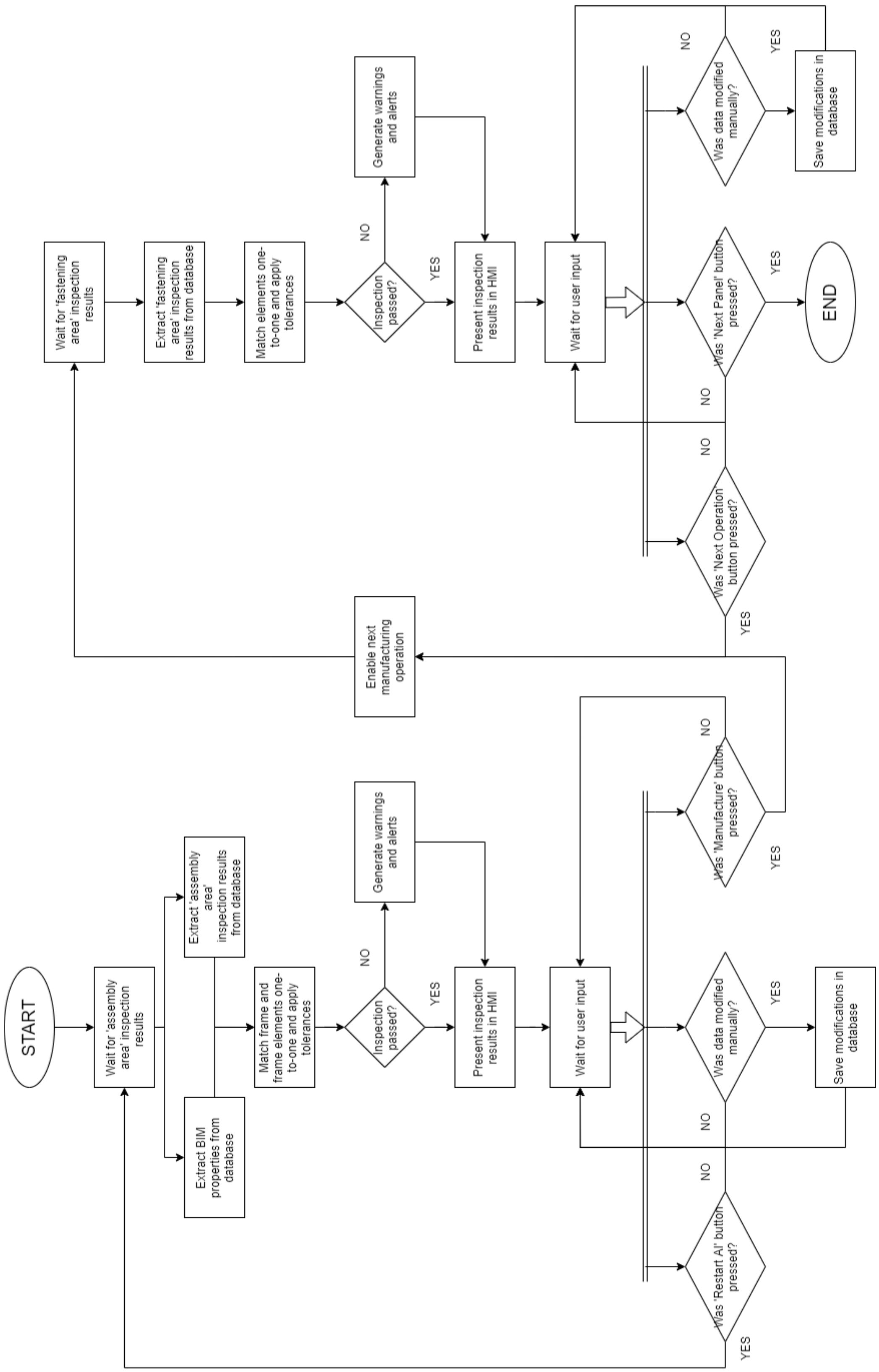


Figure 6.10: Flowchart of the visualization process for the inspection results of steel frame assemblies manufacturing.

in Section 4.2. That list defines each frame component by stud identification name, stud width and length, and quantity [210]. All the components in the BoM comply with the industry standard nomenclature for defining framing products specified in the International Building Code (2012) and the North American Specification for the Design of Cold-Formed Steel Structural Members (AISI S100-07) with the supplement (S1-10). As such, all the structural members use a four-part designate that identifies the web depth, style, flange width, and thickness, as well as identifying the element length. Thus, relevant information can be parsed from the BoM for each frame element and stored in the database.

Then, the measurement validation consists in matching one by one all the detected studs with the BIM model components and labeling the detected studs by the assembly inspection as needed. This process considers that the same stud has been detected when all three metrics, height, length and width, match within the vision system tolerance values, (v_{tol}^{d}), for each measurement (d) as per Equation 6.2. Further, the validation algorithm compares the relative position between the matched stud and its BIM counterpart. Similarly, the corresponding tolerance values are applied to this step. Using the proposed inspection system, the tolerance solely depends on the camera resolution; as such, at least medium resolution wide angular cameras are advised to obtain accurate results.

$$S_{area} = S_{BIM} \iff \begin{cases} w_s = w_{BIM} \pm v_{tol}^{w} \\ l_s = l_{BIM} \pm v_{tol}^{l} \\ h_s = h_{BIM} \pm v_{tol}^{h} \\ (x_i, y_i) = (x_{BIM}, y_{BIM}) \pm v_{tol}^{p}, i = 1, ..., 4. \end{cases} \tag{6.2}$$

A limitation in the frame inspection algorithm is the impossibility to detect multiple studs (double or triple) which are quite common when door or window components are present in a frame. Those multiple studs, in most occasions, do not have identifiable or visible edges in between and, therefore, the algorithm detects them as a single stud. As such, the detected stud will most probably not match with any of the studs found in the BIM information, thus, those studs are labeled as undefined. In any case of undefined studs, the validation process checks for the possibility of those studs being the combination of multiple studs. For a detected undefined stud, (uS_{area}), the width is compared to any possible linear combination (up to 3 studs, due to the usual structural combinations for steel frame assemblies) of all the remaining unmatched studs from the BIM, (uS_{BIM}). The process tries first to generate double studs as they are more common than triple studs.

$$
\begin{gathered}
\forall i, j = 1, ..., U, uS_{area} = uS^{i}_{BIM} + uS^{j}_{BIM} \iff w_i + w_j = W \\
\forall i, j, k = 1, ..., U, uS_{area} = uS^{i}_{BIM} + uS^{j}_{BIM} + uS^{k}_{BIM} \iff w_i + w_j + w_k = W
\end{gathered}
\tag{6.3}
$$

where (U) is the number of remaining unmatched studs from the BIM and (W) is the total width of the detected undefined stud. If Equation 6.3 is satisfied, then the detected stud is 'divided' to generate the correct studs. For example, the process to divide into two new studs, (nS_1) and (nS_2), of different widths, (w_1) and (w_2), is shown in Equation 6.4. A similar approach can be taken for triple studs of different width.

$$
\begin{gathered}
nS_1(x_1, y_1) = uS_{area}(x_1, y_1) \\
nS_1(x_3, y_3) = nS_2(x_1,y_1) = uS_{area}(x_1, y_1) + w_1 \\
nS_2(x_3, y_3) = uS_{area}(x_3, y_3) \\
nS_1(x_2, y_2) = uS_{area}(x_2, y_2) \\
nS_1(x_4, y_4) = nS_2(x_2,y_2) = uS_{area}(x_2, y_2) + w_1 \\
nS_2(x_4, y_4) = uS_{area}(x_4, y_4)
\end{gathered}
\tag{6.4}
$$

To conclude, this support system offers the user three possible outcomes for each stud: either it has been correctly matched and positioned, or it has been correctly matched but misplaced, or it has been mismatched against the BIM model. The logic flowchart of this module is shown in Figure 6.11.

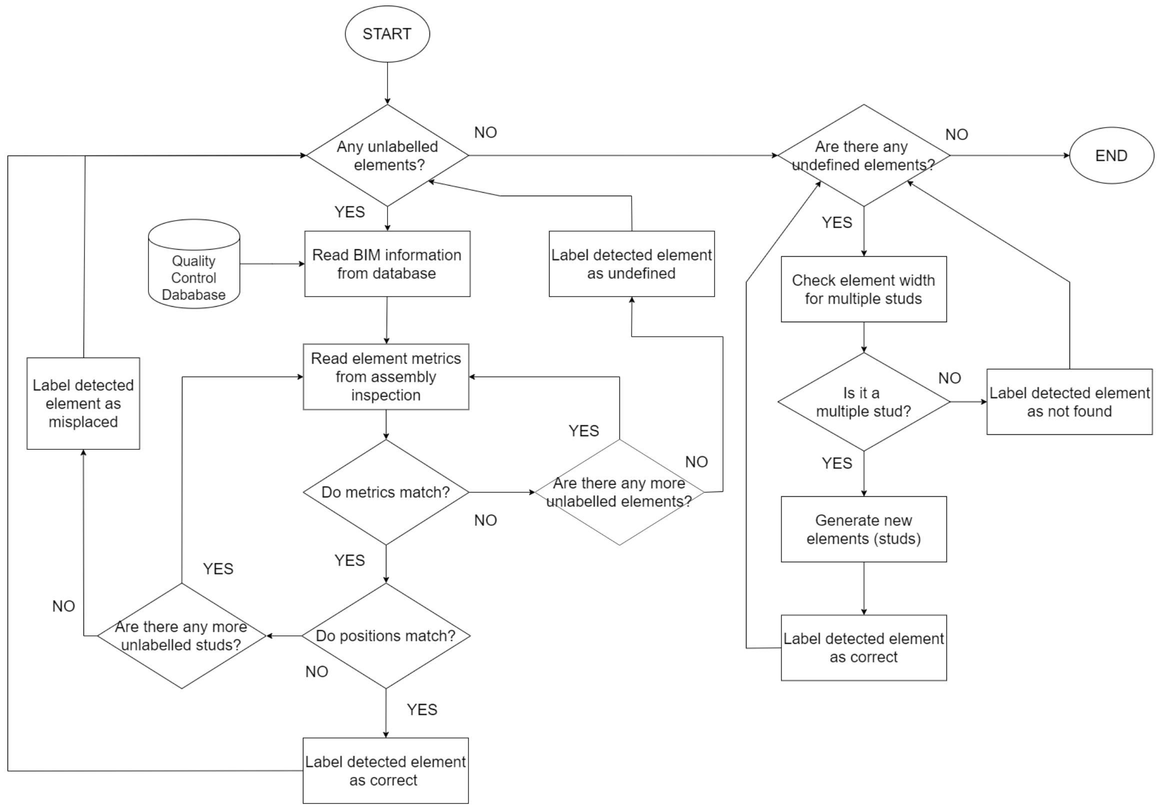


Figure 6.11: Flowchart for measurement validation of assembly inspection results.

Once the system has finished labeling the frame elements, decisions can be identified as potential solutions for deficiencies in the manual assembly process. Whilst some encountered problems give any doubt as to which solution should be offered, i.e. a mismatched stud needs to be replaced, the measurement precision and standard tolerances make offering a clear solution to misplaced studs slightly more complex. Obviously, if no problems were encountered in the previous step, the system simply allows the manufacturing process to start. In order to create an industry-level decision-support system, the Standard Specification for Installation of Load Bearing Steel Studs, ASTM C1007-11a (2015), is used to define the appropriate solutions for each misplacing error, (ϵ^d). The previously mentioned standard defines two possible errors for each stud placement: spacing error (lateral displacement) and vertical/horizontal alignment error. Thus, a misplaced stud could be considered as correct by industry standards if it is within tolerance values for both misplacement errors as per Equation

6.5. Otherwise, the misplaced stud requires to be relocated.

$$\Delta(x,y) \leq \epsilon^d \leftrightarrow \forall i = 1, ..., 4, \mid S_{area}(x_i, y_i) - S_{BIM}(x_i, y_i) \mid \leq \epsilon^d \tag{6.5}$$

With the presented approach, the user can identify potential issues in the manually assembled frame by looking at the digitized frame in the human-machine interface for quality control purposes. Once results are presented, the user has the final say on the actual rework operations that occur physically on the frame. If the user introduces changes to the frame, the user should restart the assembly inspection process to obtain a new set of data, however that still remains a user decision. The proposed assembly inspection decision-support system cannot overcome user actions as it does not monitor human intervention in the manual assembly process, hence it is biased towards user input.

6.6.2 Fastening Inspection Decision Support System

For each frame, the fastening inspection provides information regarding the squareness of each connection and an assessment of the screw fastening operation quality as described in Sections 5.3 and 5.4. Each instance of fastening inspection provides data from the last iteration of screw fastening operations and its corresponding frame connections, usually a pair of connections due to the machine operating two screw manipulators simultaneously. Then, the validation process consists in matching the acquired data to the correct quality specifications so that appropriate tolerances can be applied. Results obtained before the screw fastening operation occurs, such as 'Connection Angle pre-SFO' or 'Screw Fastening Location pre-SFO', are ignored in this step. That is due to having more updated results from the post-manufacturing inspection or that the *Cyber Level* upgraded the obtained results from a quality perspective. As such, two sets of data are used for this decision-support system: 'Connection Angle post-SFO' and the SFO quality assessment results from Section 6.5.2. Remind that CSA S136-07/S1-10 sets as 3.25° the maximum deviation for the connection angle and that quality of screw fastening operations, based on the same CSA specification, is already considered during the labeling of classes during the training process of the machine learning algorithm, hence, already considered in the showcased results.

Therefore, decisions regarding the quality of the screw fastening operations can be taken. This process considers that the inspection has passed for the fastening area if all the connection angles are within the maximum tolerance as per Equation 6.1 and the machine learning algorithm determines that all SFO are conforming. If that is the case, the operator is informed and the suggested action is to continue with the next set of screw fastening operations or, in case of this inspected set being the last one, to proceed to the next panel as scheduled. In case of any errors beyond tolerances or non-conforming quality assessments, results are visualized for the operator's knowledge and rework orders are suggested. The logic flowchart for this module is shown in Figure 6.12.

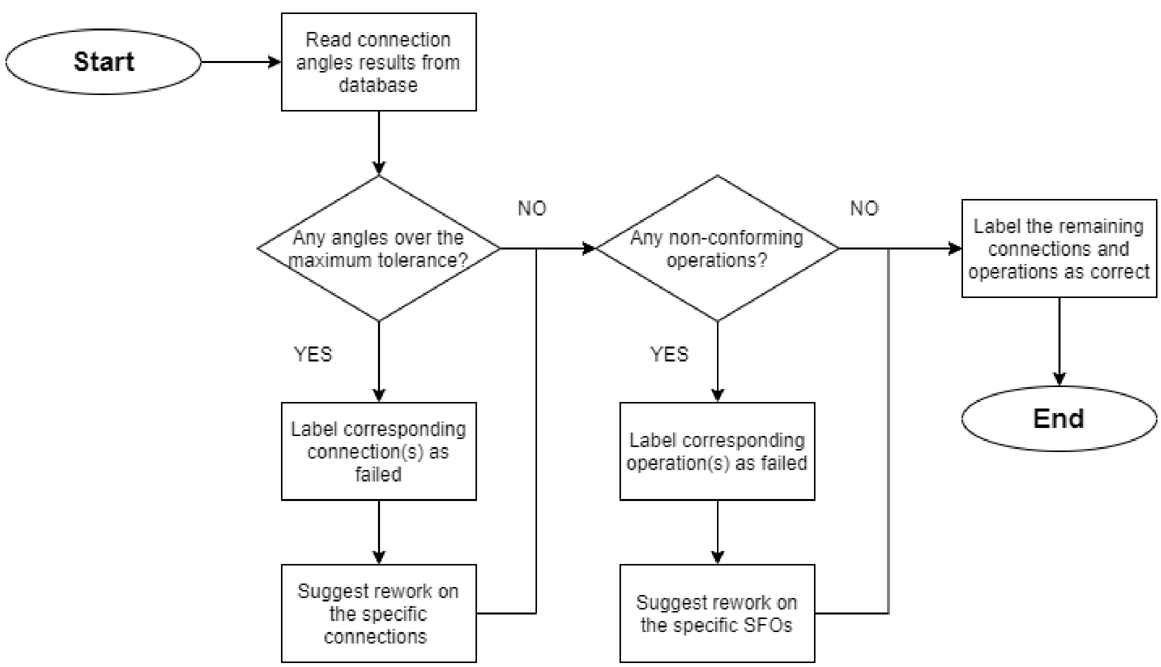


Figure 6.12: Flowchart for measurement validation of fastening inspection results.

For a connection angle beyond tolerance values after the screw fastening operation has occurred requires a three-step process to be reworked: 1) removal of the SFOs (top and bottom); 2) adjustment of the non-fixed connection element, usually studs, until a correct angle is manually measured; and finally, 3) re-manufacturing of the SFO. As the SFO needs to be re-manufactured, the initial quality assessment for those steel frame connections is ignored. For the rest of the frame connections, the quality assessment of the SFOs is still valid. For any non-conforming operation, reworking the screw fastening process (in case of 'Non-conforming SFO' prediction) or performing an additional screw fastening process (in case of 'No SFO') is required.

Similarly to the previous subsection, the operator (user) has the final say on the rework operations that occur physically on the frame. Then, the final decision regarding rework falls solely on the expert decision of the operator. If the user introduces changes to the frame connection, either by reworking the connection angle or the screw fastening operation, the user should restart the inspection process to obtain an updated set of data that judges the quality of the rework process, however that still remains a user decision as the proposed solution cannot identify if rework has been performed or not.

6.7 Configuration Level

The Configuration Level acts as a supervisory agent to the user input and the CPS results showcased in the human-machine interface. Currently, the supervisor role for the proposed CPS is twofold: 1) tracks the performance of the *Cyber Level* predictions and results over time, such as machine learning algorithm performance metrics; and 2) tracks the necessity for human intervention and the need for corrective actions to the frame through quality key performance indicators (KPIs). First, tracking the performance of cyber actions in the physical world enables the long-term evaluation of models, simulations, and any machine learning applications developed. As the data collection grows, and consequently the data-set too, models may deviate from its original training purpose, i.e. a different model of screw can be used which features a different aesthetic look may alter the performance of the SFO quality assessment algorithm aforementioned. Then, understanding and quantifying the effort undertaken by operators working alongside the proposed CPS in frame rework supports management decisions in regard to the continuous improvement of the studied machine environment.

6.7.1 Monitoring of Machine Learning Predictors

For the example provided in Section 5.4, the machine learning performance metrics may be updated following the results obtained and by analyzing user interaction with the system. Let (N) be the 3×3-diagonal matrix such that $[N_1, N_2, N_3]$ be the number of prediction results for the classes 'Conforming SFO', 'Non-conforming SFO', and 'No SFO' respectively. Therefore, for a total set number (n) of inspection results for a frame, Equation 6.6 must always be satisfied.

$$tr(N) = \sum_{i=1}^{3} N_i = n \tag{6.6}$$

Also, let (E) be the 3×3-matrix that represents the user intervention in the quality of the construction product, such that the non-diagonal values, $E_{j,k} = [E_{1,2}, E_{1,3}, E_{2,1}, E_{2,3}, E_{3,1}, E_{3,2}]$, be the number of classification errors for a predicted class (k) when the true class is (j), and the diagonal values represent the total amount of prediction errors for a class. These diagonal values are calculated as the sum of the values in the column, following the equation below:

$$E_{i,i} = -\sum_{j=1,i\neq j}^{3} E_{j,i} \tag{6.7}$$

Considering an inspection round for any frame assembly, the user is offered two options, either proceed to the following panel or restart the inspection process. User can introduce changes to the inspection results based on his/her own volition as well. For each user interaction with the system, the prediction results are analyzed. In the first case, where the manufacturing process goes forward with the next frame, the user is validating the 'Conforming SFO' predictions and ignoring/invalidating the 'Non-conforming SFO' and 'No SFO' predictions. Therefore, in these conditions, (E) is defined as follows:

$$\begin{cases} E_{2,1} = E_{2,3} = E_{3,1} = E_{3,2} = 0 \\ E_{1,2} = N_2 \\ E_{1,3} = N_3 \end{cases} \iff E = \begin{bmatrix} 0 & N_2 & N_3 \\ 0 & -N_2 & 0 \\ 0 & 0 & -N_3 \end{bmatrix} \tag{6.8}$$

In the second scenario, the user has restarted the inspection process after performing corrective actions as suggested by the inspection results or not. If suggested corrective actions are followed, then $E = 0$ as user determines that the system was correct in its predictions and assumptions. If alternative corrective actions were needed, user input is required to provide a list of the SFO IDs that required rework and the corresponding corrective action taken. The possible corrective actions to be taken are limited to 'Tighten SFO' and 'SFO Replaced', as they represent the solution to the non-conforming options that can be predicted. As those corrections were not suggested due to the prediction confirming a 'Conforming SFO' or the suggestions provided were incorrect, i.e. suggesting 'Tighten SFO' when 'No SFO' was the correct prediction, each user correction needs to be evaluated individually depending on the previous prediction. As such, (E) is defined as follows:

$$\begin{cases} E_{1,2} = a \\ E_{1,3} = b \\ E_{2,1} = c \\ E_{2,3} = d \\ E_{3,1} = e \\ E_{3,2} = f \\ S = a + b + c + d + e + f \end{cases} \iff E = \begin{bmatrix} -(c+e) & a & b \\ c & -(a+f) & d \\ e & f & -(b+d) \end{bmatrix} \tag{6.9}$$

where (S) is the number of extra corrective actions specified by the user: (a) and (b) are the number of SFO that were predicted 'Tighten SFO' and 'SFO Replaced' respectively and user did not perform any action, (c) and (e) are the number of SFO that were predicted 'Conforming SFO' and the user performs 'Tighten SFO' and 'SFO Replaced' respectively, (d) is the number of SFO that the system suggested 'SFO Replaced' and the user performs 'Tighten SFO', and (f) is the number of SFO that the system suggested 'Tighten SFO' and the user performs 'SFO Replaced'. Then, using both inspection results and user input, the confusion matrix (CM) can be updated after an inspection round following Equation 6.10.

$$CM_{n+1} = CM_n + N_{n+1} + E_{n+1} \tag{6.10}$$

As defined, Figure 6.13 illustrates the process to update the confusion matrix of the machine learning algorithm discussed based on user feedback.

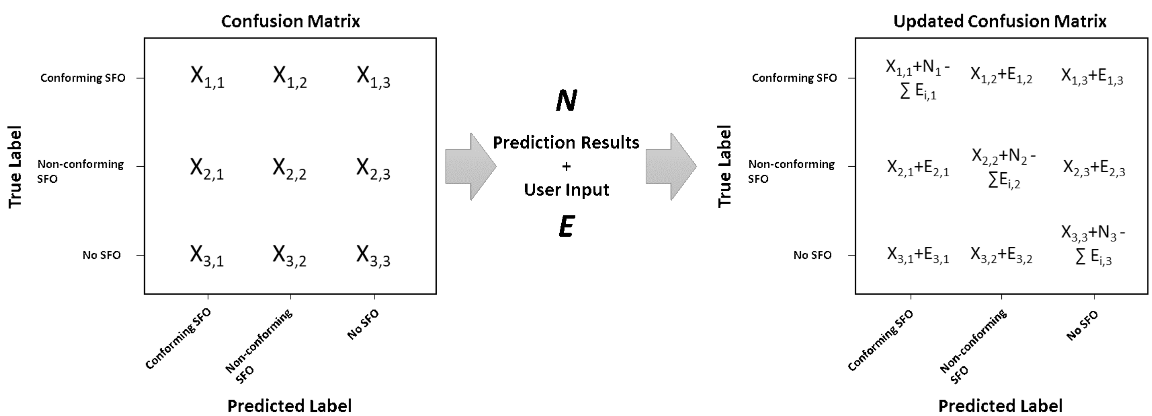


Figure 6.13: Overview of the confusion matrix updating process based on current predictions and user feedback.

By having a framework in which, for each classification label, true positives, true negatives, false positives, and false negatives are updated as the machine learning algorithm is used enables the supervisor agent to monitor its performance. In addition, the algorithm's accuracy, precision, recall, error-rate, or F1-score can be plotted over time, providing a simple yet efficient tool to manage implemented machine learning algorithms as drops in performance can be easily detected. (*Accuracy*) is an intuitive performance metric that presents the ratio of correctly predicted observations over the total number of observations. ($Precision$) is the ratio of correctly predicted positive observations for a specific label in regard to the total predicted results. ($Recall$) or sensitivity is the ratio of corrected predicted positive observations for a specific label to all the observations of that label. The ($ErrorRate$) is the ratio of incorrect predicted observations to the total of observations obtained. The (F_1) score is a weighted average of precision and recall, that takes into consideration both positive and negative observations, and results in a metric that represents the overall accuracy of a specific label. Those metrics have been consistently used in academia to measure neural network performances where a small number of positive instances for a label are present, which is the case for this study. Those performance metrics can be obtained from the confusion matrix values. In this case, for each label (i), the classification performance is calculated following the equations below, after [211]:

$$\begin{cases} TP_i = X_{i,i} \\ TN_i = \sum_{j=1, j\neq i}^{3} X_{j,j} \\ FP_i = \sum_{j=1, j\neq i}^{3} X_{j,i} \\ FN_i = \sum_{j=1, j\neq i}^{3} X_{i,j} \end{cases} \tag{6.11}$$

$$Accuracy_i = \frac{TP_i + TN_i}{TP_i + TN_i + FN_i + FP_i} \tag{6.12}$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \tag{6.13}$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \tag{6.14}$$

$$ErrorRate_i = \frac{FP_i + FN_i}{TP_i + TN_i + FN_i + FP_i} \tag{6.15}$$

$$F_{1,i} = \frac{2 * Precision_i * Recall_i}{Precision_i + Recall_i} \tag{6.16}$$

where ($X_{i,j}$) are the values in the updated confusion matrix as illustrated in Figure 6.13.

6.7.2 Supervision of Quality KPIs

In production systems, many raw measurements are monitored and collected, however, when considering engineering and management interests, key performance indicators (KPIs) can be derived and evaluated, for instance, efficiency or quality. Thus, the directly monitored elements can become the supporting metrics for KPIs. These KPIs mostly reveal a single aspect of system performance, as such named as basic KPIs. To represent the overall performance, more comprehensive KPIs, supported by several basic KPIs, can be obtained. To monitor quality performance, most comprehensive KPIs (introduced later on) depend on quantity elements, referred to as logistical elements in the ISO 22400-2 (2014) [212]. For the case study presented, the quantity elements can be all obtained directly from inspection results and human intervention, as presented in the previous subsection. Examples of supporting elements for quality KPIs are:

- *Good quantity* (GQ): number of products that meet quality requirements in the first time of an operation process and is obtained as the sum of true observations for 'Conforming SFO';

$$GQ = \sum_{i=1}^{3} X_{1,i} \tag{6.17}$$

- *Processed quantity* (PQ): total number of products that a machine (work unit) has processed, including reworked products) and is calculated as the grand sum of the confusion matrix;

$$PQ = grandsum(CM) = \sum_{i=1}^{3} \sum_{j=1}^{3} X_{i,j} \tag{6.18}$$

- *Rework quantity* (RQ): number of products that initially did not meet quality requirements, but these can be met through reprocessing, repair, or other re-manufacturing approaches, and can be obtained as the sum of the true observations for 'Non-conforming SFO' and 'No SFO';

$$RQ = \sum_{i=1}^{3} X_{2,i} + X_{3,i} \tag{6.19}$$

- *Scrap quantity* (SQ): number of products that do not meet quality requirements and have to be scrapped or recycled. For steel frame assemblies manufacturing, all operation errors can be reworked and other potential errors not accounted for cannot be identifiable with the proposed inspection system. As such:

$$SQ = 0 \tag{6.20}$$

- *Produced quantity in the first operation process* (PQF): total number of products that a machine (work unit) has processed for the first time. As no scrap is considered in this manufacturing process, the total number of products processed only once is identical to the number of products that meet quality requirements at first, due to the rest requiring rework.

$$PQF = GQ = \sum_{i=1}^{3} X_{1,i} \tag{6.21}$$

Assuming that all rework operations are successful, meaning that are reworked parts meet quality requirements, then a relationship exists between all the quantity elements (basic KPIs) as shown in Equation 6.22. In practice, (PQF) is the first time quantity that is used to define quality in most industrial settings.

$$\begin{gathered} PQF = GQ + SQ + RQ \\ PQ = PQF + RQ \end{gathered} \tag{6.22}$$

Based on that, some important quality-related KPIs can be calculated (note that scrap related KPIs are omitted due to the nature of this study). Those are defined as follows:

- *Rework ratio* (RR): identifies the ratio of rework quantity to the processed quantity;

$$RR = \frac{RQ}{PQ} = \frac{\sum_{i=1}^{3} X_{2,i} + X_{3,i}}{\sum_{i=1}^{3}\sum_{j=1}^{3} X_{i,j}} \tag{6.23}$$

- *Quality rate* (QR): notes the ratio of good quality parts leaving the manufacturing process.

$$QR = \frac{GQ}{PQ} = \frac{\sum_{i=1}^{3} X_{1,i}}{\sum_{i=1}^{3}\sum_{j=1}^{3} X_{i,j}} \tag{6.24}$$

Considering the lack of scrap for this specific study, the relationship between both ratios remains simple, as seen in Equation 6.25.

$$QR = 1 - RR \tag{6.25}$$

To summarize, quality KPIs obtained via the inspection systems proposed and the cognitive interaction of the machine operators target rework operations as the main concern quality-wise. However, as rework operations are suggested by an autonomous process as well as independent human decision-making, current rework ratio only computes the final result on the product. This ignores current efforts for rework in conditions such as false rework suggestions by the proposed system or operator's expert decision to rework a part when the system considered it to be good enough. In other words, rework is required to fix 'Non-conforming SFO' and 'No SFO', either due to human decisions or as suggested by the inspection results. As such, an index is proposed to monitor the human effort for rework operations (no matter if they happen or not). Let the human effort for rework, (HR), be the ratio of human operations required to assess and rework screw fastening operations to the total of processed operations in steel frame assemblies, and can be determined by:

$$HR = \frac{RR + X_{1,2} + X_{1,3}}{PQ} = \frac{PQ - X_{1,1}}{PQ} = 1 - \frac{X_{1,1}}{PQ} \tag{6.26}$$

6.7.3 Validation Results

The results presented in this subsection showcase the monitoring of the performance metrics of the machine learning algorithm designed for classification of screw fastening operation (SFO) quality over the production of three frames. All the frames are designed with simple studs distributed over the length of the track. In total, 76 SFO are considered. For each panel, first, the inspection results are obtained (N), then the system awaits for human input and generates the error matrix accordingly (E). Finally, the confusion matrix (CM) is updated after each frame, as proposed, and the performance metrics monitored over the production process in order to finally calculate the quality KPIs (rework ratio and human effort for rework). The initial seed of the confusion matrix, from where all calculations of the performance metrics derive, is obtained from the validation set during the training stage of the algorithm (labeled 'Start Implementation' in the figures below). As observed, classification metrics are evaluated over the usage of the machine learning algorithm, enabling supervision of its performance. For the quality KPIs, a differential approach is presented as shown in Equation 6.27 for the rework ratio and human effort for rework after the n^{th} frame. This is due to the large amount of rework operations used for training purposes, which would bias the results presented and would not represent accurately the manufacturing behavior studied.

$$\begin{aligned} RR_n &= RR - RR_0 \\ HR_n &= HR - HR_0 \end{aligned} \tag{6.27}$$

At the start of the system, considering the initialization of the *Configuration Level* supervision, the confusion matrix, (CM), is obtained from the end results of the training and validation steps. Remind that:

$$CM_0 = \begin{bmatrix} 15 & 1 & 0 \\ 0 & 16 & 0 \\ 0 & 3 & 13 \end{bmatrix} \tag{6.28}$$

With those results, Table 6.5 lists the performance metrics for each one of the classes ('L_1:Conforming SFO', L_2: 'Non-conforming SFO', and L_3: 'No SFO') and quality KPIs of screw fastening operations.

The first panel has 22 SFO and the inspection yields that 17 of those are conforming

Table 6.5: List of values for the performance metrics and quality KPIs monitored at the 'Start Implementation' step.

	Accuracy	**Precision**	**Recall**	**Error Rate**	F_1 **Score**	RR_0	HR_0
L_1	0.9778	1	0.9375	0.0208	0.9677		
L_2	0.9167	0.8	1	0.0833	0.8889	0	0
L_3	0.9362	1	0.8125	0.0625	0.8966		

to quality requirements, 2 of those are non-conforming, and that 3 connections are missing screws. After manual inspection and rework process, an extra connection had a non-conforming SFO while the inspection system predicted that it was conforming. Therefore, for this panel, it is obtained that:

$$N_1 = \begin{bmatrix} 17 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}, E_1 = \begin{bmatrix} -1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{6.29}$$

Following Equation 6.10, the updated confusion matrix after the manufacture of panel 1 is as follows:

$$\begin{aligned} CM_1 &= CM_0 + N_1 + E_1 \\ &= \begin{bmatrix} 15 & 1 & 0 \\ 0 & 16 & 0 \\ 0 & 3 & 13 \end{bmatrix} + \begin{bmatrix} 17 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} + \begin{bmatrix} -1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 31 & 1 & 0 \\ 1 & 18 & 0 \\ 0 & 3 & 16 \end{bmatrix} \end{aligned} \tag{6.30}$$

Finally, the performance metrics and quality KPIs can be computed from the updated confusion matrix. The obtained results are listed in Table 6.6.

Similarly, panel 2 has 30 SFO: 26 of which are conforming, 2 of those non-conforming, and 2 missing SFO. However, after manual inspection, the operator corrects that all the SFOs in this panel are actually conforming. Consequently, N_2 and E_2 are defined

Table 6.6: List of values for the performance metrics and quality KPIs monitored after panel 1 manufacturing process.

	Accuracy	**Precision**	**Recall**	**Error Rate**	F_1 **Score**	RR_1	HR_1
L_1	0.9701	0.9688	0.9688	0.0286	0.9688		
L_2	0.9286	0.8182	0.9474	0.0714	0.8780	0.0857	0.0857
L_3	0.9559	1	0.8421	0.0429	0.9143		

as follows:

$$N_2 = \begin{bmatrix} 26 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}, E_2 = \begin{bmatrix} 0 & 2 & 2 \\ 0 & -2 & 0 \\ 0 & 0 & -2 \end{bmatrix} \tag{6.31}$$

Again, the confusion matrix can be updated with the new set of results for panel 2:

$$\begin{aligned} CM_2 &= CM_1 + N_2 + E_2 \\ &= \begin{bmatrix} 31 & 1 & 0 \\ 1 & 18 & 0 \\ 0 & 3 & 16 \end{bmatrix} + \begin{bmatrix} 26 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix} + \begin{bmatrix} 0 & 2 & 2 \\ 0 & -2 & 0 \\ 0 & 0 & -2 \end{bmatrix} \\ &= \begin{bmatrix} 57 & 3 & 2 \\ 1 & 18 & 0 \\ 0 & 3 & 16 \end{bmatrix} \end{aligned} \tag{6.32}$$

Thus, the performance metrics and quality KPIs are evaluated from the updated confusion matrix and listed in Table 6.7.

At last, panel 3 requires 24 screw fastening operations. The inspection system proposed identified 23 conforming SFOs, one non-conforming, and none missing. However, the operator corrected that the non-conforming SFO is actually missing, so the rework operation is corrected as such. Then, the process yields:

$$N_3 = \begin{bmatrix} 23 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, E_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{6.33}$$

Table 6.7: List of values for the performance metrics and quality KPIs monitored after panel 2 manufacturing process.

	Accuracy	**Precision**	**Recall**	**Error Rate**	F_1 **Score**	RR_2	HR_2
L_1	0.9381	0.9828	0.9194	0.06	0.95		
L_2	0.9286	0.75	0.9474	0.07	0.8372	0.06	0.10
L_3	0.9479	0.8889	0.8421	0.05	0.8649		

The confusion matrix for this last panel, CM_3, is updated as follows:

$$\begin{aligned} CM_3 &= CM_2 + N_3 + E_3 \\ &= \begin{bmatrix} 57 & 3 & 2 \\ 1 & 18 & 0 \\ 0 & 3 & 16 \end{bmatrix} + \begin{bmatrix} 23 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 80 & 3 & 2 \\ 1 & 18 & 0 \\ 0 & 4 & 16 \end{bmatrix} \end{aligned} \tag{6.34}$$

Finally, the end results for the performance metrics and quality KPIs after all the three manufactured steel frame assemblies can be obtained. The resulting values are listed in Table 6.8.

Table 6.8: List of values for the performance metrics and quality KPIs monitored after panel 3 manufacturing process.

	Accuracy	**Precision**	**Recall**	**Error Rate**	F_1 **Score**	RR_3	HR_3
L_1	0.950	0.9877	0.9412	0.0484	0.9639		
L_2	0.9344	0.720	0.9474	0.0645	0.8182	0.0565	0.0887
L_3	0.950	0.8889	0.80	0.0484	0.8421		

Finally, Figure 6.14 and 6.15 illustrate the variation of the performance metrics and quality KPIs discussed over the continuous production of the three steel frame assemblies. Regarding the monitoring of the machine learning algorithm, all relevant metrics can be actively and dynamically monitored throughout the use of the algorithm in real-time. For example, by introducing a minimum threshold for the accuracy, precision, recall, and/or F_1 score, or a maximum threshold for the error rate, the *Configuration Level* can automatically deactivate the algorithm and notify the appropriate personnel [213]. Machine learning algorithms would require, i.e. in case of changes in its behavior, retraining on a new (updated) data-set to be re-implemented in the environment. At that point, all the values of the performance metrics need to be reset. Nonetheless, further work is necessary to showcase a complete integration of a more complex supervisory control agent that does not block the production system, such as the one described in [214], or commercial solutions such as MonitorML.

As observed, both discussed quality KPIs are plotted over time after each panel manufacture has finished (quality rate, QR, is omitted due to its linear relationship with the rework ratio, RR, is this study). In this machine environment, after three frames manufactured, the rework ratio stands below 6%, representing a little over 1 screw fastening operation reworked per frame, while the human effort for rework, (HR), stands around 9%. As defined, (HR) considers the uncertainty of rework orders provided by the system proposed, whereas (RR) represents accurately the amount of rework performed in the product. As such, considering an scenario where all the rework orders proposed by the system are followed by the operator(s) then both indexes provide identical results (see frame 1), however, those ideal situations only occur in conditions where the system provides 100% accurate rework orders or where false positives compensate false negatives. In other more probable situations, the errors in rework orders come from false positives in 'Non-conforming SFO' or 'No SFO' predictions where the true label is 'Conforming SFO', which are not considered by the rework ratio as rework is deemed not necessary by the operator. Nevertheless, the operator has to go and re-inspect the SFO that is flagged, and reassess the inspection results.

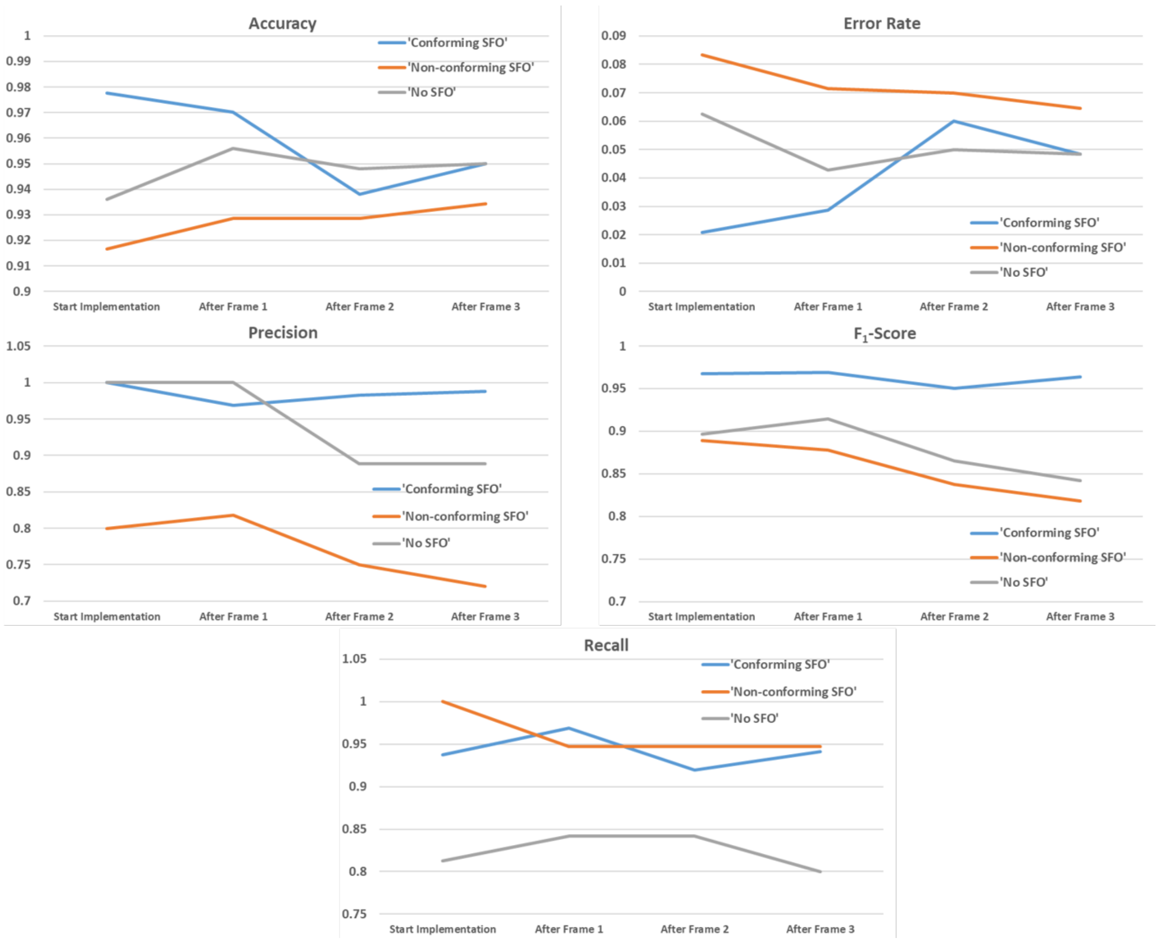


Figure 6.14: Evolution of performance metrics during continuous production of steel frame assemblies.

From a management perspective, (HR) gives a more comprehensive insight on the utilization of resources for rework operations than (RR) does. Potentially, when including time studies on rework operations, (HR) could explain delays on certain frame assemblies, for example, that had no rework done and where (RR) could not help with. Although the proposed index looks promising to quantify rework in semi-autonomous systems where rework orders are automatically suggested, it still requires further integration with other supporting elements, i.e. time and maintenance elements, to further understand the implications and limitations of common quality KPIs as currently defined.

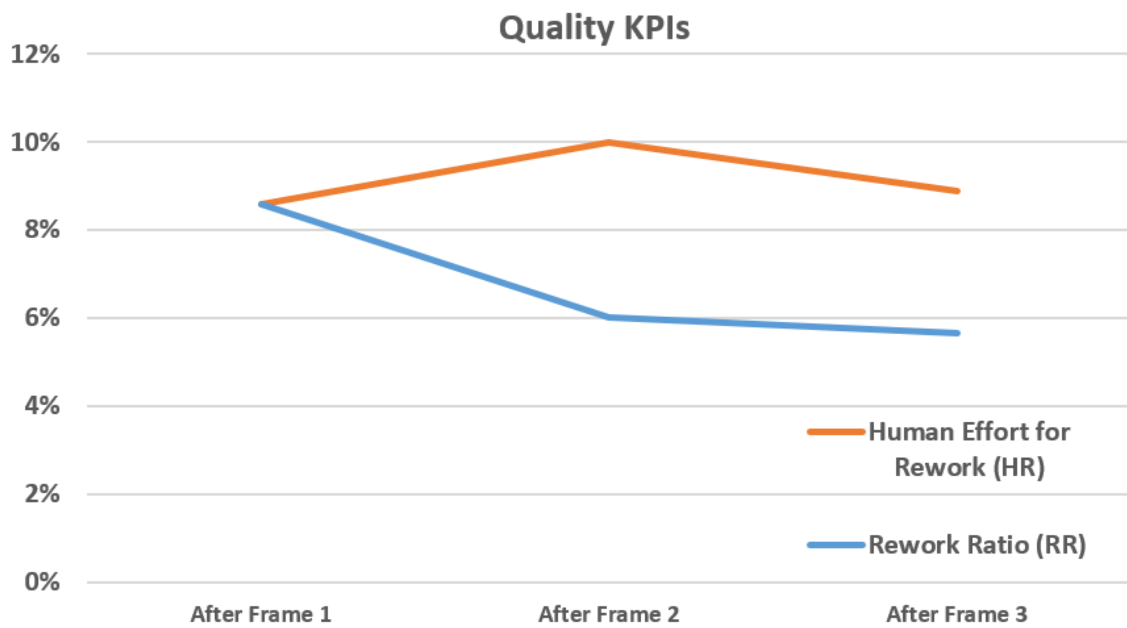


Figure 6.15: Evolution of quality KPIs during continuous production of steel frame assemblies.

6.8 Discussion & Limitations

In conclusion, the proposed cyber-physical system introduces the capability of current steel framing machinery to perform automated quality control and assessment during the manufacturing process. By relying on visual inspection and data analysis, steel frames are manufactured in a more accurate and safer way, while its quality can be judged and quantified. Based on the quality results obtained, the system enables the opportunity for steel framing operators to perform data-driven rework, by following (or not) the automated suggested corrective operations. The proposed system also monitors the rework operations using user input and quality inspection results by automatically computing relevant quality KPIs: rework ratio and a novel KPI introduced that computes the total human effort for rework. This new indicator serves as un upper boundary for rework monitoring that considers the uncertainty introduced by the results obtained by the system's algorithms.

In fact, the proposed system encounters several limitations regarding the probabilistic nature of its data. As most image processing and machine learning algorithms, the resulting output contains a varying uncertainty that depends on several external factors, for example, changes on lighting or introducing novel components onto the screw fastening operations. As the main objective of the cyber-physical system developed is to support data-driven improvements to the manufacturing process and design of steel frames, those altering changes to the environment modeled in this research are inevitable. By introducing a culture of continuous improvement, the stochastic processes defined herein would see their uncertainty potentially increase as changes are introduced on the system. If that were to be the case, image processing algorithms would need to be updated to match novel conditions and machine learning approaches would need to be retrained on an updated data-set.

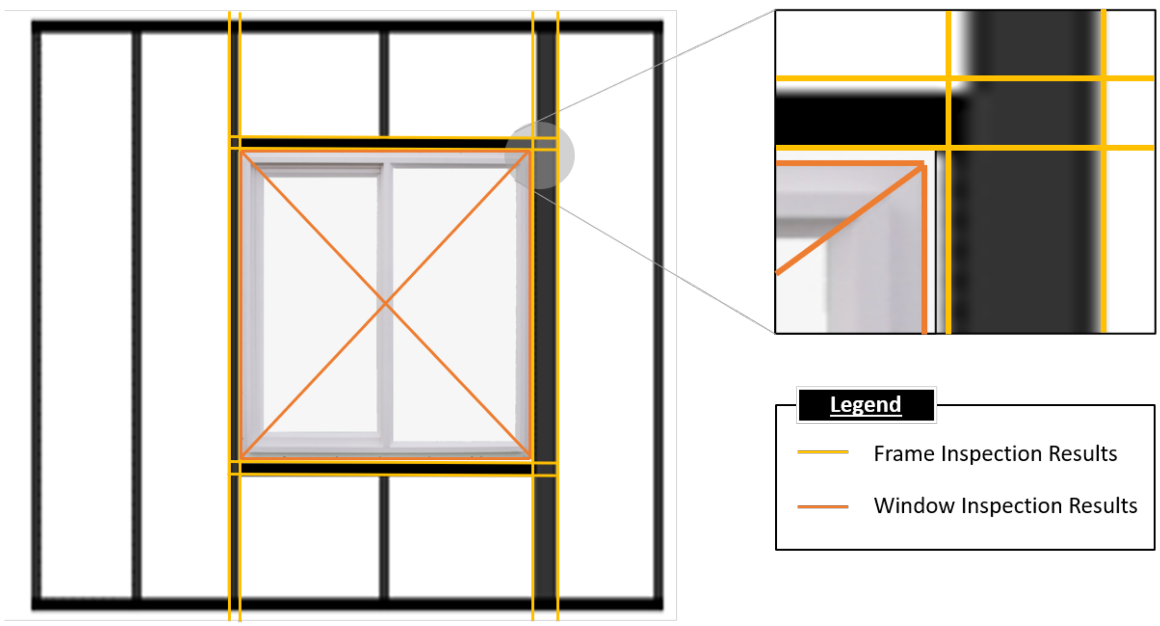


Figure 6.16: Quality relationship between window component and steel frame.

With those limitations in mind, the proposed cyber-physical approach can be generalized to other BIM-based manufacturing processes in offsite construction facilities, assuming the necessary adaptations to inspection algorithms and knowledge models to the selected environment. Following the inspection approach proposed in this thesis, several similar products can be addressed in a similar fashion: products where squareness or assembly assurance are the main quality concerns. For example, other types of framing could benefit from such analysis such as wood framing or cross-laminated timber panels, as well as other products that rely on frame squareness (or overall quality) for its assembly processes such as windows or doors. An example of such relationships is illustrated in Figure 6.16: deviation in frame opening squareness and window squareness, as well as individual corner angles for the frame and window, should be minimized to ensure fitting of the window in the opening and ease the installation process, often manual and physically extenuating for workers.

Chapter 7

Conclusions, Discussion, & Future Work

7.1 Conclusions

Steel framing has become a popular solution for prefabricated commercial and mid-rise buildings. As offsite construction develops as an alternative to traditional construction, automation of construction processes is in demand in their facilities. In this context, the research presented aims to introduce a framework adapted to the offsite construction workflow for automatic inspection and quality assessment of steel frame assemblies. The developed framework enables offsite construction practitioners to (a) prepare their quality procedures from the design stage by establishing a link between design elements and features and quality specifications; (b) providing real-time quality control and assessment in an integrated manner with its manufacturing process; (c) establishing a platform to support and automatically suggest rework operations in the current manufacturing workflow; and, (d) supporting data-driven analysis of manufacturing defects at bay to promote continuous improvement culture towards zero-defect manufacturing in offsite construction facilities.

The framework proposed is evaluated for steel frame assemblies manufacturing in a semi-automated environment where machine and human output impact the end-product quality. Initially, a knowledge model for steel frame assemblies is developed using ontologies that establishes a link between the product design, manufacturing, and quality domains. By looking at element intersections, a set of quality specifications can be accessed by querying BIM models, therefore information regarding the quality requirements of designed steel frames can be dynamically accessed from the BIM software. Then, considering the list of features that need inspection as per quality specifications, a vision-based inspection system is developed to generate quality-oriented data at the pre-manufacturing, online, and post-manufacturing stage following a cyber-physical approach. By applying novel image processing techniques, i.e. Hough transform or edge fitting among others, geometrical measurements of the required quality specifications can be obtained with sufficient accuracy. Those measurements are first used for real-time quality control, providing machine operators with quality information during the manufacturing process, and are stored in a database to enable further offline analysis. Posterior analysis allows for more powerful and computationally demanding approaches to be used, such as data mining or machine learning, that can provide more robust quality information about the steel frame assembly manufacturing process. For example, a deep learning model (R-CNN) is used to determine the correct physical aspect (location and finishing) of a conforming screw fastening operation. Finally, an interface is developed to visualize the inspection results to the machine operator at several stages of the frame assembly manufacturing, as well as to suggest rework operations based on those inspection results. The interface serves also as an interactive platform with the operator, in which cognitive assessment of the inspection results can be communicated. A supervisory agent is then developed to monitor the inspection results and the final decisions taken by the operator in regard to the quality of the frame. This agent can supervise the results provided by the cyber-physical system over time and automatically computes quantity and quality key performance indicators, hoping to quantify quality issues through lean metrics that can support continuous improvement in the manufacturing process of steel frame assemblies.

7.2 Research Contributions

The research presented in this thesis contributes several additions to the body of knowledge of quality inspection systems for construction products designed in BIM, as well as the manufacturing process of steel frame assemblies. Overall, the work reported in this thesis supports the automation of quality control and assessment in offsite construction facilities from the source to the bay. The main contributions of this research are summarized below.

- Developed an ontology-augmented BIM environment that allows to visualize and query quality information at the design stage. Formalized the relationship between product design (BIM schema), manufacturing operations, and quality specifications by determining key design features and key operations of the steel frame assembly process.

- Designed novel machine vision algorithms for inspection of the steel framing manual assembly process, previous to any manufacturing, that enables to measure the overall features of the frame and each individual element: frame squareness and element length, width, and spacing. As such, the system can identify each frame element and match it against BIM model components to confirm the correct manual assembly per quality specifications.

- Developed a vision-based approach to determine the correct feasibility of screw-fastening operations in an automatic environment, providing online feedback to the machine actuators and securing the conformity of the manufacturing process from a quality perspective, i.e. screw fastening location, even in highly constrained situations such as using pre-drilled studs for steel framing.

- Developed a novel real-time image processing technique to measure the squareness of frame element connections before and after the connection is permanently secured using self-drilling screw fasteners.

- Integrated all the inspection systems within the available steel framing machinery as a cyber-physical system.
- Evaluated the use of machine learning approaches to identify conforming and non-conforming manufacturing operations in automated steel framing processes.
- Developed a user interface for quality inspection that displays inspection results, and if needed, suggest corrective actions to rework the frame to conformity, and enabling operators to interact with the system in case of mistaken suggestions, overriding the system results.
- Developed a supervisory agent that monitors the automated inspection results, specially from stochastic algorithms such as machine learning, and keeps track of the additional human intervention for necessary rework of the steel frames manufactured. This agent communicates its monitoring aspect to managers through well-known metrics such as confusion matrices (for machine learning) and quality KPIs (for rework operations).

7.3 Limitations and Future Research

Despite the successful achievement of its goals, the research presented in this thesis is confronted by the following limitations that should be addressed by researchers in the near future:

- The current knowledge model provided to establish a link between product design, manufacturing, and quality specifications is tailored to the manufacturing environment available. As such, the model provided is partially untested as certain limitations were encountered when manufacturing capacity is to be included: for example, how to identify if a connection can be manufactured with certain systems available in a deterministic fashion. Whereas the knowledge approach provided is sufficient to reach the goals set, it is dependent of current knowledge of the situation at the shop floor and does require an extensive amount of work to adapt it to new manufacturing circumstances. Although the re-configuration capability of ontology models will definitely ease the effort to be performed, the approach provided is still limited when the main objective remains to introduce a culture of continuous improvement (thus change) within offsite construction facilities.

- Although the inspection systems and image processing algorithms are product-centric, they are still developed tailored to the manufacturing capabilities of the machine used. As such, several combinations and types of steel frames and frame elements are not considered during this research, namely frame features that relate to wall-to-wall connections. An extension of the algorithms used, as well as the features targeted by the knowledge model, would be required to adapt the current framework to a generic steel framing process.

- Considering the limited number of frames inspected to validate the proposed approach, the models and analysis provided in this research represent just an example of a more comprehensive analysis that can be performed using the database created. On top of that, with currently around 200 entries in the database, further experimentation would be necessary to expand on more generic knowledge discovery approaches, i.e. data mining, that could provide more insight on the inherent quality issues related to steel framing.

- Current supervisory agent to monitor the manufacturing process is developed based on the inspection results only, providing mostly quantity elements that enable to calculate certain quality KPIs. By introducing other mechanisms in the framework, such as RFID for timing elements, more complex performance indicators could be computed that would, theoretically, provide further insight on the current manufacturing process. For example, including quality and timing indicators, delays related to rework operations could be identified, thus, highlighting the cost of rework in steel frame assemblies manufacturing.

- Further work is needed to fully implement zero-defect manufacturing principles as a whole in the proposed methodology: as stated in this thesis, product-centric research is the focus; however, machine-centric inspection, i.e. tool inspection, has been ignored. In the near future, such algorithms need to be developed to provide machine information and finally correlate quality issues, i.e. defects, with tool condition. As such, data-driven predictive maintenance of the studied machine environment is enabled with a focus on quality.

- Although the culture of continuous improvement has been discussed in this thesis, the data provided in this thesis has not been used for such purposes using lean approaches, i.e. *poka yoke*. In the near future, discussion regarding the application of *poka yoke* in Industry 4.0 (or Construction 4.0) manufacturing environments will be addressed.

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Appendix A: Scientometric Analysis of Computer Vision Applications in Construction

A.1 Introduction

Image processing and computer vision have been used in numerous different scientific fields to provide information or data as a substitute for human eyes. Due to the decreasing cost of visual sensors and the availability of robust visual systems, the integration of computer vision in industrial environments has grown exponentially in the last decades in a broad range of sectors, such as retail, security, automotive, healthcare, and agriculture. In the construction industry, computer vision has drawn attention because it can be used for the automation of critical tasks that require continuous object recognition, identification, and monitoring, or motion, behavior, location estimation, and so forth. The rich data-set of information that can be obtained from a construction-related scene by taking images or videos that facilitate the understanding of complex construction tasks rapidly, accurately, and comprehensively. However, the dramatic increase in the amount of literature published regarding the development of computer vision-based systems for civil construction operations has not had the desired impact on the construction industry. Despite their importance, current practices are still time-consuming, costly, and error-prone.

In the last decades, computer vision research has been diverse as more emerging technologies have been integrated into construction-related projects. Literature review is regarded as an expedient approach to gain an in-depth understanding of a research area. Existing review publications target relevant topics of computer vision applications in civil construction. For example, computer vision technologies have been applied to monitor for unsafe conditions and actions with the aim of mitigating potential hazards in construction projects in a timely manner. Although its application is still premature, it demonstrates that major research contributions and challenges for technical and practical automatic vision-based safety and health monitoring are needed. Also, image processing techniques are the key factor in the research and development of the most recent building information model (BIM)-based technologies applied in construction. As-built modeling has proven to be a challenge that involves both disciplines, computer vision and civil engineering, and an important effort is being made to consolidate and integrate existing techniques, along with developing new methods, to automatically generate a working BIM. The increasing demand on intelligent technologies requires pragmatic and cost-effective methods that not all the proposed methods provide for the construction industry. In fact, as-built BIM automatically generates digital representations for existing assets from very different visual techniques and devices, such as camera systems, laser scanners mounted on mobile robots or flying unmanned aerial vehicles (UAV). These systems generate 3D point clouds that provide detailed information to reconstruct the BIM model of an existing element. BIM information is also collected using the same methods for project control purposes, targeting the inspection and quality control of building elements. Whereas existing review publications showcase detailed analyses on certain areas of research, the application of computer vision methods has been diverse and with varying degrees of complexity, thus a research effort is needed to provide a full scope of the use and impact of computer vision in construction-related fields.

Scientometrics is defined as the "quantitative study of science, communication in science and science policy", and includes the measurement of research impact, investigates the impact of institutions and journals in a certain field of research, and provides deeper understanding of scientific citations. Scientometrics has been used for the analysis of the latest research in other construction-related research fields, such as construction engineering and management (CEM), or BIM. The study presented in this paper attempts to conduct a scientometric review of the scientific literature relating to computer vision in construction-related activities and to gain an overall description of the developments in this research field over the past two decades (1999–2019). The findings can provide researchers with a better understanding of the current state of visual applications and research in civil construction and identify the main topics in the literature.

A.2 Research Methodology

To achieve the research objectives of this paper, academic publications within the field were identified. The list of publications was obtained using Scopus database. Given the difficulty of searching each related article, a delimitation of the research boundary is frequently necessary. The main points of each publication will be determined by its research title, objectives, methodology, and major contributions. The methodology for this current study will be explained below and an overview can be found in Figure A.1.

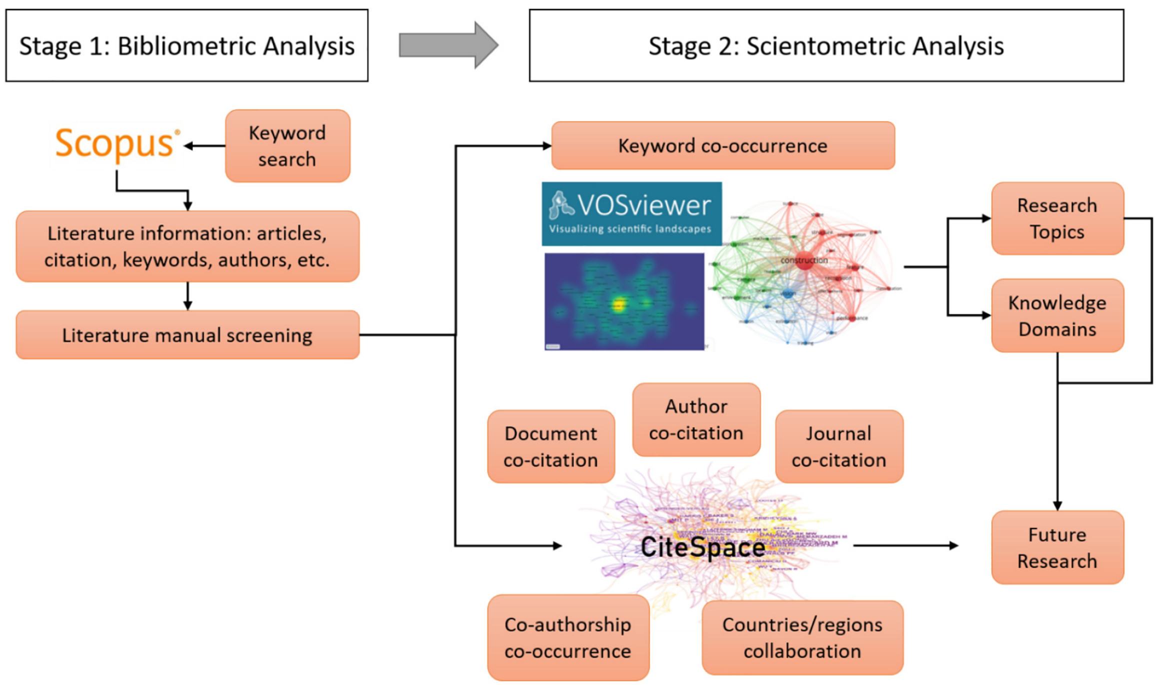

Figure A.1: Research methodology for the scientometric analysis.

A.2.1 Bibliometric Analysis

Data acquisition of existing literature is crucial in this research since it determines the scientific articles from which any conclusions will be drawn. For this reason, the database selection and searching strategy are carefully selected. For this study, Scopus database was selected as the literature database due to the wide range of coverage in the domain of construction-related research compared with other databases such as Web of Science, Google Scholar, and PubMed, among others. Scopus database is a better choice for inter-disciplinary research topics, such as the one reviewed in this paper, than the previously mentioned databases, and also has a wider range of journal publications.

The existing literature related to computer vision applications in the construction sector in this database was then retrieved by using keywords, i.e. ”computer vision*” and ”construction*” (note that the wildcard character * is used to capture variations of one keyword, such as ”vision system”, ”visual system”, and ”vision-based system”). According to the objective of this review, the selected keywords were: (”Computer vision*” OR ”Machine vision*” OR ”Vision systems*”) AND (”Construction*”). The keyword search in Scopus was set as title/abstract/keywords in order to retrieve all the publications containing the selected keywords in their title, abstract, or selected keywords section. The search period was set to include the last 20 years, from January 1999 to February 2019, which is suitable considering the development history of computer vision within construction-related research. A screening process was conducted successively for the purpose of refining the results to the relevant engineering scope. For example, research papers within the subject area of medicine or agriculture that may mention ”construction” in another sense of the word were excluded in this step. Only papers in peer-reviewed English journals or conference proceedings were considered for the review process and book reviews or editorials were also excluded so that all the retrieved papers could be screened using an identical construct in terms of research aims and methods. A further refining process was conducted by checking the source title and abstract in order to exclude papers from irrelevant journals or conference proceedings. Those remaining after the screening process were fed into the bibliometric analysis. The initial search yielded over 3000 documents, while the results after the manual screening filtered down the number of documents to 1158, namely 325 journal papers and 833 papers published in conference proceedings. The large number of irrelevant papers that needed to be filtered out can be explained by the colloquial use of the word ”construction” in other contexts and research fields.

A.2.2 Scientometric Analysis

The definition of scientometrics is first proposed by Mulchenko as "a quantitative study of the research on the development of science". It can be considered as a technique that measures research impact and citation processes and maps the current knowledge and its evolution in a domain based on large academic data-sets. Due to the wide spectrum of research topics related to computer vision in construction, there is little prospect of characterizing the overall field through systematic literature analysis. Although manual review provides insightful overview of the research field, it remains prone to bias and is limited in terms of subjective interpretation. Therefore, the current study proposes a holistic analysis of computer vision within construction-related activities using the scientometric technique, a research method to ease visualization and mapping of knowledge domains. This methodology applies bibliometric techniques to published literature and is used to map the structure and evolution of numerous subjects based on large-scale scholarly data sets. Through network modeling and visualization, scientometric research aims to analyze the intellectual landscape of a knowledge domain and to perceive questions that researchers may attempt to answer, as well as methods that authors have developed to achieve their goals. Visualizing the entire field of computer vision in construction will enable readers to gain a global perspective of research patterns and trends in the field.

Keywords and abstracts are considered clear and concise descriptions of the research contents, which require these keywords as units of analysis to identify prominent groupings that affect the structure of the researched field. In this study, the literature of computer vision for construction was analyzed in terms of keywords and abstract terms to retain the opinions of the authors as much as possible. The following methodologies were applied to reveal research patterns: Keyword co-occurrence analysis and keyword clustering, co-author analysis and burst detection, country co-occurrence and co-citation analysis, and abstract term cluster analysis. Firstly, the keyword and author co-occurrence analysis makes an aggregate representation of the research field and the network indicators provide evidence for the posterior clustering analysis. Secondly, the burst detection sheds further insight on the relative changes of significance over time to identify trends and changes in computer vision for construction, in contrast to the previous analysis that simply provides a static description of the field as a whole. Finally, abstract term clustering indicates the research patterns within the field in detail, as well as various specific research themes associated to lay out the research conceptual framework. These techniques have been recommended in previous studies of similar nature.

A.3 Results

A.3.1 Data Acquisition

The keyword search strategies aforementioned were employed to identify relevant academic articles in journals and conference proceedings, which have been summarized in Tables A.1 and A.2. The majority of academic publications on computer vision applications for construction are found in journals related to both fields, including Automation in Construction, Advanced Engineering Informatics, Journal of Computing in Civil Engineering, International Journal of Computer Vision, Computer Vision and Image Understanding and Machine Vision and Applications. Among these journals, Automation in Construction is the journal that includes the most publications on this topic. Similarly, conference proceedings that make considerable contributions to the field are Proceedings of the IEEE Computer Science Conference on Computer Vision and Pattern Recognition, and Proceedings of the IEEE International Conference on Computer Vision. Notably, most of the selected journals and conference proceedings contained one or two publications related to the researched field: 37.22% of the journal articles and 79.84% of the conference proceedings were published in such conditions.

Table A.1: List of most widely read academic journals from January 1999 to February 2019 that published research related to computer vision applications for construction.

Journal Title	**Number of Relevant Articles**	**% Total Publications**
Automation in Construction	45	13.85%
Advanced Engineering Informatics	18	5.54%

(Table continues on next page...)

Journal Title	Number of Relevant Articles	% Total Publications
Journal of Computing in Civil Engineering	16	4.92%
International Journal of Computer Vision	15	4.62%
Computer Vision and Image Understanding	13	4.00%
Machine Vision and Applications	11	3.39%
Advances in Intelligent Systems and Computing	9	2.78%
Pattern Recognition and Image Analysis	9	2.78%
Advanced Materials Research	7	2.15%
Image and Vision Computing	7	2.15%
Pattern Recognition	7	2.15%
Industrial Robot	6	1.85%
Applied Mechanics and Materials	6	1.85%
IEEE Transactions on Image Processing	5	1.54%
IET Computer Vision	4	1.23%
Journal of Intelligent and Robotic Systems Theory and Applications	4	1.23%
Procedia Computer Science	4	1.23%
Journal of Visual Communication and Image Representation	3	0.92%
Pattern Recognition Letters	3	0.92%
IEICE Transactions on Information and Systems	3	0.92%
Procedia Engineering	3	0.92%

(Table continues on next page...)

Journal Title	**Number of Relevant Articles**	**% Total Publications**
IEEE Transactions on Cybernetics	3	0.92%
IEEE Transactions on Robotics	3	0.92%
Autonomous Robots	3	0.92%

Table A.2: List of most widely read academic conference proceedings from January 1999 to February 2019 that published research related to computer vision applications for construction.

Conference Title	**Number of Relevant Articles**	**% Total Publications**
Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition	54 6.48%	
Proceedings of the IEEE Conference on Computer Vision	45	5.40%
ACM International Conference Proceeding Series	15	1.80%
IEEE International Conference on Intelligent Robots and Systems	14	1.68%
Proceedings IEEE International Conference on Robotics And Automation	13	1.56%
Proceedings International Conference on Pattern Recognition	5	0.60%
Congress on Computing in Civil Engineering Proceedings	4	0.48%

(Table continues on next page...)

Conference Title	Number of Relevant Articles	% Total Publications
Proceedings of the International Joint Conference on Neural Networks	3	0.36%
Proceedings of the IEEE International Conference on Systems Man and Cybernetics	3	0.36%
International Conference on Signal Processing Proceedings ICSP	3	0.36%
Canadian Conference on Electrical and Computer Engineering	3	0.36%
IEEE International Conference on Image Processing	3	0.36%
Proceedings of The World Congress on Intelligent Control and Automation WCICA	3	0.36%

Figure A.2 shows how the number of publications, in either journals or conference proceedings, on the research topic under review varies each year. Publications on computer vision applications in construction show an overall upward trend since 2003-2004, showing two main bursts of publications in 2007-2008 (+87% number of publications) and 2015 (+47% number of publications), that curiously match with the initial development of BIM and big data techniques in construction, respectively. Note that the study considers, for the year 2019, publications in the first two months of the year, hence the lower number of publications in that year. If a linear regression is performed, 2019 keeps the upward trend and estimates over 100 publications on the reviewed topic.

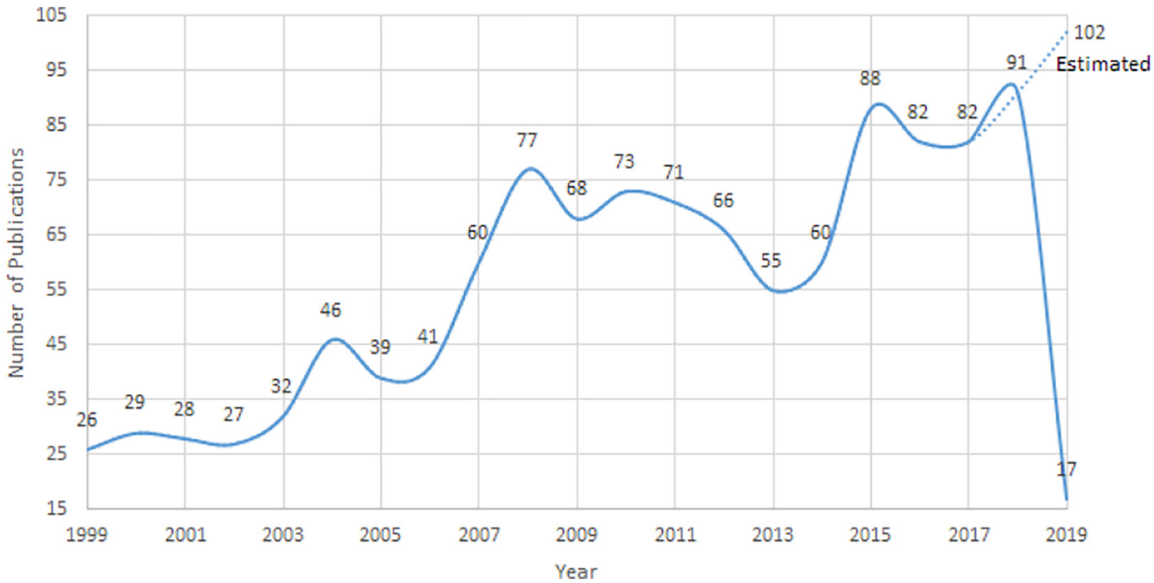

Figure A.2: Historical trend of published studies in computer vision for construction (period 1999–2019).

A.3.2 Keyword Co-occurrence Analysis

Keywords represent the core content of the published documents and showcase the range of areas researched within the boundaries of any domain. To construct and map the knowledge domain between construction and computer vision, keyword co-occurrence in the research area was obtained using VOSviewer. The visualization of the keyword's network was chosen to demonstrate the results of the bibliometric analysis of the literature. The output of the VOSviewer software is a distance-based map in which the distance represents the strength of the relation between two knowledge domains. A bigger distance generally indicates a weaker relationship between the two items. The item label size is directly proportional to the number of publications in which the keyword was found and different colors represent different knowledge domains clustered by the clustering technique of VOSviewer. The minimum number of occurrences was set to 5 so that 44 of the 510 keywords meet the threshold. This threshold selection was based on multiple experiments with other parameters to generate the optimal clusters. Figure A.3 shows the network of co-occurring keywords with 44 nodes, 145 links, and a total link strength of 263. Table A.3 summarizes the keyword occurrences and each individual node strength.

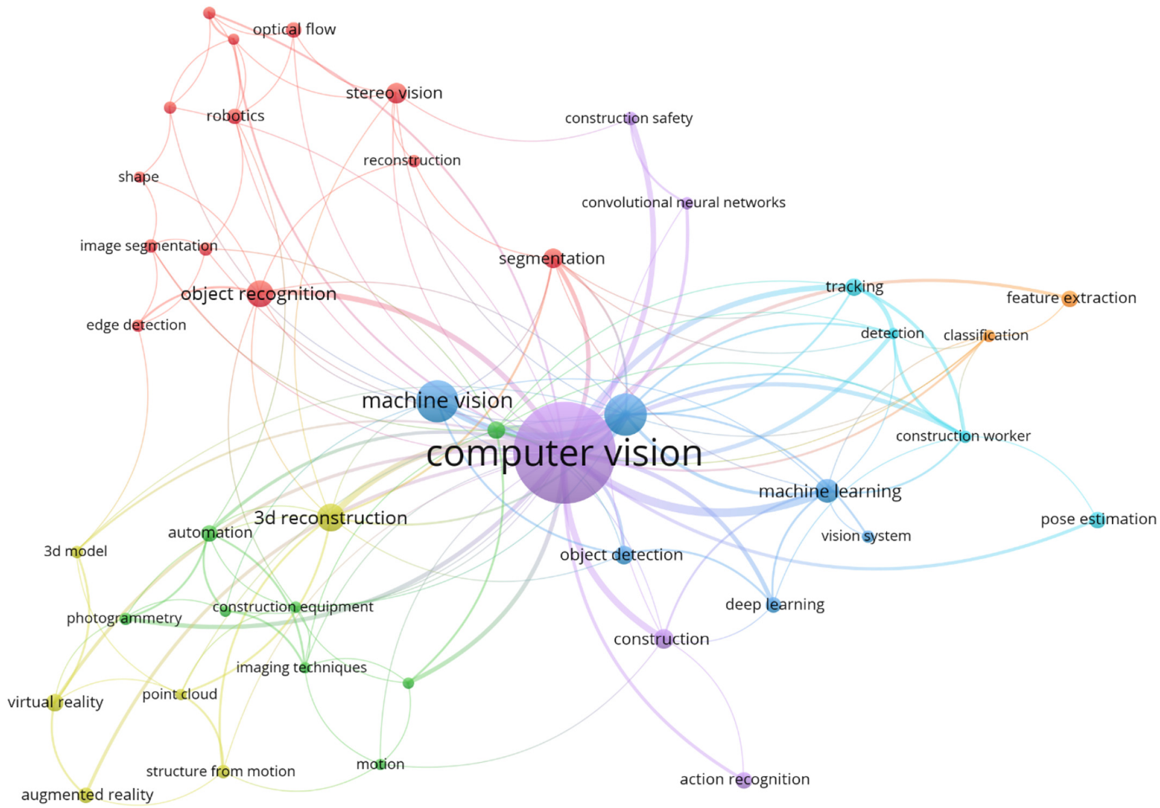

Figure A.3: Network of co-occurring keywords related to computer vision application in construction (1999–2019).

Table A.3: List of selected keywords and relevant network data.

Keyword	Occurrences	Average Year Published	Links	Total Link Strength
Computer vision	237	2013	37	125
Image processing	36	2011	17	39
Machine learning	15	2016	10	22
3D Reconstruction	20	2013	11	21
Construction worker	6	2016	9	19

(Table continues on next page...)

Keyword	Occurrences	Average Year Published	Links	Total Link Strength
Machine vision	36	2011	10	18
Detection	5	2013	8	17
Pattern recognition	10	2010	11	17
Tracking	10	2012	6	17
Construction	12	2013	7	14
Object recognition	19	2013	8	14
Segmentation	12	2012	8	13
Automation	9	2014	7	12
Deep learning	8	2018	5'	10
Virtual reality	10	2009	5	10
Imaging techniques	5	2013	7	9
Monitoring	5	2013	5	9
Object detection	11	2014	5	9
Photogrammetry	6	2012	5	9
Classification	6	2013	7	8
Construction safety	7	2018	3	8
Point cloud	5	2016	6	8
3D Model	6	2013	5	7
Construction Equipment	5	2015	7	7
Information Technology	5	2013	5	7
Mobile robots	6	2010	5	7
Navigation	5	2009	5	7
Stereo vision	13	2013	7	7
Structure from motion	7	2013	5	7

(Table continues on next page...)

Keyword	Occurrences	Average Year Published	Links	Total Link Strength
Augmented reality	8	2012	3	6
Convolutional neural networks	6	2018	3	6
Robotics	8	2009	6	6
Edge detection	6	2011	4	5
Image segmentation	7	2008	5	5
Motion	5	2011	5	5
Neural networks	5	2007	5	5
Robot vision	7	2011	5	5
Action recognition	9	2014	2	4
Feature extraction	9	2012	2	4
Optical flow	8	2012	4	4
Pose estimation	9	2014	2	4
Shape	5	2010	3	4
Reconstruction	6	2011	3	3
Vision system	6	2008	2	3

As shown in Table A.3, the occurrence shows the number of times each keyword was retrieved in the existing literature from the author keywords. For example, other than the main keyword "Computer Vision", "Image Processing" is the keyword that appears most frequently among all the keywords, which means that it has been widely researched in this field. The average year published shows the average time period in which a given keyword is used by researchers in their publications. For example, studies involving mobile robots or robotics received more attention during the period 2009–2010, while studies involving construction workers or construction safety were published with greatest frequency in 2016 and 2018, respectively, indicating the latest applications of computer vision in construction research. The links are the number of linkages between a given node and others, while the total link strength reflects the total strength linked to a specific item. For instance, the total link strength of "Image Processing" is 39, which is in the high level of all the keywords and indicates the strong inter-relatedness between "Computer Vision" and "Image Processing".

Keyword co-occurrence networks are static representations of the researched field that do not consider changes over time. However, VOSviewer provides a time zone perspective so that each node is represented by the average year in which the keyword was used in literature. As shown in Figure A.4, the evolution of computer vision application in the construction sector continued in the past decade. Notably, the first applications (2006–2008) were related to "robotics" and "virtual reality", tending to focus on well-known techniques that required minimal integration within the construction field, and thus were easier to implement. Unsurprisingly, general keywords such as "computer vision", "machine vision", "construction", "image processing", and "object recognition" are represented in the middle spectrum (around 2010). This result could be due to an emphasis on such topics around that period of time (2009–2011) or that the topic was evenly researched during the whole period of time researched (1999–2019). This last option is considered as the most plausible explanation. The latest research topics relate to "construction safety" and "construction worker", potentially indicating a shift in the focus of research in this field. Whereas earlier contributions considered the construction sector as a plausible target area of application for certain computer vision applications, later publications target more specific problems in the construction industry, while the computer vision methods and technologies used are relegated to second place. An exception would be the keywords related to novel techniques such as "machine learning" or "deep learning".

A.3.3 Co-author Co-occurrence Analysis

The information with respect to the article authors is available from the bibliographic records, and, thus, identification of the leading researchers in the field, as well as the collaborations between researchers, can be mapped. Then, a co-authorship network can be generated. According to the number of publications, the top 10 most

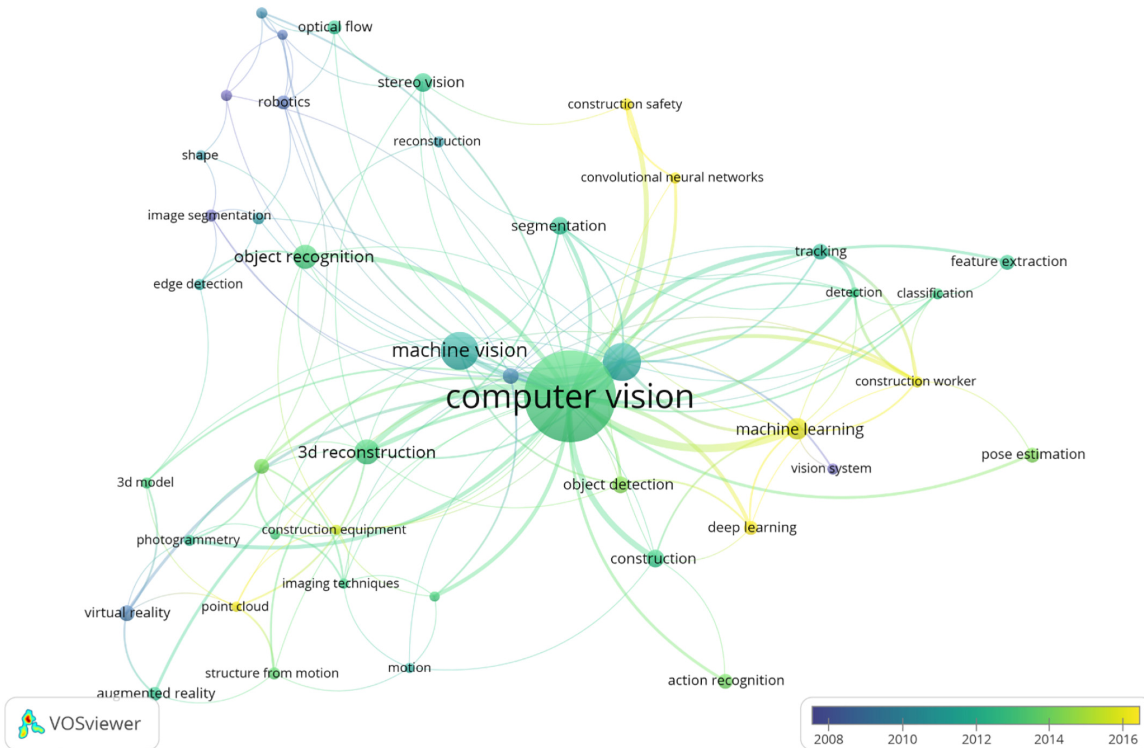

Figure A.4: Network of co-occurring keywords timeline related to computer vision application in construction.

productive authors were identified first. As shown in Table A.4, I. Brilakis (University of Cambridge), M. Golparvar-Fard (University of Illinois), and Z. Zhu (Concordia University) occupied the top three positions.

Co-authorship networks can be generated in CiteSpace, as it can visualize and analyze scientific knowledge to capture the notion of a logically and cohesively organized body of knowledge. Such an approach has been recognized as an advantageous scientometric method to discover the hidden implications of a vast amount of information. CiteSpace is strong in mapping knowledge domains through systematically creating various accessible graphs. Therefore, it was used to generate and analyze the co-author networks, country co-occurrence, and co-citations networks, as well as generate the abstract clustering. In CiteSpace, the burst detection is based on the algorithm developed by Kleinberg.

The co-authorship network is shown in Figure A.5, where each node represents an author and the links between the authors represent collaboration established through co-authorship in publications. The network pruning was used to remove excessive

Table A.4: List of the top 10 most productive authors in the 1999–2019 time period.

Author	Institution	Country	Count	Percentage
I. Brilakis	University of Cambridge	UK	13	1.12%
M. Golparvar-Fard	University of Illinois	USA	9	0.78%
Z. Zhu	Concordia University	Canada	9	0.78%
M. Park	Myongji University	South Korea	8	0.70%
S. Zafeiriou	Imperial College London	UK	8	0.70%
H. Kim	Yonsei University	South Korea	7	0.60%
H. Li	Hong Kong Polytechnic University	Hong Kong	7	0.60%
H. Luo	Huazhong University of Science and Technology	China	7	0.60%
B. Y. McCabe	University of Toronto	Canada	7	0.60%
K. K. Han	North Carolina State University	USA	6	0.52%

links through Pathfinder, which is recommended in previous studies. Finally, there were 153 nodes and 203 links in the generated network. The node size represents the number of publications and the link thickness represents the level of cooperation between authors. Table A.5 summarizes the overall characteristics of the presented network. In particular, modularity Q and mean silhouette scores are two significant metrics, yielded by CiteSpace, that determine the structural properties of the network. Notably, a modularity Q of 0.9278 is high ($Q \geq 0.3$), which indicates that the network is reasonably divided into loosely coupled clusters, and a mean silhouette score of

0.5625 suggests that the provided clustering for the network is quite heterogeneous.

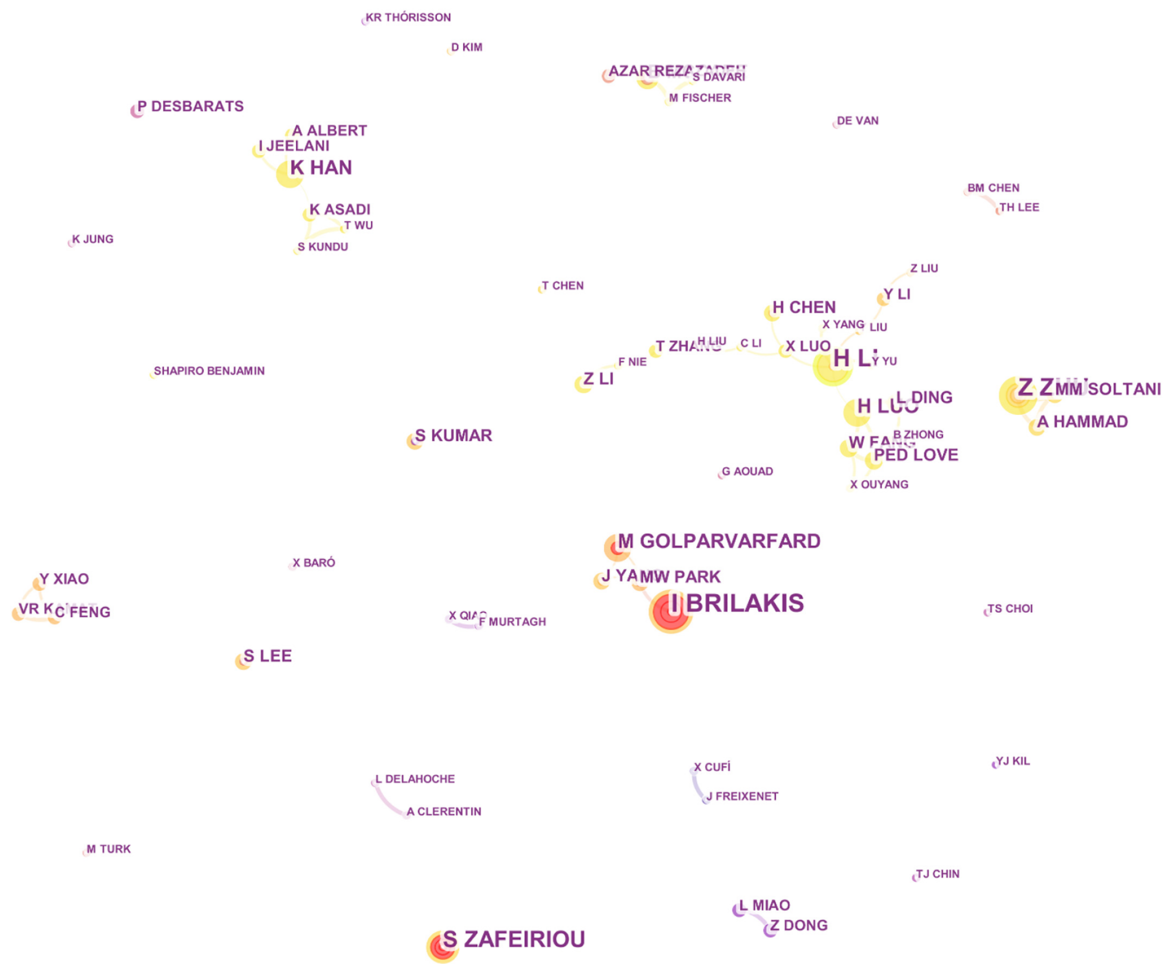

Figure A.5: Network of co-authorship for publications related to computer vision application in construction.

Table A.5: Characteristics of the co-authorship network.

Network	Nodes	Links	Density	Q	Mean Silhouette Score
Co-authorship	153	203	0.0175	0.9278	0.5625

In terms of collaboration, there are some small circuits in Figure A.5, indicating that the researchers in these circuits have established strong collaborations, such as the circuit of I. Brilakis, M. Golparvar-Fard and M. Park, or the slightly larger one led by H. Li and H. Luo. However, none of the circuits represented groups responsible for $\geq 4\%$ of the research in the field. In general, this research field could benefit from more international research collaboration. Centrality is defined as the ratio of the shortest path between two nodes, in this case authors, to the sum of all such shortest paths. In this research field, the highest centrality node is H. Li (centrality = 0.02).

Such a low value justifies the need for further collaboration between researchers in this field. However heterogeneous this field may be, several key contributors can be identified by burst detection. Author bursts represent notable increases in citations over a short period of time. Three bursts are identified within the network: I. Brilakis (burst strength: 3.87 - 2011), M. Golparvar-Fard (burst strength: 3.40 - 2013) and S. Zafeiriou (burst strength: 3.37 - 2014). These authors attracted an extraordinary degree of attention in the corresponding years. It is also worth mentioning that no bursts have been identified in the last 5 years, which is consistent with the fact that the field has been getting world-wide attention in recent years. Thus, a single author may find it difficult to receive high citations over a short period of time.

A.3.4 Network of countries/regions and institutions

Similarly, a network was produced based on the contributions of countries/regions to explore the distribution of research publications on computer vision applications in civil construction. This network includes 48 nodes and 55 links. As shown in Figure A.6, the USA (335 articles), China (154 articles), United Kingdom (87 articles), Japan (76 articles), France (65 articles), Canada (58 articles), Germany (56 articles), and Australia (42 articles) have made major contributions to the publications in this field of research. It is implied that the larger the number of publications, the more advanced the research is in the country/region. In contrast to the co-author network presented previously, the countries/regions network is quite homogeneous and efficient. Nodes with high centrality were identified and highlighted with darker outer rings (purple) in Figure A.6. Countries or regions such as Hong Kong (centrality = 0.80), United Kingdom (centrality = 0.70), Canada (centrality = 0.60), United States of America (centrality = 0.51), Netherlands (centrality = 0.46), France (centrality = 0.33), or Switzerland (centrality = 0.19) have occupied key positions in the network and connected research activities between different countries/regions. Furthermore, citation bursts representing notable increases in citations over a short period of time were found in some countries/regions. Citation bursts are summarized in Figure A.7.

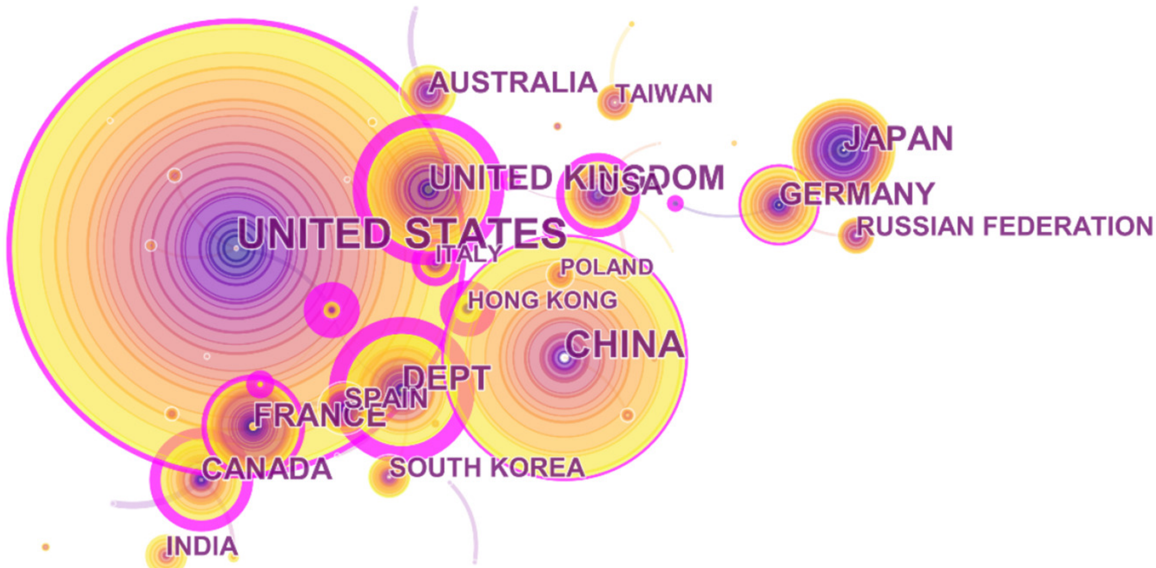

Figure A.6: Network of countries/regions for publications related to computer vision application in construction.

The contributions of institutions were also identified. Computer vision research for applications in the construction sector has been quite active at institutions such as the University of Michigan (22 publications), Carnegie Mellon University (20 publications), and Georgia Institute of Technology (19 publications). However, similarly to co-authorship, no relevant institutions can be considered as main centers of research around the world as they represent a very low percentage of the world-wide research (around 1%).

A.3.5 Author Co-citation Network

Author co-citation analysis can identify the relationship among authors, whose publications are cited in the same publications and analyze the evolution of the research community for the studied field. Figure A.8 presents the author co-citation network, containing 317 nodes and 657 links. The node size reflects the number of co-citations of each researcher, and the links between authors represent indirect collaborations established by co-citation frequency. Thus, the most highly cited authors were identified, including D. Lowe (frequency = 89, Canada), J. Yang (frequency = 58, China),

N. Dalal (frequency = 52, USA), M. Golparvar-Fard (frequency = 51, USA), H. Bay (frequency = 49, Switzerland), I. Brilakis (frequency = 48, United Kingdom), K. Mikolajczyk (frequency = 46, United Kingdom), P. Viola (frequency = 42, USA), and J. Gong (frequency = 42, USA). The diversity in the location of these most cited authors demonstrate that this field of research had been widely performed around the world.

Furthermore, several authors had citation bursts with rapid increases in citation frequency over short periods of time. The top identified bursts in the network are included in Figure A.9 Their articles, while not necessarily directly linked to the research field, tended to affect in great measure the direction of computer vision in construction research and were worth following.

A.3.6 Journal Co-citation Network

As shown in Table A.1, the top source journals and conference proceedings for computer vision in construction were identified, according to the statistics from Scopus database. The references cited in those publications were analyzed and then a journal co-citation network with 337 nodes and 1195 links was generated to identify the most cited journals, as indicated in Figure A.10. The node size denotes the co-citation frequency of each source journal. With respect to co-citation frequency, the top most influential journals were International Journal of Computer Vision (frequency = 287), IEEE Transactions on Pattern Analysis and Machine Intelligence (frequency = 235), Pattern Recognition (frequency = 160), Automation in Construction (frequency = 100), Journal of Computing in Civil Engineering (frequency = 85), Image and Vision Computing (frequency = 68), Computer Vision and Image Understanding (frequency = 65), and Advanced Engineering Informatics (frequency = 59). It is worth noting that these journals were also among the top source journals in which publications related to computer vision for construction were published. Thus, the journals with more contributions to this research field also attracted more citations. However, it is worth noting that this effect is multiplied in journals which focus on the civil engineering field, as a lesser amount of source publications generated more citations than regular computer vision journals.

A.3.7 Document Co-Citation Network & Clustering

Document co-citation analysis enables underlying intellectual structures of a research field and demonstrates the quantity and authority of references cited by publications. In this section, a network of document co-citation is generated to represent the relationship between citations at an individual level. According to Figure A.11, the top 25 cited documents in the field are summarized in Table A.6. It is important to note the low centrality of the most cited documents. Note that centrality is defined as the ratio of the shortest path between two nodes, in this case publications, to the sum of all such shortest paths. A node is considered central to a mapped network when its centrality value is above 0.3. Meaning that even the most cited documents cannot be considered as central for the co-citation network.

A network of document co-citations and co-citation clusters, which contains 315 nodes and 661 links, is presented in Figure A.11. Each node represents a publication and its label shows the first author's name and the publication year. Each link represents the co-citation relationship between the corresponding publications. The co-citation frequency between documents is represented by the node size. As seen previously, centrality is represented by a darker outer ring (purple) and the selected documents with high centrality are shown in Figure A.11. They can be seen as the major intellectual turning points for the researched field, and almost all of them were included in the top 25 most cited publications, as shown in Table A.6.

A total of 11 co-citation clusters were identified based on the abstract of each of the documents cited in each cluster. Note that all the presented clusters are loosely coupled but their boundaries are clearly defined. In Table A.7, alternative labels are shown, such as the log-likelihood ratio (LLR) algorithm that selects cluster labeling based on keywords and provides uniqueness and a decent coverage.

Given the data in Figure A.11 and Table A.7, in the first decade of the period studied in this review, the research was focused on developing computer vision algorithms that could be easily applied to construction tasks. As the reviewed research field was starting to grow at the time, most of the initial cited documents were related to previous computer vision algorithms or the image processing techniques used. As such, cluster 4 (mean publication year = 2006) and cluster 2 (mean publication year =

Table A.6: The top 25 most cited documents in the 1999–2019 time period.

Rank	Article	Total Citations	Q	Rank	Article	Total Citations	Q
1	Memarzadeh et al.	64	0.03	14	Yang et al.	7	0.02
2	Brilakis et al.	58	0.05	15	Golparvar-Fard et al.	6	0.05
3	Park et al.	52	0.04	16	Gong et al.	6	0.00
4	Seo et al.	48	0.07	17	Yang et al.	5	0.04
5	Golparvar-Fard et al.	46	0.21	18	Chi et al.	5	0.08
6	Gong et al.	43	0.04	19	Felzenszwalb et al.	5	0.00
7	Cao et al.	41	0.04	20	Han et al.	5	0.03
8	Dalal et al.	37	0.09	21	Navon et al.	5	0.04
9	Lowe	31	0.04	22	Ray et al.	5	0.03
10	Siebert	24	0.17	23	Bay et al.	4	0.03
11	Cheng et al.	17	0.06	24	Brilakis et al.	4	0.00
12	Fang et al.	9	0.04	25	Dimitrov et al.	4	0.10
13	Park et al.	7	0.04				

2007) contain publications that are grouped by the use of either images or collections of images and videos, respectively, to implement existing or novel computer vision algorithms in construction activities.

The construction activities may vary from earth moving operations monitoring to

Table A.7: Co-citation clusters of vision-based research for construction 1999–2019.

Cluster ID	**Size**	**Abstract Cluster Label**	**Mean Publication Year**	**Main Documents**
0	232	Workers	2012	Brilakis et al.
1	112	Tracking	2012	Memarzadeh et al.
2	77	Videos	2007	Gong et al., Gong et al.
3	47	Visual Monitoring	2011	Golparvar-Fard et al.
4	42	Key Frames	2006	Lowe
5	36	Activities	2013	Han et al.
6	34	Health Monitoring	2016	Ding et al.
7	33	Workers	2014	Teizer et al.
11	27	Inspection	2015	Siebert et al.
12	24	Defects	2013	Bay et al.
16	5	Large Concrete Structures	2010	Silberman et al.

equipment tracking and optimal utilization. Such variation in the research topics makes their analysis more complicated. The publication in 2011 by Gong et al. on object recognition and contextual decision making introduced the possibility of productivity analysis from vision-based data in construction, thus opening the link between previous computer vision work and the complexity of construction operations and management. Since then, most researchers have focused on the integration of computer vision within on-going construction operations (cluster 3, mean publication year = 2011), in tracking resources (cluster 1, mean publication year = 2012 and cluster 16, mean publication year = 2010), and ensuring safety within construction sites (cluster 0, mean publication year = 2012 and cluster 7, mean publication year = 2014). More recent work includes inspection and as-is modeling of construction products (cluster 11, mean publication year = 2015) and the assessment of possible defects (cluster 12, mean publication year = 2013). Note that different clusters that are located far away from each other in the network present similar cluster labels. For example, cluster 0, cluster 6, and cluster 7 contain publications that target the safety of operators, either by monitoring unsafe operations and personnel or by identifying on-site operators not wearing personal protective equipment (PPE). Encountering similar research topics with limited common co-citations shows that solutions targeting the same problem are provided within the same research field using completely dissimilar sources of information. Interestingly, different researchers using different literature are proposing solutions to similar problems.

A.4 Current Research

Based on the data presented in Table A.7, this section will provide insight by reviewing the most representative and recent works grouped by the previously mentioned clusters. The analyzed research topics are ordered based on the overall research interest and number of publications found in literature, starting from the most relevant topic.

A.4.1 Construction Safety & Personnel Monitoring

For construction safety and workers' health, continuous monitoring of unsafe conditions is essential in order to eliminate potential hazards in a timely manner. Computer vision has been applied in this case as a robust and automated means of field observation. Information and images extracted from site videos are regarded as effective solutions complementary to manual observatory practices to mitigate safety risks. Safety at the construction site has been the main target of many researchers in the past decades and is the most researched and prolific area (publication wise) in the computer vision field for construction. Three clusters were mapped in Table 6 around this research area: cluster 0, cluster 6, and cluster 7. Cluster 0 is the biggest cluster in the map (see Figure A.11) with 232 publications, while cluster 6 and cluster 7 are smaller, but no less significant, with 34 and 33 publications, respectively. Looking at Figure A.11, the three aforementioned clusters are closely located; however, the links between clusters are not numerous. Namely, 5 publications from cluster 6 and 3 publications from cluster 7 are cited by several publications in cluster 0. Given the size of the clusters, the number of co-citations between clusters is considered low.

First, the most representative work in cluster 0, published by Brilakis et al., suggests using vision systems to automatically track construction resources, such as equipment, materials, and personnel. The suggested vision-based framework served as the foundation for enhancing safety on site and monitoring health in real-time. At the time of writing, this framework is still cited in the most recent construction safety publications. For example, a real-time warning system was proposed to prevent collisions between heavy equipment and people working on construction sites. To address safety with respect to scaffold work platforms, verification of regulation compliance was accomplished automatically using 3D point cloud data. To improve current capabilities to monitor dynamic work-spaces and ensure worker safety, recent AI-based detection and tracking algorithms were proposed.

Then, for cluster 6, its most representative work, published by Ding et al., proposes applying computer vision and pattern recognition approaches to recognize unsafe behaviors on construction sites. By focusing on spatial and temporal information, the detection and recognition of workers' actions were possible through the use of deep learning methods. The proposed method of combining convolutional neural networks (CNN) with long-short term memory architectures (LSTM) enabled very detailed motion recognition in unsafe operations such as ladder climbing. In general, cluster 6 contains publications related to the use of new artificial intelligence algorithms in this research field. For example, the use of CNN improved the approaches to assess worker's labor and health. By using more accurate detection and tracking algorithms, a more complex and individual risk assessment is targeted.

Finally, cluster 7's most representative work, published by Teizer and Vela, discusses the possibility and need for tracking a workforce on construction job-sites using video cameras. To gather the information and then store the relevant knowledge for the purpose of recognizing unsafe behaviors and operations was a process first recognized from a management perspective by Rezguiet al. However, due to the enormous amount of data generated by onsite video cameras, ensuring workers' safety has become a knowledge modeling problem. To store and analyze the data and provide meaningful changes to improve construction site safety is the current challenge.

A.4.2 Resource Tracking & Activity Monitoring

Recordings of construction operations provide understandable data that can be used for bench-marking and analyzing resource performance. Such recordings support project managers in taking corrective actions on performance deviations and support decision making to improve operational efficiency. Analysis of productivity in a construction site requires tracking of resources and monitoring activities. Four clusters were mapped in Table 6 around this research area: cluster 1, cluster 3, cluster 5, and cluster 16. Keeping track of the available resources on a construction site and linking that availability to the project schedule, site productivity, and construction activity monitoring is a tedious task for project managers that researchers are aiming to automatize. Cluster 1 is the second biggest cluster on the map, with 112 publications, and is only linked to cluster 0 and cluster 5. The relationship between the clusters has some significance, as safety, activity monitoring, and resource tracking have a meaningful correlation. Current research publications highlight this relationship: 12 publications from cluster 5 and 38 publications from cluster 0 are cited by multiple publications in cluster 1. Cluster 3 contains 47 publications and is interestingly quite isolated from its 'similar' clusters and is only linked by 4 publications to cluster 0. Cluster 5 contains 36 publications and is connected to clusters 0, 1, and 7. As mentioned previously, cluster 5 has a strong co-citation relationship with cluster 0 and cluster 1. However, the co-citation links between cluster 7 and cluster 5 are limited to 3 publications. Finally, cluster 16 contains 5 publications and, similarly to cluster 3, is only linked by 2 publications to cluster 0.

First, cluster 1 includes all the publications that pertain to research on visual resource tracking, i.e. equipment or workers, and their effect on productivity on the construction site. Cluster 1's most representative works were published by Memarzadeh et al. and Golparvar-Fard et al. The first publication proposes a vision-based algorithm to detect construction workers and equipment from site video streams. The suggested detector was based on histograms of oriented gradients and colors (HOG+C) and support vector machine (SVM) classifiers and could differentiate between resources performing construction activities or sitting idle. The second work presents a computer vision-based algorithm to recognize earth-moving construction equipment actions. It showed successful results detecting, tracking, and identifying excavator and truck activities on the construction site, introducing the application of such techniques for construction activity analysis.

Then, cluster 3 groups the publications that aim at visual monitoring of on-going construction activities or construction progress. Its main representative work, published by Golparvar-Fard, employs observations of a concrete column and its periphery to recreate the as-built status of the project and assess discrepancies between the as-built and as-planned progress. Such an approach would facilitate the decision making with respect to the necessary remedial actions and provide robust means for recognition of progress and productivity on the construction site.

Next, cluster 5's most representative publication, published by Han et al., employs the use of stereo cameras to improve the accuracy and efficiency of motion analysis by monitoring construction workers' behavior and measuring the impact on safety management.

Finally, cluster 16's most representative work, published by Silberman et al., proposes a segmentation algorithm to support the analysis of indoor complex scenes, such as indoor on-going construction scenarios. By using cameras inside construction sites, real-time working conditions can be assessed and reconstructed in virtual 3D scenarios. The capacity to observe and extract data from complex scenarios enabled researchers to track and monitor activities in late stages of construction projects.

A.4.3 Surveying & As-Is Modeling

Building information models (BIM) are becoming the official standard in the architecture, engineering and construction (AEC) industry for storing and exchanging information about current assets. Throughout the construction process, the ability to use BIM to automatically generate asset's representations is expected to have a big impact on various construction stakeholders. Visual systems, as a data acquisition platform, are becoming an important instrument for as-is modeling and surveying applications. The surveying of construction sites helps to visually monitor work-in-progress, which is particularly important in hard-to-reach areas. From static or mobile platforms, such as unmanned aerial vehicles (UAVs), visual systems play an important role in streamlining the collection, analysis, visualization, and communication of as-built infrastructure systems. All the relevant publications in this research area were grouped into a single cluster: cluster 11. This cluster contains 27 publications and is only connected loosely to cluster 0 by 2 publications with common co-citations.

The most representative publication, published by Siebert et al., develops a novel platform for data acquisition of dense point clouds of large infrastructure projects using UAVs. The presented work detailed the process by which UAV systems are used as data acquisition systems and evaluated their performance against conventional surveying methods. The system was successfully tested in excavation and earth-moving construction sites. More recently, aerial photogrammetry has been used in construction surveying for various tasks as the platform has grown more popular. For example, a framework to automatically assess the structural condition and support the planned maintenance of bridges was proposed based on UAV data. Additionally, a study by Kang et al. used surveying methods to identify construction materials on construction sites for on-going large-scale projects in order to monitor construction progress.

A.4.4 Inspection & Condition Monitoring

Computer vision techniques are advancing to support civil infrastructure inspection and monitoring. Manual inspection is currently the main means of assessing the condition of infrastructure, but manual inspection can be time-consuming, laborious, expensive and/or dangerous. Adopting vision-based frameworks is a natural step forward and will eventually replace manual visual inspections. The condition assessment is performed by leveraging information obtained by inspection or monitoring processes. As such, applications vary from damage detection, i.e. concrete cracks [76], to structural change detection. In general, vision-based inspection algorithms are researched to support real-time monitoring of critical systems in civil infrastructure systems. A total of 24 publications found in the literature delve into this research area and are grouped in cluster 12. This cluster is the most isolated one on the map is only connected by a single co-citation to cluster 0.

The most representative work in this area, published by Bay et al., presents a novel detector and descriptor based on speeded-up robust features (SURF). This detector and descriptor enables researchers to detect interest points on site images based on predefined parameters. SURF has served as a base framework whereby researchers are evaluating the possible utilization of descriptors to recognize field objects in construction applications. Given that the algorithms are less computationally demanding and that the detectors and descriptors are optimized, on-site operators can use mobile devices, such as smartphones, to update project information or interpret what is happening on the construction site. However, civil infrastructure is usually composed of a mixed environment of small and large components, which renders the selection of distinctive features more difficult, and researchers end up selecting features on a case-by-case basis.

A.5 Discussion & Future Trends

A.5.1 Overview

This study uses scientometric analysis in order to review the existing literature data-set on computer vision applications for construction-related research. It extends earlier partial review work of the field by complementing existing subjective critical and integral studies with a strong quantitative approach delivered through science network mapping tools.

Studies were first published in the field in the late 1980s but it was only in the mid-late 1990s that double figures per year are seen. Indeed, almost two decades later, publication numbers keep rising, reaching 91 publications in 2018. This trend confirms the growing interest in research in the field of computer vision in construction. However, publications are highly dispersed between 64 different journals and conference proceedings. This is especially true for research studies presented at conferences, where only 20.16% of the total number of publications are found in the top conference proceedings ($\geq$ 2 publications in the field) listed in Table A.2. Although journal publications are equally dispersed, Automation in Construction seems to have published the highest number of research studies in the field (13.85% of the total journal publications). This suggests that researchers working on computer vision applications for the construction sector encounter issues when deciding where to publish their work; this is due especially to the lack of an international conference that gathers together authors around the topic.

This study considered the relationships between key individual researchers, research journals, and the countries of research origin by means of co-citation network analysis. The results of the co-citation network mapping, performed in the previous sections, highlight the global and homogeneous interactions between researchers all around the world. First, the USA is shown to be the lead country in terms of research influence, along with, perhaps, China. In particular, the US maintains research links with all the countries represented in Figure A.6; however, those links seem to be weak with Germany, Japan, and the Russian Federation. Similarly, most of the co-citations between researchers are focused around important journal papers in the field of computer vision A.3 and then branch out from these initial contributions. This concurs with the observation that initial contributions were focused on developing computer vision algorithms with possible applications in construction and, in the end, evolved over time into fully integrated solutions for the construction industry.

Finally, the story is more complex with regards to the publication outlets in which research is published on computer vision applications for construction. An obvious measure of a journal's worth as a source of knowledge is the number of studies in the field any particular journal publishes. In this respect, Automation in Construction has published the largest number of articles on the reviewed topic, 45 in total. However, other journals present a higher number of citations compared to Automation in Construction, such as International Journal of Computer Vision, IEEE Transactions on Pattern Analysis and Machine Intelligence, and Pattern Recognition. This is explained by the importance that is given to the origins of the methods and algorithms used in the research publications. Focusing only on civil engineering related journals, Automation in Construction presents the higher number of citations, followed by the Journal of Computing in Civil Engineering and Advance Engineering Informatics. In a nutshell, Automation in Construction seems to be established as the main voice in the field.

The limitations in this body of knowledge become apparent, however, when analyzed for content. As previously presented and further analyzed in Section A.4, publication keywords are representative of the core content of the publications in the field. In general, the keyword co-occurrence map (A.3) shows weak links and detached keywords reflecting how scattered the knowledge is within the field. The most relevant applications of computer vision within construction activities, namely resource and safety monitoring, are on opposite sides of the network with minimal interconnections. Furthermore, the document co-citation mapping generated provides more insight and confirms the poor connection between some topics within the reviewed field, where, for example, a single publication is the only existing link between cluster 0 and cluster 12 (see Figure A.11). This sharp compartmentalization, with little to no cross-fertilization between the researched areas, limits the impact that the previous research could have had in such an interdisciplinary field and its corresponding industry. While some sub-fields within this field of research can be identified, the impact and interference between sub-fields is almost negligible. Similarly, the co-authorship map explicitly shows that most of the researchers in the field work in isolation; though some small but relevant research circuits can be found led by I. Brilakis and H. Li. It is worth mentioning that researchers in collaborative circuits, as small as they are, populate the authorship of the most cited documents in the field (Table A.6) and are authors of some important research documents associated with citation bursts, thus exhibiting once more the importance and relevance of collaboration in research.

A.5.2 Future Trends

Although the knowledge seems to focus on all major themes in construction research, such as operational and management issues, safety and resource optimization, inspection and monitoring of construction sites, and resource and activity tracking, rising topics within the field and potential collaborations between research clusters can be identified. This section proposes to extend the current agenda in the research field of computer vision in construction to include the following topics.

Smart construction

In recent years, the terms Industry 4.0 or smart manufacturing have been introduced to describe the trend towards digitization, automation of processes, and increasing use of information and communications technology (ICT). In this context, the term Industry 4.0 comprises a variety of technologies to enable the development of a digital and automated environment, as well as the digitization of the value chain. The expected outcome is to bring improvements in product quality and a decrease in time-to-market and costs by improving enterprise performance. The impact of Industry 4.0 has already been analyzed from the supply chain management perspective and its implications with respect to the digitization of the construction industry have been examined. Researchers aiming to develop smart construction sites will require systems that delve with data related to workers and resources alike, as well as generated as-is models. With real-time data provided by visual systems, a digital framework for a safe, efficient, and connected construction site can be developed.

In cyber-physical processes, computer vision plays a very significant role as a data generation and acquisition system, which is one of the key components in Industry 4.0. Targeting the integration of the current visual sensors, among others, into an internet of things (IoT) network and enabling a new level of connectivity between the construction site and other stakeholders should be a target for researchers in the near future. As a paradigm of smart construction sites, computer vision algorithms would provide real-time feedback to assess construction site status from all the perspectives mentioned in Section A.4 in a general framework. Recently, an initial framework to automate digital twinning, a digital replica of the real-world asset, was developed for reinforced concrete bridges from 3D labeled point clusters. The proposed method showed better results than manual inspection of large structural components, but complex geometries are still a challenge. However, once these challenges are overcome, the entire digital twinning process can be streamlined, and the cost-benefit ratio of such techniques will be improved.

Furthermore, as computer vision systems are added to construction projects, the cost to store all the obtained data will become a challenge. Many industries, including the construction management sector, have developed ontology models to efficiently manage the knowledge acquired by their systems. With newer visual systems in place, current ontology models will need to be extended to include the knowledge obtained. A few publications in the use of computer vision for manufacturing of construction products have already been published, targeting the knowledge modeling of manufacturing and quality information.

In summary, computer vision has an important role to play in the future research of construction as the digital era pushes industries towards digitization and smart construction based on Industry 4.0 principles.

Quality Inspection for Construction Products

Computer vision is a real-time quality control technique that has been widely adopted by several industries. The quality of construction components and the performance of the infrastructure have always been criticized, both in regards to life expectancy and maintenance requirements of the materials used. Although great efforts have been made in past decades to promote quality within the construction industry, some quality issues still remain. In residential housing, 68% of new homeowners claimed that rework was needed in their homes at handover according to a 2011 survey in New Zealand. The amount of rework needed to rectify issues is a critical area for improvement.

Recent works can be found on the inspection of defects, quality control, and assurance of construction products, and product-centric computer vision algorithms in construction-related activities. For example, a vision system was developed recently to automatically perform quality inspection of slate slabs based on construction requirements. Other developments include automatic quality inspection for masonry activities using photogrammetric point clouds, image processing to provide real-time quality inspection of external wall insulation, a vision-based real-time quality monitoring system for extruded products, and a visual framework for pre-inspection of steel frames. However, given the enormous amount of different materials, shapes, and products, in general, used in construction projects, research on this area has barely started. As quality inspection and conformance assessment is a rule-based problem, analogies between frameworks could exist between safety regulations and quality specifications. Currently, automated check of compliance with safety regulations using computer vision is a widely studied field, and a similar approach could be used for quality inspection to deal with varying specifications and codes.

Off-site Construction

Cluster labeling is able to highlight how current research is heavily biased towards the practicalities of computer vision applications in on-site construction. However, in the last decade, there has been steady and growing interest in the adoption and development of off-site construction (OSC) within the architecture, engineering and construction (AEC) industry. In fact, the research contributions associated with OSC have spiked in the last 5 years. However, computer vision applications for OSC remain under-researched. A quick search for publications related to computer vision and OSC, following previous works to determine the keywords that define OSC correctly, yielded two results. Recent work was published to ascertain the quality of steel framing in an OSC environment. Considering the expansion of OSC in the construction industry, researchers will need to address this gap to participate actively in the development and improvement of the field and, thus, benefit the modular and off-site construction knowledge domain.

A.6 Conclusions

Computer vision has started to transform certain key aspects of the construction industry and has attracted increasing attention from researchers and practitioners. A scientometric study was proposed to explore the status and global trends of computer vision research related to construction applications. Although a number of literature reviews have already been undertaken, this paper presents the first scientometric study of the field as a whole, in which 1158 journal articles and conference proceedings were examined using a 'science mapping' approach. The key scholars and institutions, the state of the research field, and relevant topics on computer vision research for construction were identified. Principally, the reviewed topic emphasizes traditional on-site construction issues that historically have been addressed by manual means, such as health and safety monitoring, resources and activity tracking, and surveying and inspection of construction sites. Moreover, the research work in this area is conducted largely in isolation; this is especially true when considered in terms of research themes and researchers. The message to be drawn out is that future work would do well to promote collaboration between researchers in order to enhance dialogue, debate, and cross-fermentation of ideas and initiatives. Certainly, the enhanced understanding that certain practices, mainly the use of computer vision for product-centric inspection and defect detection, are neglected in the research may cultivate industry support for deeper and more carefully focused research into the field, which in turn may aid research planning and funding efforts by policy makers and practitioners. Moreover, this study provides valuable information to off-site construction researchers about the current lack of initiative within the field with respect to research related to computer vision.

Despite the contributions offered in this study, the findings are to be considered in light of certain limitations. As discussed, the findings are circumscribed by the initial selection of keywords and thus limit the coverage of the current literature. In addition, given the objectives of the study, delving into the aspects of "why" and "how" research has been conducted so far remains beyond the scope of this paper. Therefore, while several problems within the research domain are identified, pursuing these problems to their source and providing solutions are study areas that may be addressed in future research. Additionally, conducting similar studies at future crucial junctures will continue to address the evolving nature of the researched field and help monitor its development.

Cited Authors	Year	Strength	Begin	End	1999 - 2019
FAUGERAS O	1999	**6.4243**	2000	2008	
MIKOLAJCZYK K	1999	**4.8663**	2009	2014	
DAUBECHIES I	1999	**4.8494**	2003	2007	
YANG Y	1999	**4.7713**	2013	2016	
HARRIS C	1999	**4.7099**	2007	2011	
THE M	1999	**4.5766**	2006	2008	
BAY H	1999	**4.5188**	2011	2014	
NAVON R	1999	**4.37**	2009	2015	
GONZALEZ RC	1999	**4.2791**	2008	2011	
PRENTICE H	1999	**4.2783**	2008	2010	
FEI-FEI L	1999	**4.1615**	2009	2014	
STAUFFER C	1999	**4.1615**	2009	2014	
SZELISKI R	1999	**4.0109**	2000	2009	
SIVIC J	1999	**3.8223**	2010	2011	
CANNY J	1999	**3.5875**	2001	2005	
LI X	1999	**3.5844**	2012	2017	
YILMAZ A	1999	**3.4152**	2011	2015	
EVERINGHAM M	1999	**3.3151**	2012	2015	
NAYAR SK	1999	**3.2838**	2004	2007	
JUNE	1999	**3.1573**	2003	2004	
CSURKA G	1999	**3.1516**	2011	2013	
FELZENSZWALB P	1999	**3.1516**	2011	2013	
SONG J	1999	**3.1516**	2011	2013	

Figure A.7: List of the relevant countries with citation bursts in the 1999–2019 time period.

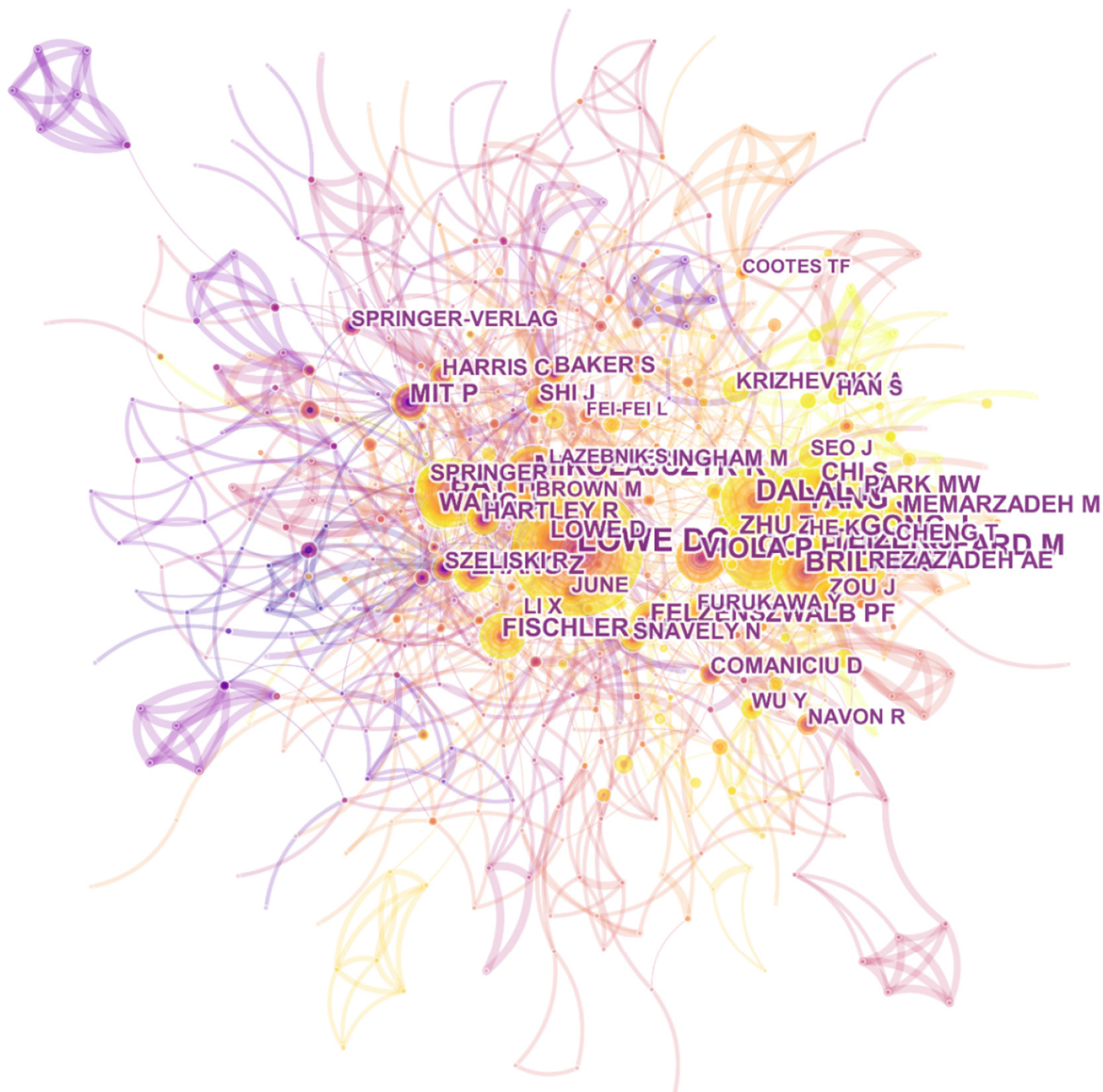

Figure A.8: Network of author co-citations for publications related to computer vision application in construction.

Cited Authors	Year	Strength	Begin	End	1999 - 2019
FAUGERAS O	1999	**6.4243**	2000	2008	
MIKOLAJCZYK K	1999	**4.8663**	2009	2014	
DAUBECHIES I	1999	**4.8494**	2003	2007	
YANG Y	1999	**4.7713**	2013	2016	
HARRIS C	1999	**4.7099**	2007	2011	
THE M	1999	**4.5766**	2006	2008	
BAY H	1999	**4.5188**	2011	2014	
NAVON R	1999	**4.37**	2009	2015	
GONZALEZ RC	1999	**4.2791**	2008	2011	
PRENTICE H	1999	**4.2783**	2008	2010	
FEI-FEI L	1999	**4.1615**	2009	2014	
STAUFFER C	1999	**4.1615**	2009	2014	
SZELISKI R	1999	**4.0109**	2000	2009	
SIVIC J	1999	**3.8223**	2010	2011	
CANNY J	1999	**3.5875**	2001	2005	
LI X	1999	**3.5844**	2012	2017	
YILMAZ A	1999	**3.4152**	2011	2015	
EVERINGHAM M	1999	**3.3151**	2012	2015	
NAYAR SK	1999	**3.2838**	2004	2007	
JUNE	1999	**3.1573**	2003	2004	
CSURKA G	1999	**3.1516**	2011	2013	
FELZENSZWALB P	1999	**3.1516**	2011	2013	
SONG J	1999	**3.1516**	2011	2013	

Figure A.9: List of the top authors with relevant co-citation bursts.

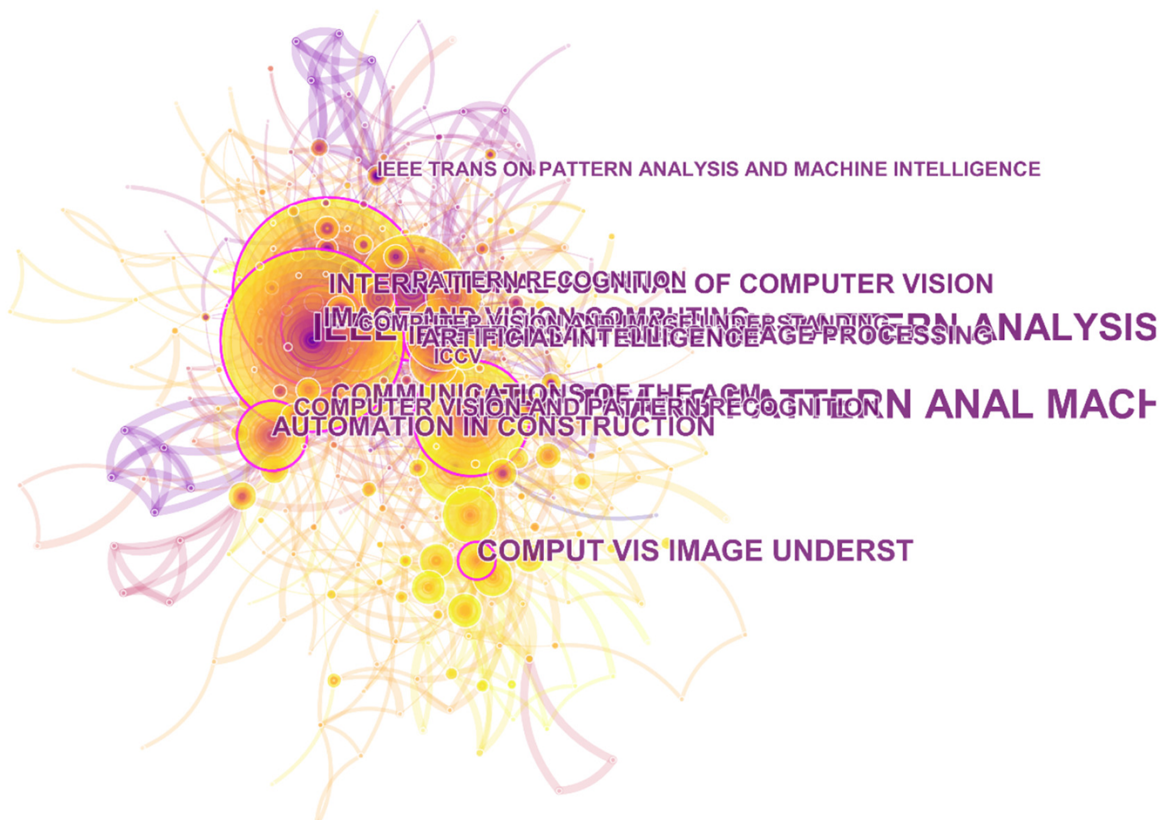

Figure A.10: Network of journal co-citations related to computer vision application in construction.

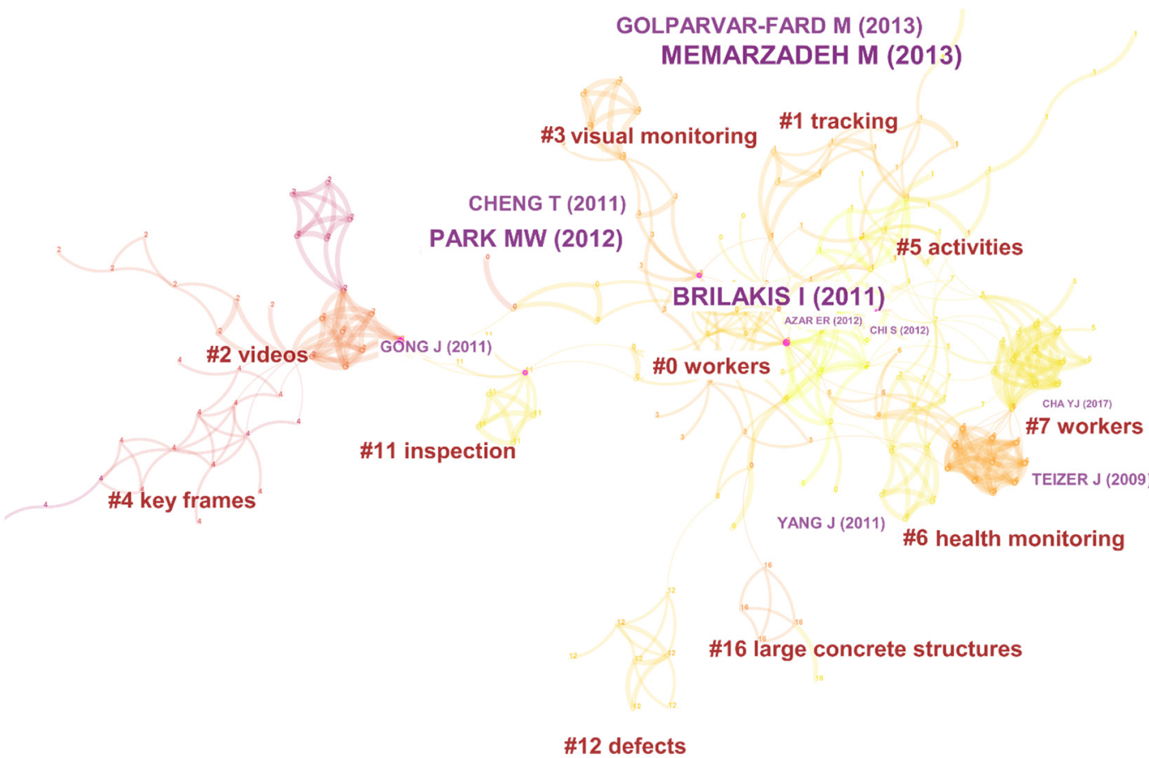

Figure A.11: Network of co-citations with abstract clustering.