An Industry 4.0 Framework for the Quality Inspection in Gearboxes Production

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Abstract. Nowadays, the development of Internet of Things (IoT) technologies have been enhancing the factory digitalization with several advantages in terms of production efficiency, product quality, and cost reduction. This opportunity encourages the implementation of digital twins related to physical systems for controlling the production workflow in real time.

Firstly, the paper studies the enabling technologies for supporting the defect analysis in the context of Industry 4.0 for mechanical workpieces. Secondly, the approach aims to study the integration between the CAD geometry and the quality check process for the inspection planning. A Knowledge-Based tool has been proposed to support the configurations of the quality control chain for each CAD geometry. The test case is focused on the fragmented production of customized gearbox parts.

Keywords: Industry 4.0; Knowledge Base; Machine Vision; Quality Control; Gearbox;

DOI: https://doi.org/10.14733/cadaps.2020.813-824

1 INTRODUCTION

Nowadays, the development of Internet of Things (IoT) has been enhancing the factory digitalization with several advantages in terms of production, efficiency, product quality, and cost reduction [2]. This opportunity encourages the implementation of digital twins related to physical systems for monitoring and controlling the production workflow in continuous [10]. The demand for more personalized products and the rapid growth of the industrial Internet and cyber-physical technologies have led to the development of several new paradigms for manufacturing in recent years, such as cyber-physical systems and cloud manufacturing [16]. In general, the Industry 4.0 revolution has been changing traditional factories in smart manufacturing environments with a high level of automation and autonomy [17]. In the manufacturing phases, including the quality check, an increasing level of flexibility is asked. The request of flexibility is related to the wide scope of product variants driven by customers' preferences and dynamic fluctuation in the annual demand [5].

IoT is considered as an enabling technology for Industry 4.0, which is a term for describing the new revolution involving the digitalization of the smart factories [23]. However, the paradigm of Industry 4.0 is still having some difficult to be spread developed in many industries [19]. The digital factories require the implementation of a digital twin [28] to replicate the physical system in a cyber one. The cost related to this transformation and the data management discourages the full implementation of IoT technologies in industry [23], especially for small and medium enterprises [15]. The digital twin is not only related to the production system but also to the quality check for the defects detection and analysis.

The production of gearbox parts, such as gears, hubs, shafts, and clutches, is a field where the quality checks are still based on manual operations [6]. Several studies are described in literature for measuring and checks the quality of gears, shafts, threaded parts, etc. However, the product characteristics, such as the geometrical complexity and the required accuracy, encourages the employed of manually operations. In fact, a completed clutch requires several checks. Up to 40 checks are estimated for a complete automotive clutch.

Even if machine vision solutions have been already developed in this engineering field [24, 29], there is still a lack of automated applications for the completed and digitalized inspection of defects in the small-batches production of gearboxes. In fact, the production of powertrain units for vehicles such as earthmoving machines, agriculture, and special vehicles, is a niche market with many configurations and small-batches. The product variabilities do not encourage the development of specific automatic lines for the quality check. The fragmentation and variability of this production is still considered as a limit for investing in Industry 4.0. In this context, the paper proposes an approach to overcome this limit enhancing the digital twin of a quality-check system.

2 DIGITAL TWIN AND GEOMETRY ASSURANCE

Some studies consider Digital Twin as a digital representation of a manufacturing system such as a production factory [16]. In the recent years, industry is employing a relevant effort to improve the connectivity, the digitization and the intelligence of machines and production systems [11]. One of the first implementation of a production Digital Twin was the digitalization of Manufacturing Execution System (MES) in Cloud-platform. As proposed by Urbina Coronado et al. [27], a MES can be Cloud-based and powered by Android devices in order to improve data management and communication with operators in small manufacturing enterprises.

Negri et al. [18] proposed a Digital Twin composed by different black-box units using a Functional Mock-up approach. Each block can be activated by different simulation tools and can elaborate data from the physical system. On the other hand, the real system can be improved by data and information elaborated in the digital model.

An important issue in the definition of a manufacturing Digital Twin concerns the interaction between physical sensors and virtual analysis. This interaction regards the whole lifecycle of a production system [12]. As a solution, STEP Tools, Inc. is developing a specification for modelling information such as geometry, CNC manufacturing, and quality inspection into a common data structure [26]. Therefore, the Digital Twin paradigms not only regard the factory digitalization, but also the twin development of each sub-level including CNC machines and product to be fabricated. The Digital Twin of a product can integrate information about machining and metrology measurements while a part is being worked [11]. In this context, the producers of CNC machine tools have been developing end-to-end platforms to connect manufacturing equipment to IoT for providing flow of information [14].

Therefore, the state-of-art work shows that both researcher and industrial stakeholders are working in Cyber-Physical Systems (CPS) for machine tools. Each CPS system needs of intelligent and embedded algorithms to analyze data from specific real-time machining data and provide efficient decision-making supports for factory users during the production phases. Other algorithms are necessary for the data fusion of the information retrieved from different data sources such as sensors, RFID tags, CNC machine tools, measurement devices, etc. [3].

Starting from CPS, literature is going to investigate Cyber-Physical Manufacturing Metrology Model (CPM^3) solutions [13]. A CPM^3 framework is a CPS system based on: 1) integration of digital product metrology information obtained from big data using BDA (big data analytics) through metrology features recognition, and 2) generation of global/local inspection plan for CMM (Coordinate Measuring Machine) from extracted information. In fact, the generation of detailed process models from quality measurements in manufacturing requires the development of dedicated framework in the context of Industry 4.0. The CPM^3 system proposed by Majstorovic et al. [13] has been implemented using a tool for the feature recognition from the information already defined in CAD/GD&T. They also highlighted the need to introduce an inspection process planning. However, their inspection sequence is point-to-point form and it is not defined by a Knowledge Base.

Generally, the geometrical variations in manufacturing require a management activity which involves different actors from the product design to manufacturing, inspection, assembly, and testing [25]. Germani et al. studied a CAD-based tool for simulating, driving and optimizing the GD&T inspection process [7]. The management of geometrical variations can be defined as a set of activities for controlling the geometrical deviations and their effects on the product quality throughout the product life-cycle [22]. Schleich et al. provided an overview of future challenges and potentials for next generation geometry assurance and geometrical variations management in the context of industry 4.0 [21].

In manufacturing industry, companies must be high flexible and agile to respond quickly to product demand changes [4]. Indeed, new levels of manufacturing precision are the key requirements to enable advanced machining processes that demands improved techniques of metrology including high flexibility, universality and accuracy. Some researchers use Digital Twin for defining the inspection planning, others use this technology for data processing in order to support the machine control and decision making. However, a fragmentated production also requires of an approach to support the configuration of the inspection sequence. Even if instruments and tools are already available and demonstrated in real production environments, the integration of a CPS analysis with a configurable process for the defect inspection is still lacking. This issue has been analyzed in the customized and variant production of gear-box parts.

The novelty of the paper concerns the automatic definition of the geometrical inspection sequence to be involved into an automatic/semi-automatic and industry 4.0 workstation. In particular, the context regards the in-line inspection of a fragmented production. The proposed inspection regards the whole production; thus, every single part is inspected in-line (100% part inspection). Therefore, the authors proposed the use of fast solutions such as laser and camera sensors. A fast and a digitalized analysis are necessary in order to avoid bottle necks in this manufacturing context (fragmented production).

3 APPROACH

Firstly, the paper studies the enabling technologies for supporting the defect analysis in the context of Industry 4.0 for gearbox parts. Secondly, the approach aims to study the integration between the CAD geometry and the quality check process. A Knowledge-Based tool has been proposed to support the configurations of the quality control chain for a CAD geometry.

Figure 1 describes the proposed framework for defects analysis in the production of gearbox parts. The quality check regards different stages of fabrication. This check starts from the early production phases and ends to the final assembling line. The checking systems concern 3D laser devices, smart cameras, and GO-NOGO gauges for thread, holes and shafts with tolerances, etc.

Even if gauges are typically manual tools, the digitalization and automation of their report and analysis is necessary in order to implement the Industry 4.0 paradigm.

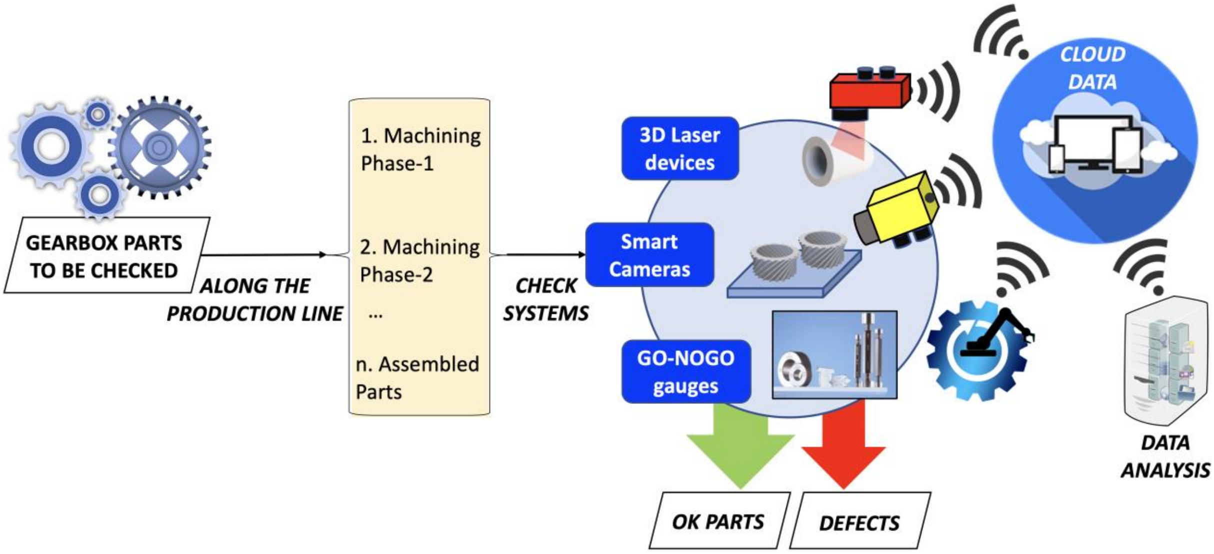

Figure 1: Framework for the quality check using inspection tools connected in cloud computing.

An automatic measurement system is proposed to evaluate the quality checks, including the use of NO-NOGO gauge tools. Where 3D-laser measures are not suitable for the analysis, gauges can be employed using collaborative robots. These systems should be re-configurable in order to be applied in different product lines. Therefore, the paper also proposes a knowledge-based tool to support the configurations of the measurement system to be employed.

3.1 Enabling Technologies for Defect Detection

The geometry assurance can be applied using contact and contactless measurements. While a contact approach is usually manual and slow, contactless solutions could be faster. As contactless solutions, machine vision systems are applied in industry to achieve high precision production. Such systems allow users to make highly accurate measurements and can also detect deficiencies in the production process [1]. In fact, machine vision is used in manufacturing lines for tasks such as defect detection, entity measurement, and object counting.

While an automatic production line can be implemented by non-contact solutions, a fragmentated production of customized products is generally based on manual contact systems. The presented approach aims at implementing a measurement process including both contact and non-contact solutions in the context of Industry 4.0. The digitalization and automation of each measurement process can achieve benefits in terms of cost, time reduction, and efficiency. The data produced by machine vision systems, sensors, automatic measurement robots, and also by operators, is sent to a Cloud-data storage and a data analysis is performed. Then, decisions are elaborated and sent to operators and machines for the process tuning.

Regarding traditional manual contact systems, operators use touch trigger probes in situ. In particular, this activity can be divided in:

- GO-NOGO gauges: operators use calibrated gauges to evaluate the dimension and tolerances of geometrical features such as holes, shaft, thread surfaces, and so on (Figure 2).

- Manual measurements: operates use Vernier caliper or similar instruments to take geometrical measurements.

During manual measurements, operators can also check the presence of all the expected manufacturing features and product geometric shape. However, using manual controls and measurements, operators are subjected to repetitive tasks and cannot provide further added value to the product.

Figure 2: A set of GO-NOGO gauges.

On the contrary, the enabling technologies for the non-contact measurements are photogrammetry and high-fidelity 3D scanning, which are usually applied in industry to seek a production which is close to zero defects. Such systems have a frame structure which is divided into physical hardware and software for image processing and analysis [29]. Figure 3 describes a typical camera-inspection hardware and process.

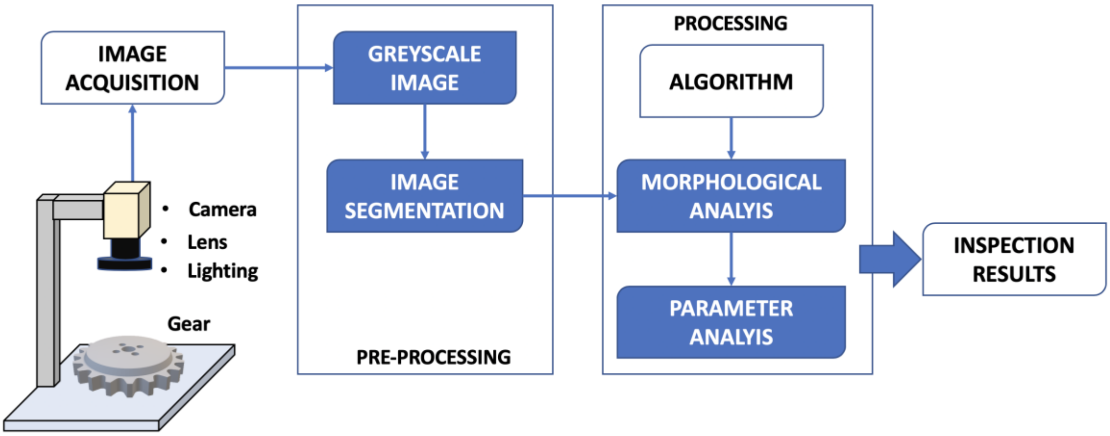

Figure 3: Camera-inspection process.

Traditional Charged-Coupled Device (CCD) cameras are used in smart vision systems for acquiring 24-bit color images using a specific lighting system [29]. The lighting system is sometime necessary for avoiding reflection problems. The resulting 24-bit image is converted into an 8-bit greyscale image for improving the processing analysis. The pre-processing phase also regards a possible image filtering to delete noise generated during the image acquisition and obtain a better image quality. A second activity, called image segmentation, is used to separate the useful picture from its background. This task can also individuate a matrix of pixels to enhance a cluster-based analysis in the processing phase. The processing phase includes a Morphological Analysis and a further Parameter Analysis. The morphological processing aims at searching shape and presence of geometrical entities, such as number of holes, face boundary, etc. On the other hand, the Parameter Analysis is an additional feature to evaluate the right dimensions and relations between specific entities. In particular, this processing is based on the edge analysis for the detection of production defects.

The use of 3D laser scanning sensors is well known in the industry for parts measuring; however, literature still shows a lack of appropriate technique to process and inspect the scanned point cloud data [8]. Figure 4 describes a typical laser scanning system.

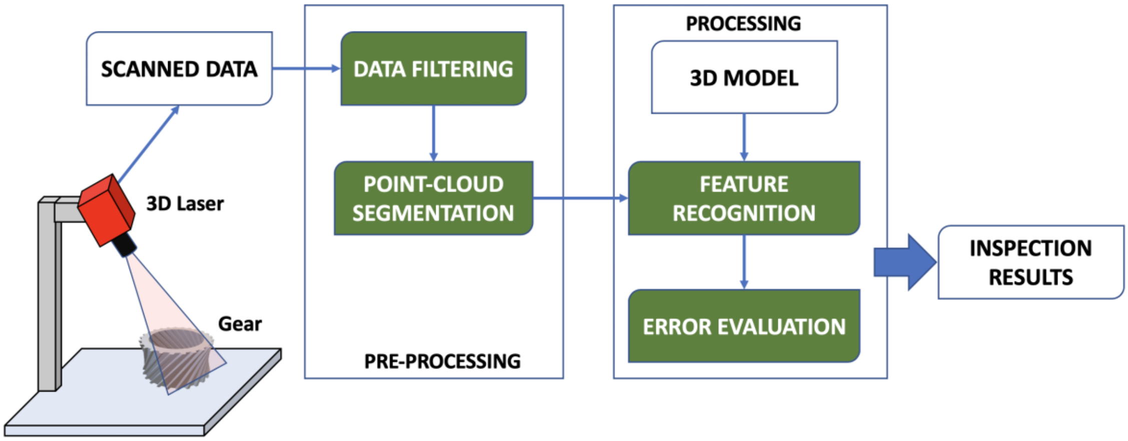

Figure 4: 3D Laser scanning process.

The laser scanning approach requires data filtering to eliminate background points. The resulting point-cloud can be further segmented in faces and edges. The processing is based on the comparison between the virtual CAD geometry and the scanned point-cloud. This comparison requires a feature recognition to individuate the scanned entities into the CAD model.

Another enabling technology for the proposed framework is the Cloud-computing, which is necessary for the data management and processing. Cloud-computing is an important feature for implementing such Cyber-Physical system. The main idea is to execute the data processing into a remote machine which interacts with the Cyber-Physical Production System (CPPS) of the facility layout. As known from the literature, Cloud systems can reduce costs because they eliminate infrastructure complexity and enhance the collaboration network providing information anytime [19]. Traditional computers are not capable of processing Big Data. On the other hand, cloud systems are a good solution to handle a great amount of data much faster than standalone systems.

Since intelligent measurement techniques closes quality control loops in production, the automation in the field of defects detection is an approach "from automation to automation" [4]. Even if sensors for the implementation of Industry 4.0 are available, a 100% automation in quality inspection is difficult to be applied in a customized and fragmented production. A Multifunction Intelligent Measurement Robot can use grippers to works on parts, special griper systems for calipers, and advanced vision units such as laser scanner and smart camera for photogrammetry. Plug and play solutions for these multifunction robots are not available. The inspection tasks should be customized for each workpiece. For instance, each object has its best positions for the camera/laser acquisition. Moreover, robots for inline GO-NOGO measurements require specific tool and instruments for the process automation.

A reconfigurable system is then necessary for automated inline gauging with the integration of different measurement units. In this field, collaborative robots with IoT sensors can led the transition from manual operations to automation. Next section deals with the definition of an inspection planning which is related to the product geometry and the manufacturing phases of the production cycle.

3.2 Knowledge Base for the Inspection Planning

The inspection planning is based on know-how and specific production expertise, therefore a tool to support the definition of quality checklist is required. The paper elaborates on the implementation of this knowledge base. In particular, Figure 5 describes the proposed methodology for assigning a quality checklist from an annotated CAD model.

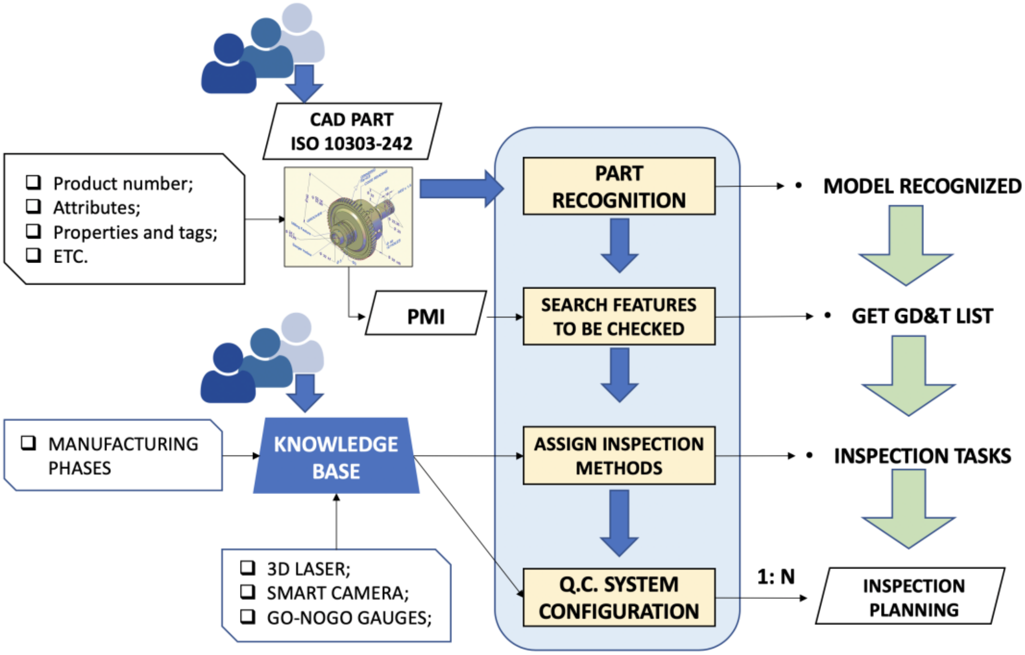

Figure 5: The Knowledge-based approach for assigning a quality check-list to a CAD.

The Knowledge Base regards the method for the part recognition, the searching of geometrical entities to be checked using the PMI (Product Manufacturing Information) definition, and the assigning of a quality control (Q.C.) operation to each entity to be analyzed. Finally, the measurement system will be configured on the basis of the quality checklist. While the framework described in Figure 1 concerns the first objective of the proposed research, the Knowledge-Based architecture reported in Figure 5 completes the achievement of the second objective. The interaction between the first and second objective allows an Industry 4.0 framework to be implemented for defects detection in the small-batches production of gearboxes.

As an assumption, the analyzed CAD models are compliant with the standard STEP AP 242 (ISO 10303-242). This standard allows the manufacturing requirements to be shared as semantic dimensions and tolerances (GD&T).

Regarding the inspection process, each entity related to the product geometry can require a particular control check in a specific manufacturing phase. Therefore, the output of the proposed inspection planning is a set of configuration systems. The relationship between a CAD model and its measurement stations is 1:N because some edges and surfaces have to be controlled two times before and after their manufacturing phases. While a final assembly check consists of heterogeneous controls and measurements, intermediated measurements stations are necessary for controlling the inline production state. Each data has to be managed and stored in Cloud-computing for a better decision making and control activity.

4 TEST CASE

The approach has been applied in the production of transmission units for automotive, agricultural vehicles and earth-moving machines (Figure 6). The research is in collaboration with a company operating as manufacturer of power transmissions. This company manages the entire production cycle, starting from the acquisition of raw material, machining, heat treatments, quality control, and assembly up to final packaging. The majority of the production consists of oil bath clutches, toothed wheels, shafts, and gears. The all production is characterized by a significant variability and small-medium batches.

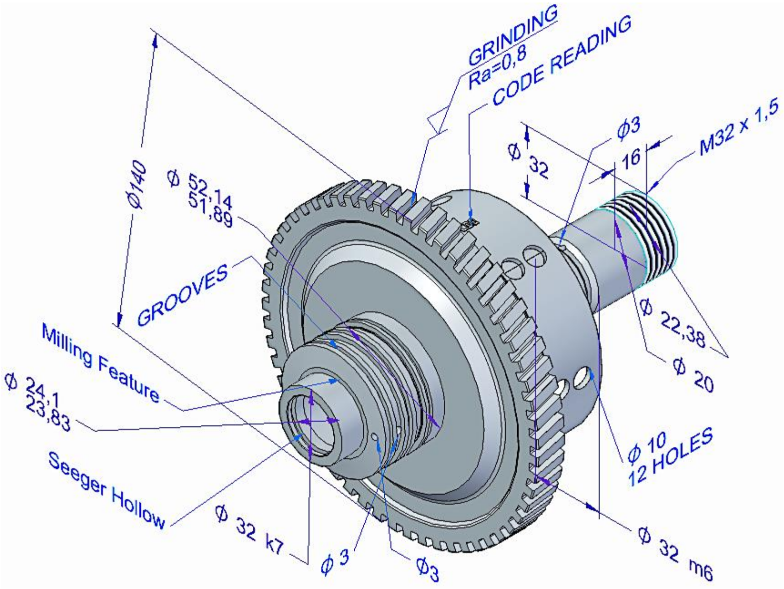

Figure 6: CAD model with 3D PMI annotations used for in-line inspection.

The fragmentation of the production into hundreds of different product codes does not allow the application of classical automation systems, because this investment and implementation would not be compatible with the quantity to be produced. Therefore, in this context, the quality-control chain is a bottleneck. Here, the traditional quality checks regard the presence of all the processing steps (for example drilling, grinding, etc.), checking dimensional and geometric tolerances, evaluation of unacceptable burrs.

In particular, the proposed test case regards an early study to compare a traditional process with an automated one in terms of processing time. The automated control line has not been yet implemented; however, the preliminary study confirms an important time reduction. The platform tool discussed in the previous section has been developed as a prototypical software as a plug-in of the CAD system. According to ISO 10303-242, the CAD model reported in Figure 6 shows a set of PMI information. This model has been used as test case to show the possible time reduction related to an automated inspection line. Following, a table for comparing traditional manually checks with an automation Q.C. line (Table 1). The comparison is based on the operation time for each task.

Operation	*Time – Manually [s]*	*Time – Automation [s]*	*Quantity*
Part handling	120	95	2
Hole presence	1	0,5	15

Diameter tolerance	5	15	4
Weldment Check	2	5	2
Writing report	60	0,5	1
Sending report	10	0,5	1

Table 1: An estimation of time consuming for manual and automated Q.C. tasks for a small clutch.

Table 1 shows an inspection planning for the model reported in Figure 7. The manually process is compared with the automated planning, which can be implemented into an Industry 4.0 context using sensors and connected robots. A process time has been evaluated and assigned for each operation. A quantity has been scheduled to each process in relation to the analyzed geometry. A time reduction of about 60% is estimated using automated and connected quality-control operations.

5 DISCUSSION

Since each industrial revolution affected the geometrical inspection techniques and the shape assurance, next generation of geometry assurance could change following the recent paradigms of Industry 4.0. In this context, inspection data are expected to be included into Digital Twin. In particular, CPS systems can provide a Cloud-computing connection for the data collection, processing, and transfer. Future scenarios could also include simulation models for checking the product assembly after the dimension measuring, as also highlighted by Schleich [22].

When geometrical variations management will be fully implemented and demonstrated in industry, unknown dependencies and between product design, including quality specifications, and process variables could be searched. The relation between the product fabrication and its design could improve the decision-making activities during the early design phases.

However, as this paper highlights, the definition of a Knowledge Base is necessary to assign an inspection planning to a set of geometrical entities. A mass customization production will obtain benefits from Industry 4.0 inspection because the dependencies between process and quality parameters will be formalized in a Knowledge-Base. The user can use this design tool and modify geometry and GD&T specification in embodiment design. It is fundamental to point out that the proposed approach does not want to replace the deep controls related to a metrology room, but it aims to enhance the geometry assurance in-line using smart and more time-efficiency tool. While a metrology room involves instruments such as Coordinate Measuring Machine (CMM) solutions for spot checks on a sample set of produced parts, the proposed in-line inspections involve the whole production (100% part inspection). Therefore, fast solutions are required to support such inspection focused on each produced part.

6 CONCLUSIONS

In the context of Industry 4.0, the paper deals with the development and integration of Internet of Things (IoT) in factory digitalization for the benefit of digital twin. In particular, the paper uses digital twin for quality control and detection of parts defect. The study is focused on a gear-boxes industry with a fragmentated production. In the proposed approach, the quality-control operations are defined and configurated by a Knowledge-Based which analyzes the geometry from the relative CAD model.

Using the proposed approach, about 60% of time reduction is estimated for quality-control operations. Therefore, in the context of quality control, the smart factory solutions can be applied with benefits also in the case of a fragmentated production, which is generally a limit for the Industry 4.0 implementation.

The paper also describes the enabling technologies to be involved for the digitalization of the inspection checks. Laser scanners and smart camera are suitable technologies to be involved in this process. On the other hand, checks with GO-NOGO gauges can be more difficult to be managed. The use of collaborative robots can be an early solution to improve these inspection digitalizing both control and decision.

The authors want to define a Knowledge Base, customized for that application, which is able to assign a suitable inspection method for each interesting geometrical feature. Each feature has been previously highlighted by a PMI annotation into the 3D model. For example, if we have a "feature of size" such as a hole diameter, the Knowledge Base can select the inspection method searching from hard gauging, camera or laser scanner sensors. The selection method has not yet described in this paper. The authors think to use information such as axis orientation, hole type, tolerance values and dimension in next step of this research. Thus, this implementation will be introduced into a future work.

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