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Smart manufacturing applications for inspection and quality assurance processes

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Abstract

Smart manufacturing had a high impact in recent years within the inspection and quality assurance processes, providing innovative technologies in machine learning. Consequently, the article presents a systematic review of the applications of automation to statistical quality control in companies in the industrial sector, deriving subtopics such as artificial vision, intelligent manufacturing, inspection in the different production processes, neural networks, automation through statistical process control techniques and finally quality assurance, in addition, a general analysis of them is shown. Additionally, it is shown that these technologies improve automated manufacturing processes, making them more efficient, with better performance and productivity, also contributing to the optimization of time, cost reduction, strengthening of inspection, and quality assurance. Finally, future research opportunities for industrial applications are identified.

Keywords: Quality; automation; smart manufacturing; machine learning.

1. Introduction

In the context of industries, in recent years, tools and new methods have been implemented to promote production processes and the global operation of companies due to current market demands, which requires high quality and

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variety in all products, prompting manufacturing companies to implement highly adaptable production lines [1–3]. A smart factory can face all the disruptions of the market, the supply chain, or even the factory itself [4]. For this reason, quality 4.0 is shown as a modern form of quality management because digital technologies used along with more sophisticated methods and intelligent processes allows high-performance teams to provide consumers with high-quality products [5]. Consequently, it is essential to study the current state of quality control assurance techniques in smart manufacturing in the industrial sector to know the impact of automation technologies on industry control processes. Despite being automated, a process is not exempted from inspection, and recent technologies allow the accomplishment of this task. S. Fahle, C. Prinz, and B. Kuhlenkötter [6] reviewed the manufacturing processes by identifying artificial intelligence (A.I.) methods for field applications. A systematic review of the application of the techniques included all methods that ML currently uses in the context of manufacturing and how these technologies are linked to different activities in the industrial sector (planning and control of the manufacturing process, predictive maintenance, quality control, control and optimization of processes, logistics, robotics, assistance, and learning).This work aims to study the current state of the art and the smart manufacturing applications focused on inspection and quality assurance. Therefore, this article is structured as follows: Section 2 presents the methodological approach used, section 3 shows the systematic review results, and section 4 shows the main conclusions and research opportunities identified.

2. Methods

In the first instance, the aspects of a systematic review of the literature were determined, within the framework of the problem addressed, from which keywords such as "quality", "automation", "statistical control," and "intelligent manufacturing" were derived. In addition, the inclusion criteria included: year (2010 - 2021), type of access (open access), type of article (review articles - research articles) for the research carried out. Databases such as Scopus and ScienceDirect were used to carry out this research. Initially, fifty results were found related to the topic that was addressed, from which a set of eighteen documents were selected which address the techniques used in the inspection processes and quality control, which are related to 4.0 technologies. The following research question was defined: What impact does the application of automation generate to statistical quality control in production processes in companies in the industrial sector?

3. Results

3.1. Systematic literature review

Table 1 presents a summary of the most relevant methods and applications identified through the literature review.

Table 1. Summary of methods and applications

Subtopic	Application	Method	Reference
Machine learning	Improve processes reducing costs.	Advanced ML models, Edge cloud computing technology.	[7], [8]
Artificial vision	Avoid incorrect operations or failures of operation.	SMCMM, machine vision-based identification of broken inserts.	[9]
	Real-time defect detection.	Visual Image Processing Algorithm, Siamese Networks.	[10], [11]

Inspection	Statistics to measure and evaluate control loops and evaluation of quality control.	Classic approach with Gaussian measurements and performance indicators.	[12]
	Support to smart inspection and corrective actions.	Neural Network actuators and collaborative robots.	[13]
	Identify objects with significant variants for the quality control process.	Time-sensitive networking commuters.	[14]
	Anomaly detection.		
		Comparison of next-generation approaches.	[15]
Neural networks	Define actual modelings, identify dimensional patterns and classify profiles.	Neural Networks, Artificial Neural Networks.	[16], [10].
Statistical process control	Improve small batch production and process capacity.	Typical SPC algorithm - six sigma methodology.	[17], [18], [19].
	Automate, control, and optimize production processes.		
Quality Assurance	Monitor Digitization and industrial automation implementation	Holistic System monitoring with 143 key performance indicators.	[20]
	Control and supervision for decision making	Intelligent control system	[21]
	Reduce post-processing and increase measurement reliability	Computer-assisted route	[22]
Smart manufacturing	Smart Manufacturing Capability Assessment	SMCMM	[23]
	Process improvement and operation with robots	Reinforcement learning	[13]

3.1.1. Machine learning

ML is usually presented as an approach used for the inspection of smart manufacturing and impacts the quality control systems of industries. [13] integrates reinforcement learning (R.L.) algorithms in the interaction between company employees and collaborative robots, allowing the process to be automated and supports intelligent inspection and subsequent corrective actions of an intelligent system built depending on the type of parts being inspected. Likewise, ML is the central axis of [7], highlighting more advanced ML models that sought to mitigate the impact of costs derived from manual inspections and reduce pre-production times. [8] also exposes ML and its applications for the benefit of quality with predictive models that fundamentally start from the collection and analysis of data, generating fewer elements to be inspected and economic advantages. The recent advances in machine learning for industrial applications include a wide variety of techniques and algorithms that have focused on process control [24], quality control [25], raw materials classification and chemical properties improvements [26].

3.1.2. Artificial vision

Q. Xia et al. [23] use artificial vision and robots to support the quality of the processes with the detection of faults through the implementation of a hybrid model that includes automated sections jointly participating in the evaluation of SMCMM correlating dimensions, criteria and levels that allow determining the feasibility of the application of the model in a manufacturing company. Likewise, [10] implemented artificial vision in real-time, with classical algorithms that processed images of the edges of profiles in a production line for extrusion of rubber seals and subsequently determined the quality of the studied product considering dimensional precision. In [11], a combination of machine vision and Siamese Networks approach to image recognition was performed, revealing defects in the steel in real-time and can be remotely inspected without causing damage.

3.1.3. Inspection Support

P. D. Domański et al. [12] measured the effectiveness of the process in an ammonia production plant evaluating five performance indicators. They used robust and asymmetric statistics to evaluate and measure the control loops of the data generated in the production process. The collaborative robots implemented in [13] support *smart* process inspection. However, its function was not limited solely to inspection but corrective actions in quality control systems, beneficial for subsequent decision-making related to the growth of the industrial process. J. Popper et al. [14] presented the implementation of technologies that led to inspection with Time-Sensitive Networking (TSN) computers for quality control of objects identified with significant variants in a production environment synchronizing with an edge device in microseconds with a real-time network. This type of implementation shows a much more reliable visual quality control, especially in ongoing production. In [15], comparative anomalies of the latest generation approaches (ABOD, LOF, onlinePCA, and osPCA) are detected during the inspection. Angle-based outliers (ABOD) were subsequently identified employing an OsPCA principal component analysis to finally be compared with a Monte Carlo cross-validation (MCCV) procedure.

3.1.4. Neural networks

In [16], they apply a holistic approach to perfect predicting the quality of the parts, which simplifies and automates the necessary data processing steps. It was carried out with the use of ANN and other methods; *to* use the adaptive model in real-time production processes. Subsequently, in [10], they show a case study, where neural networks were presented to identify the different patterns in the dimensions of the studied profiles and classify them, which allowed cost reduction.

3.1.5. Statistical process control

In [17], the authors demonstrates the adaptability of common SPC solutions suitable to produce parts and small batches and presented the possibility of using Shewhart control charts to obtain a fair evaluation of the processes and thus reduce the cost of actions for quality improvement. Likewise, in [18], the SPC and Six Sigma metrics implement to evaluate the processing capacity and reduce the processing time in an Italian company belonging to the food industry. For a long time, the manufacturing industry has sought the total automation of the processes for the processing; for this reason, in [19], they carry out an analysis of SPC applied to the processes of wear of tools. Also, [27] shows the interrelation between SPC, TPM, and APC as a coherent and successful fusion for the technical control of production processes. He structured the models to provide an overview of their functions and opened a door for the possible prescription, description, and improvement of control in industrial settings.

3.1.6. Quality Assurance

In [20], they show a holistic monitoring system that ensured the implementation of A.D. 143 performance indicators were used for the application in nine dimensions, all of the above was integrated with the objective to contribute to continuous improvement. In addition, [21] presents a general description of the different approaches used for failure forecasting, the challenges, and emerging trends related to automated assistance for supervisory control. Finally, [22] presents technologies that can contribute to the improvement of the inspection in the injection manufacturing process used for the molding of electromechanical parts; the above was achieved with the integration of methods and the use of algorithms of recognition of specific characteristics.

3.1.7. Smart Manufacturing

Smart manufacturing is known as advanced manufacturing, where technologies are integrated with the manufacturing system; in [23], they expose an empirical method for measuring the performance of the smart factory and to evaluate the capabilities of a company using four facets and the use of customizable roadmaps for business set-up. Also, in [13], they propose an innovative approach with the use of robots to support intelligent inspection and then the respective corrections of the quality control systems in the manufacturing process; this is complemented by an intelligent system that implements an algorithm that allows a more robust approach. These technologies improve automated manufacturing processes, made them more efficient, with better performance and productivity, contributed to optimizing time, reducing costs, and therefore strengthening inspection and quality assurance.

4. Conclusions

This article analyzed the most relevant research related to the applications of automation to statistical quality control in companies in the industrial sector during the years (2010 - 2021), using a Systematic Literature Review methodology. Different sub-topics addressed inspection and quality assurance techniques, showing significant improvements in industrial contexts due to their implementation. The strengths and contributions that each method provides to the quality control of smart manufacturing processes in industries were identified. Several of these methods show great results by working in conjunction con others. It is pertinent to highlight that the analyzed papers at a general level contribute to the improvement of automated manufacturing processes, time optimization, cost reduction, and therefore the inspection and assurance of quality standards. As a future research proposal, it is recommended to continue studying automation technologies in quality control but focused on case studies due to the few investigations found on the subject. In addition, it is suggested that companies in the industrial sector evaluate the benefits of using artificial vision, given the optimal results shown by the analyzed research.

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