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Fundamentals of Smart In-process Inspection in Advanced Manufacturing Systems

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Abstract

Advanced manufacturing is envisioned to be fulfilled by various cutting-edge technologies, making the production environment more complex and dynamic. To maintain production quality in manufacturing processes and increase system responsiveness towards faulty procedures, in-process inspection is an efficient strategy that manufacturers should consider adopting. This paper proposes a holistic framework for implementing in-process inspection in advanced manufacturing systems. It identifies four essential technical issues, including in-process inspection in advanced manufacturing, real-time process control through inspection feedback, human-technology interaction towards human-automation symbiosis, and responsive manufacturing system and operations management. These technical issues are analyzed from three levels of the manufacturing system hierarchy: the workstation level, the process level, and the system level. It further examines and elaborates on eight fundamental issues to address the four technical issues.

Keywords

In-process inspection, Advanced manufacturing systems, Manufacturing inspection, Process control, Manufacturing operations planning

1. Introduction

Since the revolution of Industry 4.0, manufacturing industries have kept integrating innovative and cutting-edge technologies into different application scenarios of manufacturing systems to improve production performance. Radical changes take place not only in single workstations but also in operations at the system level, which are driven by multiple factors, such as increased data availability, real-time data analysis and decision-making, advances in robotics and automation, and so on (Arinez et al., 2020). In this context, the manufacturing environment becomes

more dynamic and complex, and advanced manufacturing can be characterized from various perspectives, such as high-precision manufacturing, self-optimization, digitalized operations management, high-mix low-volume manufacturing, human-automation collaboration, and so on.

To fit in this dynamic, complex, and connected working environment, new challenges arise, and manufacturers need to reexamine and adjust their current operations. Among them, in-process inspection can be a prioritized strategy to deploy in an advanced manufacturing system. In-process inspection aims to conduct inspection operations within the same workstation where the part is processed, which is seen as an additional procedure in the original process and occurs between consecutive operations. This is opposite to inspection that occurs in an independent workstation as a separate process. There are several reasons to apply the in-process inspection strategy. Firstly, defective parts can be identified in time to avoid further processes, thus reducing the cost of poor quality. Secondly, it enables real-time process control and optimization. Inspection results can be used as feedback on current manufacturing processes to inform operators of potential issues, and process configurations can be adjusted as a control approach for process optimization. Thirdly, because in-process inspection serves as a quality control purpose in each workstation, it helps maintain a smooth workflow and leads to increased productivity by reducing defect-related disruptions. In this regard, in-process inspection plays a significant role in manufacturing systems. It not only helps maintain manufacturing speed with automation technologies but also enables process control and optimization at a more real-time scale.

To examine the fundamental issues of in-process inspection in advanced manufacturing systems, this paper conducts the analysis at three levels of the manufacturing system hierarchy: the workstation level, the process level, and the system level. Considering inspection can be performed using different approaches, this paper mainly studies vision-based inspection. The structure of this paper is as follows. Section 2 reviews the topic background, including manufacturing inspection, human-automation interaction, and production planning and control. A holistic framework for implementing in-process inspection in advanced manufacturing systems is proposed in Section 3. Fundamental issues are examined in Section 4. Finally, the summary is made in Section 5.

2. Background Review

2.1 Manufacturing Inspection

In manufacturing industries, inspection is an essential part of the processes for maintaining product quality. Inspection can be defined as an activity that measures, examines, tests, or gauges one or more characteristics of a product or service and compares the results with specifications to understand if conformity is achieved for each characteristic (Genta et al., 2020). If a product or a part is identified as a defect, there will be several actions before the next stage: it can be sent back to the station for rework modification, it can be replaced by a new defect-free one, or it can be scrapped.

In a multi-stage production system, inspection can be conducted in any production process and any process structure. Based on the flow of items, there are three main types of process structure: serial structure, convergent structure, and non-serial structure (Mandroli et al., 2006). In serial structure, products pass successive manufacturing processes sequentially. In convergent structure, different products pass their own sets of successive processes sequentially while they may converge in some processes. In non-serial structure, different products pass certain sets of processes sequentially but can have multiple successors and predecessors in a certain process. Meanwhile, inspection can happen in different stages of production, such as raw materials, intermediate work, or final products. The part quality inspection planning problem typically studies which processes and what strategies of inspection are used so that the total expected cost of quality inspection can be minimized (Rezaei-Malek et al., 2019).

Inspection can be categorized into online inspection and offline inspection based on the timing of the operation. Online inspection involves real-time monitoring and examination of a manufacturing process and conducts the inspection during the process, while offline inspection happens after the process is completed. Online inspection can be more effective than offline inspection, but it has more challenges in data acquisition and control algorithms (Shi, 2023).

Inspection can be conducted with destructive and non-destructive methods. For non-destructive methods, conventional approaches include vision-based approaches, radiography, acoustic or ultrasonic testing, and so on. Visual inspection is one primary approach in manufacturing inspection, and prevailing approaches include manual inspection, machine vision, statistical methods, deep learning, and so on (Wang et al., 2024). Manual inspection relies on operators' observations and experience for judgment decision-making, and the performance can be influenced by human fatigue

and subjectivity. To conduct fast and reliable inspection for productivity improvement, advanced vision techniques are needed, such as machine vision and deep learning algorithms.

2.2 Human-automation Interaction

The relationship between humans and technologies has continuously evolved during the integration. With the advances of Industry 4.0, it is an emerging trend to study human-technology collaboration in the human-automation interaction paradigm with the support of cyber-physical systems (CPS). CPS is a system of systems where heterogeneous subsystems interact with each other and is a subject that integrates several disciplines: computing, control, and communication (Khaitan and McCalley, 2014). Compared to the age where humans and machines work independently, the two are more engaged and form a human-automation system, and the performance of this system is the product of the quality of both the automation support and the manner in which humans use this support (Sanchez, 2009). Therefore, human-automation interaction aims to study the interactions between humans and automation as well as different factors that influence the results of interactions. In this way, an optimal interaction or interaction strategy can be selected to maximize the system performance, which usually requires the adaptive capacity of automation agents towards humans and the environment in different scenarios and contexts.

Studies of human-technology collaboration also facilitate an emergent research paradigm, the human-cyber-physical system (HCPS), which is formed with cyber systems, physical systems, and human systems, marking the start of Industry 5.0 (Liu and Wang, 2020). As a digitalized and automated system, HCPS is proposed by adding a human system. There are three major views of this human system (Liu and Wang, 2020): the first view is to treat human agents as physical entities, and humans' interactions are controlled and coordinated by the cyber system; the second view is to see HCPS as the integration of CPS and cyber-social systems, focusing on the social aspects of humans (Frazzon et al., 2013); and the third view is the integration of human psychology and cognitive behaviors and their interactions with CPS, aiming at augmenting cognitive intelligence and improving system performance (Zhou et al., 2019; Jiao et al., 2020).

Human-automation symbiosis has gained consensus as a vision for the future of human-technology collaboration. It is a concept stemming from "man-computer symbiosis", in which symbiosis emphasizes the coexistence and mutual benefits from it (Licklider, 1960). Similarly, human-automation symbiosis distinguishes itself from other human-automation relations because of the partnership and mutual benefits (Gerber et al., 2020). It entails several objectives, including developing an effective system that augments human capabilities and coordinates both agents to work towards a common goal, optimal and dynamic use of resources, human-like communication, and so on (Jacucci et al., 2014). These objectives depict a dynamic human-automation system where human and automation agents are interdependent, and their collaborative performance is better than the sum of individual performance.

2.3 Production Planning and Control

In manufacturing systems, production planning and control involves a set of decision-making activities targeting the global improvement of manufacturing systems, including both the commercial planning that satisfies profitability (what, how much, and when to produce, buy, and deliver products to match customer demands) and production process control for increasing factory productivity and efficient utilization of resources (how and when to use resources, when and who to dispatch a job) (Bonney, 2000; Leitao, 2009). It needs to continually adapt to the business environment as well as the supply chain opportunities, making it necessary to be dynamic, adaptive, and integrative (Bueno et al., 2020). To evaluate the performance of production planning and control, several performance indicators are proposed, such as flexibility, cost reduction, quality improvement, reduction of delivery time, productivity improvement, reliability, and so on (Moeuf et al., 2018; Buer et al., 2018).

Production planning and control usually comprises a hierarchical structure (Bueno et al., 2020), and the primary use cases include demand forecasting, sales and operations planning, master production scheduling, material requirements planning, inventory planning and control, capacity planning and control, shop floor control, and production scheduling. Demand forecasting is to forecast future customer demands using historical sales data as well as data from aggregate planning and inventory management. Sales and operations planning aims to develop a unified plan that integrates sales, marketing, and operations to match customer demands with the manufacturer's supply. Master production scheduling and material requirements planning focus on the implementation of sales and operations planning, including establishing production schedules to satisfy the demand and planning the capacities of parts or sub-assemblies to meet the demand. During production, capacity planning and control as well as inventory planning and control ensures the production capacity to be dynamically aligned with the demand and schedules while the materials or components are

available in the warehouse at a low cost. Shop floor control and production scheduling includes job dispatching and scheduling, and resource allocation in a dynamic and disruptive environment. The job dispatching and scheduling problem is to determine which order should be prioritized and which machine should undertake the job by providing the optimal job sequences and routes (Arinez et al., 2020). Resource allocation is to optimize the allocation of limited manufacturing resources, including operators, machines, and robots, to achieve certain production performance goals.

3. Holistic Framework of In-process Inspection in Advanced Manufacturing Systems

As one of the quality control strategies, in-process inspection performs inspection operations within a manufacturing stage, which identifies defective parts right when or after they are processed. It is therefore expected to increase the overall product quality and yield through prompt handling of defects and real-time process control. Meanwhile, advanced manufacturing is characterized by a dynamic, complex, and fast-paced production environment. To integrate in-process inspection into the manufacturing system, many operations and processes need to be adjusted. This section discusses how in-process inspection influences manufacturing from the system hierarchy perspective and proposes a holistic framework for achieving in-process inspection in advanced manufacturing systems.

There are three levels in the manufacturing system hierarchy: the workstation level that executes manufacturing tasks, the process level that controls the process of a production line, and the system level that manages and plans the production operations. To understand the challenges, the fundamentals of in-process inspection in advanced manufacturing systems are examined and summarized in a holistic framework, as shown in Figure 1. The objective is to formulate the practical issues to assist the implementation of in-process inspection. The proposed framework is concerned with the objectives of three levels of the system hierarchy, including defect inspection, process control and optimization, and advanced manufacturing management. They are converted into four technical issues, which are further decomposed into eight fundamental issues (FI). The four technical issues are elaborated as follows (Figure 1).

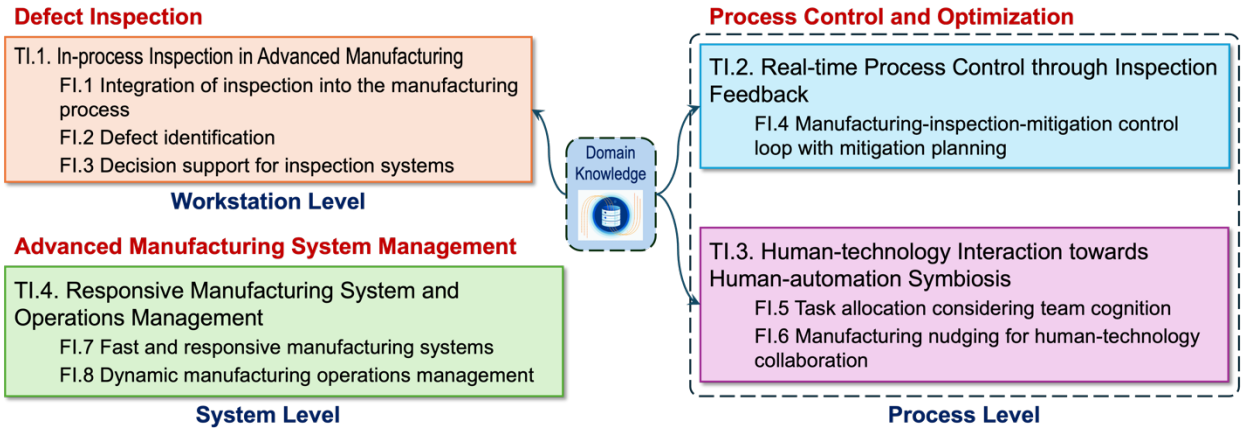

Figure 1. Holistic Framework for In-process Inspection in Advanced Manufacturing Systems

(i) In-process inspection in advanced manufacturing. Implementing inspection in the same process as the manufacturing operation is the first and essential technical issue. It involves three fundamental issues. Firstly, the integration of inspection into the manufacturing process changes the existing manufacturing procedures to allow an additional inspection task during or after the manufacturing operation. One example is 3D printing inspection, which uses infrared cameras during the printing process to monitor part quality (Gradl et al., 2020). Secondly, defect identification requires the detection and classification of defects with selected vision equipment and inspection algorithms. To fit in the advanced manufacturing environment, challenges exist in both hardware and software for defect inspection. Thirdly, decision support for inspection systems is to automate decision-making activities partially or fully during inspection and process control. The activities include but are not limited to inspection algorithm selection, defect disposition, and defect cause analysis.

(ii) Real-time process control through inspection feedback. The objective of in-process inspection is not only the identification of defective parts but also the mitigation of defect generation from the process control perspective. To achieve the latter, this paper identifies the fundamental issue as a manufacturing-inspection-mitigation control loop with mitigation planning. The control loop refers to a self-configuration process that relies on mitigation planning to correct process configurations that lead to defective parts based on inspection results.

(iii) Human-technology interaction towards human-automation symbiosis. Because of the cognitive complexity of inspection and other manufacturing tasks, collaboration between human operators and technology is both essential and inevitable. How to plan human-technology interaction to achieve human-automation symbiosis becomes a significant question in the era of Industry 5.0. This paper approaches human-automation symbiosis from the planning and execution perspectives. In the planning stage, the fundamental issue is task allocation considering team cognition. Different from conventional human-machine task allocation where the objective is to minimize cost and time, this paper introduces human cognition into system performance to enable human-centered collaboration. In the execution stage, the fundamental issue is manufacturing nudging for human-technology collaboration. Manufacturing nudging aims to influence operators' behaviors or decision-making during their interactions with technology to improve collaboration efficiency.

(iv) Responsive manufacturing system and operations management. To manage a manufacturing system with in-process inspection, this paper identifies system responsiveness and operations management as two important directions for successful inspection integration. First of all, inspection-related events, such as defect disposition and process control, add uncertainties to system operations, which requires the development of a fast and responsive system to handle disruptions. Secondly, inspection changes manufacturing procedures and influences the processing time, and operations like production scheduling need to be re-examined. Therefore, fast and responsive manufacturing systems and dynamic manufacturing operations management are listed as two fundamental issues for this technical issue.

4. Fundamental Issues

After having an overview of the proposed framework, this section further elaborates on the four technical issues through eight fundamental issues to facilitate the understanding of implementation challenges.

4.1 Fundamentals of In-process Inspection in Advanced Manufacturing

In-process inspection in advanced manufacturing is a workstation level issue, and it aims to deploy inspection in the current manufacturing process. Therefore, the three fundamental issues are (i) integration of inspection into the manufacturing process, (ii) defect identification, and (iii) decision support for inspection systems (Figure 2).

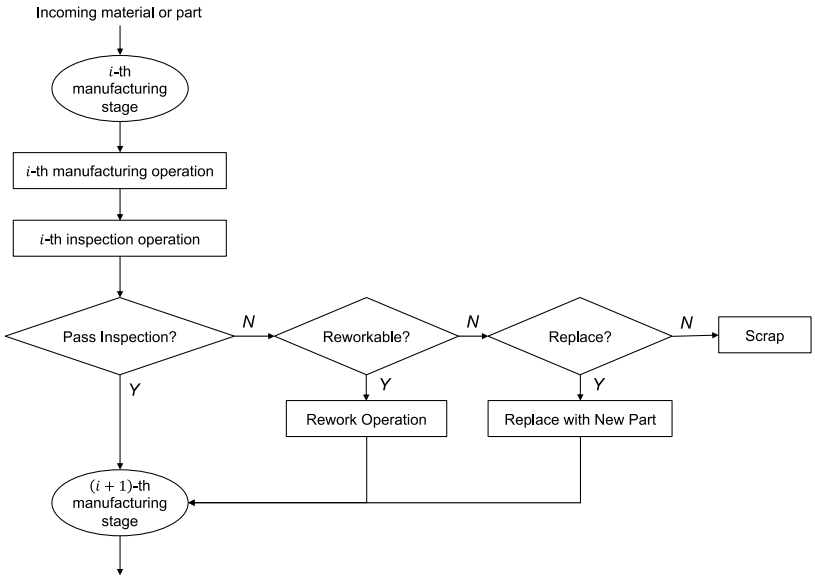

Figure 2. A Manufacturing Stage with In-process Inspection

The first issue is to integrate inspection into the existing manufacturing process. In-process inspection has several positive influences on manufacturing system performance, such as consistent quality from the current workstation, reduction of resource waste and disruptions, providing real-time manufacturing information for process monitoring, and so on. To inspect products in situ, the current manufacturing procedure needs to be changed. Figure 2 presents a manufacturing stage with in-process inspection. After the material or part enters the i-th stage, the manufacturing operation is conducted, and the processed part or material will be inspected directly after the operation is completed. If the part passes the inspection, it will be sent to the next manufacturing stage. If not, defect diagnosis will be conducted to determine if the part should be reworked, replaced, or scrapped, and the rework operation will also be assigned.

To have smooth integration, the deployment of the inspection system should be coupled with the manufacturing context. Figure 3 presents different categories of inspection based on deployment situations (Dickins et al., 2018). In-process inspection includes both in-line inspection and in-situ inspection. In-situ inspection refers to the scenarios where inspection occurs on the production machine during production, while in-line inspection occurs within the process but off the machine. For continuous processing, in-situ inspection, such as cable extrusion, is usually adopted (Gamage and Xie, 2009). The inspection system needs to monitor the product quality in real-time without stopping, which requires better cycle time performance for the vision system to collect data and detect defects. For discrete or batch manufacturing, such as assembly, the deployment of inspection systems may need to consider system installation as well as part handling for smooth item flow in Figure 3.

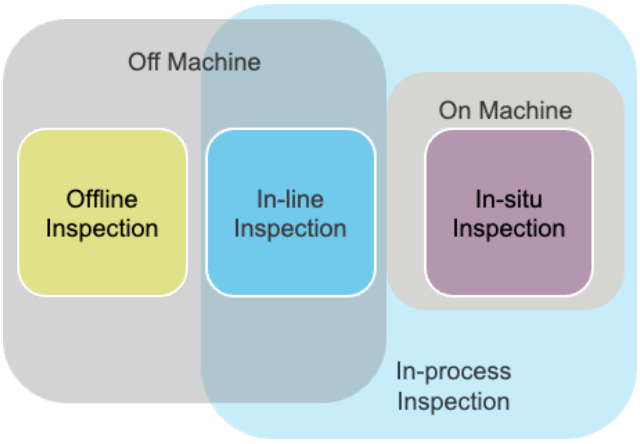

Figure 3. Inspection Categorization

The integration of in-process inspection influences multiple characteristics of a production system. For workstations, because of the addition of an inspection operation and potential rework operations, the manufacturing procedures of this process change. The process cycle time should also consider time for inspection and rework. Furthermore, the integration changes the overall processes and interactions between workstations. Since inspection is usually considered a separate process in a single workstation, in-process inspection will change the sequence of system processes. With the sequence changed, the production structure can change accordingly. Besides this, item flow could be influenced, too. There are four types of item flow (Mandroli et al., 2009): the same product in a single item, the same product in a batch, mixed products in a single item, and mixed products in a batch. With in-process inspection deployed, fewer parts will be accumulated as a batch, and the proportion of single items should increase.

The other two fundamental issues are defect identification and decision support for inspection systems. Conducting inspection operations, either by human operators or automated machines, includes two types of common tasks: defect identification and diagnostic decision-making (Wang et al., 2024). In regard to defect identification, there are some confusing concepts, including defect detection, defect identification, and defect recognition. Defect detection is a binary decision that determines if a product has a defect or not, which is usually the initial stage during inspection. Defect identification requires more detailed analysis of the defect type, and this process can be done by human judgment or automated classification. Defect recognition represents the most in-depth understanding of the defect, which not only includes analysis of the defect type but also its potential causes and consequences. Therefore, defect

identification and diagnostic decision support regarding how to process defective parts are identified as fundamental issues. With the use of advanced technologies during manufacturing processes, defect features become more challenging to detect, and defect identification and diagnosis may require some logical reasoning activities. Figure 4 presents the information hierarchy of an inspection process. Firstly, raw image data is collected from products or parts with the inspection system. The data is then analyzed through various algorithms for defect identification with the objective of obtaining defect features, such as shape, area, or category. By combining defect information with predefined knowledge, reasoning and inference activities can be performed to determine the required actions for a defective part.

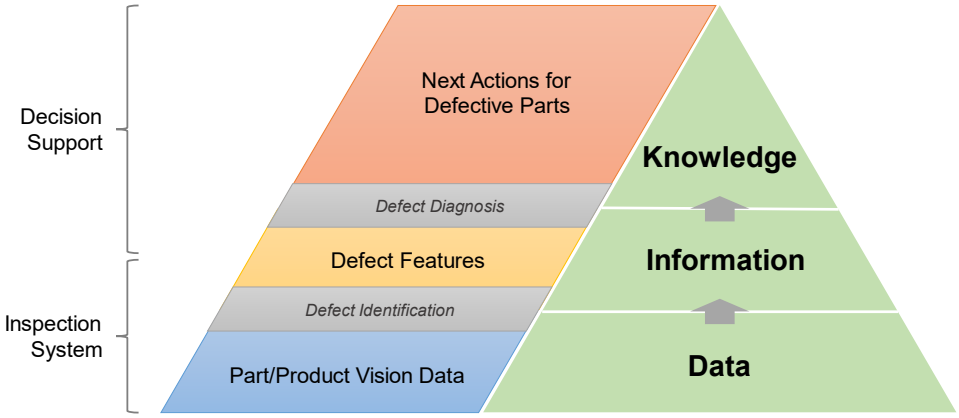

Figure 4. Inspection System Information Hierarchy

Inspection systems with decision support are critical components to perform complex inspection tasks successfully. Corresponding to the information hierarchy in Figure. 4, inspection systems consist of vision equipment that collects product vision data and inspection algorithms that enable defect identification, while decision support assists defect diagnosis based on defect features. (i) Vision equipment. Selection of vision equipment refers to finding a proper combination of camera, lens, and light to enable the collection of high-quality image data (Hornberg, 2006). This process should consider the manufacturing environment, including process cycle time, required inspection precision, environmental lighting conditions, and so on. (ii) Inspection algorithms. To conduct effective defect detection, a proper set of inspection algorithms needs to be used. Challenges exist from several perspectives. Firstly, defects can be difficult to detect and classify. Detection aims to detect defect features from the background, while classification aims to classify detected features into defect and non-defect features as well as different types of defects. Secondly, algorithm selection for defect detection and classification is a manual process that requires time and engineering experience. Because manufacturing inspection is performed on different products with different criteria, there is no one universal inspection approach that can solve all inspection problems. Therefore, to accurately capture defect features and recognize flawed components, algorithm selection is usually a manual process with trial and error. Thirdly, the trade-off between the false positive and false negative rates should be made. A false positive error implies missing a defective part, and a false negative error means rejection of a defect-free part. These two types of errors should be controlled at a reasonable level, because the former influences product quality and customer trust, and the latter diminishes yield and increases additional manufacturing costs. (iii) Decision support. In-process inspection also entails complex decision support for judgment of product quality and determination of next actions for defective parts, which are knowledge-intensive cognitive tasks. To facilitate inspection efficiency and accuracy and reduce the cognitive load of operators, it is imperative to develop a reasoning system capable of conducting inference for defect diagnosis, including part judgment, rework operation assignment, and so on.

4.2 Fundamentals of Real-time Process Control through Inspection Feedback

The fundamental issue for real-time process control through inspection feedback is essentially to develop a manufacturing-inspection-mitigation control loop to enable inspection-based process control. In-process inspection aims at not only identifying defective parts but also recognizing the root cause and correcting it to prevent defects from happening again, enabling quality improvement during production by providing process feedback and online configuration adjustment in real time. To achieve this goal, a manufacturing-inspection-mitigation control loop can be established to enable inspection-based process control. Figure 5 presents manufacturing process control with in-

process inspection. There are two control loops. One inner control loop uses conventional process signal feedback exists to adjust operation inputs. The process signal can be in-situ sensor data, such as the position and pressure data for stamping operations. For in-process inspection, an additional control loop based on defect diagnosis and mitigation planning is added to adjust the process configurations.

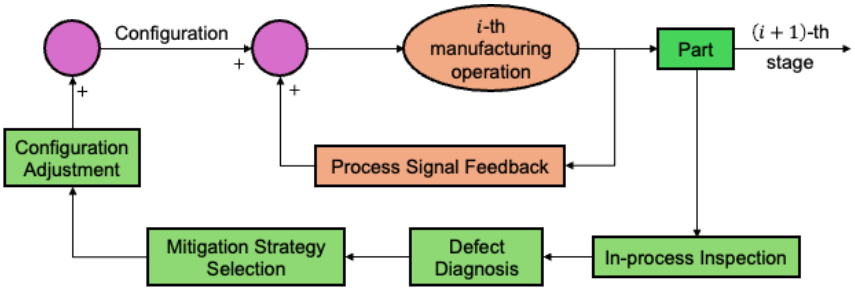

Figure 5. Manufacturing Process Control with In-process Inspection

Different from the conventional control loop that is based on control theory, the manufacturing-inspection-mitigation control loop is through decision-making using predefined knowledge of defects and mitigation strategies, which is essentially a mapping process from defect features to a mitigation strategy with specific settings for correcting a process. Therefore, this paper decomposes mitigation planning into three activities: defect diagnosis, mitigation strategy selection, and process configuration adjustment. Defect diagnosis is conducted first to analyze the root cause of the defect, which can be achieved through data analysis of defect features with tools like decision trees, neural networks, and so on. The information is further used to assist in the selection of the mitigation strategy to correct the process. This decision-making process can be done by the expert system, which conducts knowledge inference using the knowledge base that stores mitigation strategies and their application scenarios. Once the optimal mitigation strategy is found, it can be applied to change the configurations of the process that causes the defect.

4.3 Fundamentals of Human-technology Interaction Towards Human-automation Symbiosis

This technical issue aims to build a symbiotic relationship between humans and technology at the process level. This paper identifies two fundamental issues from task planning and execution perspectives for achieving this objective: (i) task allocation considering team cognition, and (ii) manufacturing nudging for human-technology collaboration.

In advanced manufacturing systems, interactions between humans and technology are inevitable. Especially with in-process inspection integrated into the manufacturing process, many knowledge-intensive reasoning tasks are required, and the fulfillment relies on both humans and machines. Because humans and technology have different strengths, how humans and technology collaborate to perform tasks in the manufacturing process has a significant influence on system performance. Meanwhile, in the era of Industry 4.0 and beyond, the manufacturing industries are looking for a symbiotic relationship between humans and automation agents during their interactions to facilitate closer partnership and mutual benefits (Jacucci et al., 2014; Zhou et al., 2019).

This paper proposes a conceptual model to elucidate human-automation symbiosis in a human-automation team, which is shown in Figure 6. This model entails three components: human agents, automation agents, and collaborative intelligence. Human-automation interaction is formed during interactions between two types of agents, while human-automation symbiosis is further achieved with the addition of collaborative intelligence. To model human-automation interaction, there are several critical factors, including human trust, human perception, machine intelligence, and level of automation. Human trust and level of automation are two factors related to automation use and production performance: if operators have high trust to automation agents, they tend to use a higher level of automation, and it may cause abuse issues. How to find the proper level of automation is a key question to be answered in human-automation interaction. Perception emphasizes human senses and cognitive capabilities, which are the strengths of human cognition. Machine intelligence refers to the computational capabilities for data analysis and automatic decision-making, which represents machine cognition. With these factors, human-automation interaction aims to optimally allocate physical and cognitive resources in a human-automation team to complete production tasks. To facilitate human-automation symbiosis, collaborative intelligence is proposed, which is characterized by team cognition and nudges for collaboration. Team cognition aims to model cognitive status of human operators and

estimate team cognition performance. On the other hand, nudges for collaboration aim to guide or influence operators' behavior towards what is desired during their interactions with automation agents. In reality, operators sometimes do not completely follow the manufacturing instructions, and nudges take effect during the execution of a task to enable closer and more accurate collaboration.

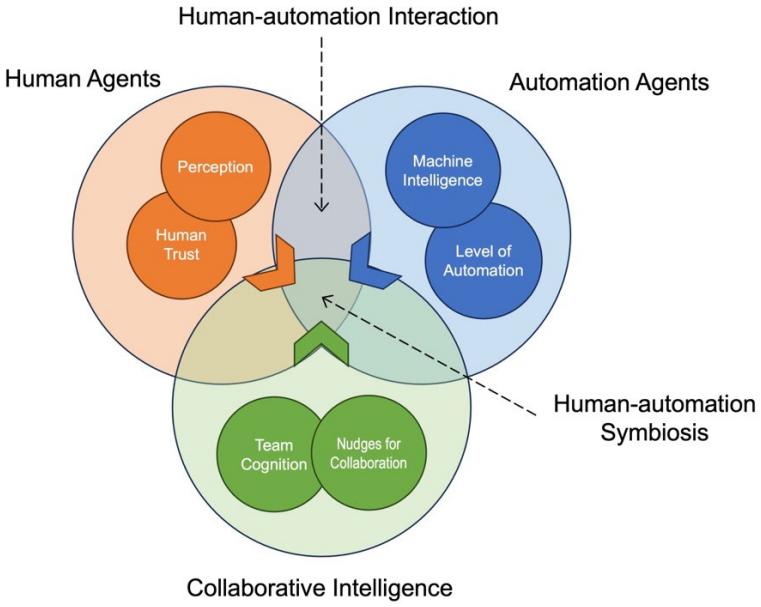

Figure 6. Modeling of Human-automation Symbiosis of a Human-automation Team

In this regard, human-technology interaction entails two fundamental issues. One is dynamic task allocation based on real-time agent status, which can be decomposed into cognitive status estimation and task allocation. Cognitive factors are an important topic for human-centered automation, which accounts for human capabilities, limitations, and tendencies in the information processing tasks during human-automation interaction (Zhou et al., 2011). Because human-automation symbiosis implies human-centered system design (Zarte et al., 2020), human cognitive status is an important metric to reflect operator well-being and cognitive load. To study cognitive status estimation, the relationship between physiological measurement and cognitive states needs to be modeled (Bulling and Zander, 2014). On the other hand, task allocation is essentially a bi-level programming problem (Jiao et al., 2021). During optimization, the human performance should be prioritized, followed by the human-automation system performance and the automation system performance. The performance evaluation for these systems needs to be designed differently, which also includes the integration of human cognitive status into team performance. The other fundamental issue is manufacturing nudging, which studies nudging design in the manufacturing context. Nudging design involves two questions: one is nudging behavioral modeling for nudge evaluation, and the other is nudging personalization. The designed nudges are expected to influence operators' behavior and decision-making and to improve human-technology collaboration efficiency.

4.4 Fundamentals of Responsive Manufacturing System and Operations Management

This technical issue is at the system level. To manage a manufacturing system, efforts are required from both system infrastructure and system operations. In this regard, this paper lists two fundamental issues for this technical issue: fast and responsive manufacturing systems, and dynamic manufacturing operations management.

In-process inspection aims to improve manufacturing system performance with consistent and fast inspection as well as real-time feedback about potential process configurations that cause product defects. Meanwhile, the responsiveness of a manufacturing system can be evaluated by its flexibility, reconfigurability, speed, dependability, machine utilization, and so on (Jimenez et al., 2015; Ebrahim et al., 2014). In this context, building a responsive manufacturing system to allow fast inspection-related operations and efficient communication is critical to achieving these objectives.

To enable the responsiveness of a manufacturing system with in-process inspection, this paper identifies three supporting pillars, which are digitalization, interconnected systems, and smart operations. This is in line with the core technology of the new industrial revolution that calls for digitalization and intelligence (Zhou, 2013). The three pillars are analyzed separately in three layers introduced in Fig. 1, which are the execution layer that conducts manufacturing and inspection activities, the control layer that monitors and adjusts production processes, and the production management layer that plans high-level system operations. Considering that an advanced manufacturing system can be studied as a human-cyber-physical system (Jiao et al., 2021), three supporting pillars target at cyber systems, physical systems, and human-technology systems separately to achieve system responsiveness.

(i) Smart operations target at improving the speed and reliability of production operations and decision-making by replacing manual operations with automatic approaches through artificial intelligence and intelligent reasoning technologies. Focusing on the integration of in-process inspection, these operations target at fulfilling the objectives of the corresponding layer. Therefore, defect inspection and part judgment are two operations in the execution layer that conducts in-process inspection. Similarly, defect diagnosis analysis, mitigation strategy planning, and task allocation are in the control layer for manufacturing process control and production line task allocation. Production scheduling and disruption management are in the production management layer for global planning.

(ii) Digitalization aims to collect usable data from the environment and production and increase its accessibility for other activities. Because in-process inspection requires analysis of image data, and task allocation should consider operator cognitive status, the execution layer should digitalize equipment data, operator data, and defect data. In the control layer, task data, configuration profiles, and production performance data are required for human-machine task allocation and process control. In the production management layer, data from actual operations and management software (such as "Systems, Application, and Products in Data Processing") should be collected for operations planning and disruption management.

(iii) The purpose of building interconnected systems is to allow data sharing between different devices as well as efficient communication between different levels of a manufacturing system for the execution of commands, such as configuration adjustment and task dispatching. This includes vision systems, machines, and sensors, process control systems, and enterprise resource planning (ERP) systems. The combination of these three supporting technologies is expected to allow fast and reliable operations and timely communication for the integration of in-process inspection into advanced manufacturing systems.

The other fundamental issue is dynamic manufacturing operations management. The integration of in-process inspection influences the operations at the system level. In advanced manufacturing systems, with the support of the Internet of Things, manufacturers expect manufacturing operations management to be dynamic, adaptive, and integrative (Ivanov et al., 2016; Adamson et al., 2017). As discussed previously, these operations range from demand forecasting at the enterprise level to production scheduling at the shop floor level. While in-process inspection can be characterized by the change in manufacturing procedures and real-time feedback about manufacturing processes, its integration will influence operations at the plant level and the shop floor level in both the planning and the execution stages.

In the planning stage, production scheduling is influenced by the addition of in-process inspection, changing the cycle time of both the workstations and the whole production line. In the workstation i, the machine operation time is t_i, and the in-process inspection is Δt_i, then the cycle time for this workstation changes from t_i to $(t_i + \Delta t_i)$. The same goes for the other workstations that are deployed with in-process inspection, changing the cycle time of the product from $\sum_{i=1}^{N} t_i$ to $\sum_{i=1}^{N}(t_i + \Delta t_i)$, where N is the number of workstations in the production line. These changes will influence both production scheduling and job dispatching with resource allocation for the planning of different production lines as well as different machines.

In-process inspection also makes the working environment more dynamic and influences the execution stage of production, requiring the system to have better disruption management. With in-process inspection integrated, the inspection results not only reflect the problems of parts but also provide information for identifying the root cause, generating different actions that will either directly or indirectly make the operations deviate from the initial plans. For instance, if a defective part needs to be reworked, a new task will be generated in the related workstation. If the root cause of a defect is identified and the process configurations need to be changed, setup time for the changes will be needed, and the operations of the production line will be influenced. In this context, disruption management should

be studied, which aims to make a recovery plan that can not only suit the changed environment brought by the disruption but also be close to the initial plan (Yang et al., 2015).

5. Summary

Automated visual inspection is envisioned as one of the cutting-edge technologies to facilitate advanced manufacturing. As one strategy of deploying inspection technologies, in-process inspection aims to conduct fast inspection right after the current operation finishes and before it enters the next stage, thus stopping defective parts from propagating and providing real-time feedback on product quality. To adopt this strategy, current manufacturing processes need to be reexamined and adjusted. In this regard, this paper proposes a holistic framework to implement in-process inspection in advanced manufacturing systems. Meanwhile, it identifies eight fundamental issues from three levels of the system hierarchy: integration of inspection into the manufacturing process, defect identification, and decision support for inspection systems, manufacturing-inspection-mitigation control loop with mitigation planning, task allocation considering team cognition, and manufacturing nudging for human-technology collaboration, fast and responsive manufacturing systems, and dynamic manufacturing operations management. These eight fundamental issues correspond to the four essential technical issues, including in-process inspection in advanced manufacturing, real-time process control through inspection feedback, human-technology interaction towards human-automation symbiosis, and responsive manufacturing system and operations management. Therefore, the contributions of this paper lie in the identification and summary of the eight fundamental issues for achieving in-process inspection in advanced manufacturing systems.

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