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REVIEW
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A Review on the Advanced Maintenance Approach for Achieving the Zero-Defect Manufacturing System

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Recently, a revolutionary change is taking place in manufacturing and production systems thanks to the development of various advanced technologies such as IIoT (Industrial Internet of Things), CPPS (Cyber-Physical Production System), digital twins, big data analytics, AI (Artificial Intelligence), and so on. One of the change is that manufacturing and production systems are now trying to transform into the ZDM (Zero-Defect Manufacturing) system. For a manufacturing company, quality takes precedence over any other competitive factors, so the implementation of a ZDM system is very important. For the implementation of ZDM, many fundamental technologies are required. Among them, the advanced maintenance approach for the facilities/equipment of the manufacturing and production system is much more important because it could support the zero-defect and high-efficiency operation of manufacturing and production systems. The advanced maintenance approach, which is often called by various terms such as predictive maintenance, condition-based maintenance plus (CBM+), and PHM (Prognostics and Health Management), requires various interdisciplinary knowledge and systematic integration. In this study, we will review previous works mainly focusing on advanced maintenance subject among ZDM research works, and briefly discuss the challenging issues for applying PHM technologies to the ZDM.

Keywords: zero-defect manufacturing, prognostics and health management, predictive maintenance, condition-based maintenance, maintenance

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1 INTRODUCTION

In the era of the fourth industrial revolution many manufacturing companies try to use various technologies such as IoT (Internet of Things), Big Data, Cloud computing, ML (Machine Learning)/AI (Artificial Intelligence), CPS (Cyber Physical System), DT (Digital Twin), and AR (Augmented Reality)/MR (Mixed Reality) to continuously change and innovate to survive in fierce global competition. In addition, in order to respond to the rapidly changing global market environment and technological change, manufacturing companies are making efforts to change their manufacturing systems in various directions. For example, the paradigm of today's manufacturing system is differentiated into various forms as follows: 1) mass customization, 2) reconfigurable manufacturing, 3) sustainable manufacturing, 4) service-oriented manufacturing, 5) networked/additive manufacturing, and 6) cloud/social manufacturing (Xia et al., 2018).

In this environment change, for a manufacturing company, quality is the most important factor, and achieving zero defects can be said to be ahead of any other competitor in the market competitiveness. As such, the quality is recognized as the most essential element of manufacturing companies, and research on the concept of ZDM (Zero-Defect Manufacturing) is receiving new attention today. Factors affecting the quality of products and manufacturing processes will indeed be immeasurable. Typical examples include materials, workers, processing methods, manufacturing facilities, workplace environments, and so on. There are innumerable factors that affect the quality of products in the manufacturing system, but one of the important factors is the health management of manufacturing equipment or facilities, i.e., maintenance. Fusko et al. (2018) mentioned that maintenance activities become gradually perceived more and more as a key factor for the success of manufacturing companies. In the case of high-tech industries such as semiconductors and displays where the manufacturing process is advanced and automated, and depend on expensive equipment or facilities, the influence of health management of manufacturing equipment or facilities on the quality of manufacturing products is increasing.

Therefore, it is very important to try to minimize the influence of manufacturing equipment on defects in products. As a solution to this, recently the interest in PHM (Prognostics and Health Management) which can preemptively perform maintenance of manufacturing facilities, is growing. So far it has been troublesome to achieve the effectiveness of maintenance operations because there is no information visibility during manufacturing facilities/equipment's usage period. However, with recent advances in ICTs (Information and Communication Technologies) such as IIoT (Industrial Internet of Things), various sensors, MEMS (Micro-Electro-Mechanical System), and wireless tele-communication, SCADA (Supervisory Control And Data Acquisition), etc., industrials and researchers are advancing toward upgraded maintenance support systems that aim at improving reliability and availability of critical engineering facilities/equipment while lessening overall expenses. PHM is the best solution for this purpose. In particular, for the large-scale plant or high valued product or high reliability and availability required systems, the PHM could be a good solution. In this vein, as of late the significance of PHM has been featured and attempted to be implemented in various areas.

Although many ZDM-related studies have been conducted recently, there are still not many studies on how the PHM technology can be utilized to implement ZDM in detail. Therefore, it is necessary to examine what are the main contents of the current ZDM studies, and what kinds of studies have applied advanced maintenance techniques such as PHM, which is the purpose of this study. To this end, in this study, we will briefly review what PHM is and look into previous works related to PHM and ZDM. Furthermore, we will discuss the challenging issues for applying PHM technologies to the ZDM system.

The research approach of this study is shortly as follows. First, in this study, relevant previous research works for the review were selected from academic papers published from 2013 to 2022 throughout searching them at the Google scholar website. The selected papers have the following keywords in the title, abstract, and keyword list: PHM or predictive maintenance or advanced maintenance; ZDM or zero defect manufacturing. In the end, a total of about 60 research papers were selected. Among them, the number of ZDM related research papers was 25. For the selected ZDM studies, the main keywords mentioned in the study, main characteristics, related projects, and what types of studies (e.g., framework, infrastructure, methodology, and so on) were conducted to understand the overall research contents on ZDM were examined. Second, among the selected ZDM studies, research papers mentioning linkages and relevance to advanced maintenance techniques and technologies were separately selected, and then the main contents and limitations of these studies were summarized.

This study is organized as follows: **Section 2** addresses the concept of ZDM and maintenance approaches. **Section 3** deals with PHM in detail with its definition, purpose and benefits, procedure and relevant standards, and so on. Furthermore, **Section 4** reviews the previous works related to ZDM and PHM. **Section 5** looks at the limitations of the studies that dealt with maintenance in ZDM summarized in **Section 4** and the difficulties in applying PHM to ZDM. In addition, to identify future research subjects, challenging issues for applying PHM to the ZDM are discussed in **Section 6**. Lastly, **Section 7** concludes this study with short summary. For reference, the abbreviations described in this study are summarized in **Table 1**.

2 ZERO DEFECT MANUFACTURING AND MAINTENANCE APPROACHES

2.1 Zero Defect Manufacturing

As mentioned by many researchers, the concept of zero-defect is a word that has been around since the 1960s in connection with the development of perishing missile system of United States army (Wang, 2013), and has been mentioned in the industry for a long time along with the history of quality control. ZDM was coined during the later part of the 1980s, with the aim to reduce the defects in the output from various production processes (Lindström et al., 2020a). ZDM is a disruptive concept that can totally reshape the manufacturing ideology (Psarommatis et al., 2020a). According to Psarommatis et al. (2020a), the ZDM consists of four strategies (detection, repair, prediction, and prevention) and it has three ZDM strategy pairs: detect-repair, detect-prevent, and predict-prevent. In order to achieve ZDM, it is absolutely necessary to detect abnormalities in the manufacturing system in real time, to predict and prevent various factors that can affect quality in advance, and to take quick action and repair for the parts where the problem occurs. According to Lindström et al. (2019, 2020b), ZDM tries to combine and integrate the following seven activities: 1) Monitoring of process parameters; 2) Collaborative manufacturing; 3) Continuous quality control; 4) On-line predictive maintenance; 5) Data storage, analytics and visualization; 6) Re-configuration and re-organization of

TABLE 1 | Nomenclature.

Abbreviation	Description
AI	Artificial Intelligence
AR	Augmented Reality
CBM	Condition Based Maintenance
CBM+	Condition Based Maintenance plus
CPS	Cyber Physical System
CPPS	Cyber Physical Production System
DCS	Distributed Control System
DoD	Department of Defense
DoE	Department of Energy
DSS	Decision Support System
DT	Digital Twin
ICTs	Information and Communication Technologies
IFaCOM	Intelligent Fault Correction and self-Optimizing Manufacturing systems
IFDAPS	intelligent Fault Diagnosis And Prognosis System
IIoT	Industrial Internet of Things
IoT	Internet of Things
JSF	Joint Strike Fighter
LCC	Life-Cycle Costs
MAS	Multi-Agent System
MEMS	Micro-Electro-Mechanical System
MES	Manufacturing Execution System
MIMOSA	Machinery Information Management Open System Alliance
ML	Machine Learning
MR	Mixed Reality
OEE	Overall Equipment Effectiveness
OSA-CBM	Open Standard Architecture Condition Based Maintenance
PHM	Prognostics and Health Management
RUL	Remaining Useful Life
SCADA	Supervisory Control And Data Acquisition
SMEs	Small and Medium-sized Enterprises
SPC	Statistical Process Control
SQC	Statistical Quality Control
TBM	Time Based Maintenance
ZDM	Zero Defect Manufacturing

production; and (7) Re-scheduling of production. ZDM has several approaches such as product-oriented, process-oriented, and people-oriented ZDM, depending on where we look at the target for reducing defects. In the era of the fourth industrial revolution, ZDM is an ideal that is increasingly attractive to companies at the point of promoting innovations such as unmanned manufacturing systems, artificial intelligence, and full automation by utilizing advanced ICTs, AI, big data, and IoT technologies.

Nowadays, manufacturing industries depend on machine tools of high complexity, comprised of several hundreds of components which ought to be monitored and kept in order to keep away from unexpected failures as much as possible (Aivaliotis et al., 2019). From a structural dependency point of view, the failure of one machine inevitably affects other machines in the upstream or downstream processes. Thus, the quality that ZDM focuses on, which indicates the completeness of the work results of these machines, is closely related to the failure or abnormal status of facilities/equipment. The quality is not limited to the condition of any one machine, but is affected by the conditions of all resources (machines, workers, materials, procedures, work environment, etc.). Among them, the quality of a product is inevitably affected considerably by the health state of the machine used in the manufacturing process. Therefore, it is necessary to look into the relations between the quality of the product and maintenance approaches for the machine.

2.2 Maintenance Approaches

Generally, maintenance can be defined as, "the combination of all technical and administrative actions intended to retain an item in, or restore it to, a state in which it can perform its required function" (British Standards Institute, 1984). The maintenance approach could be simply classified into two types: breakdown maintenance (corrective maintenance) and preventive maintenance. In the breakdown maintenance, the maintenance action is initiated after certain problems such as breakdowns in a product are found (Jun 2018). However, in the preventive maintenance, the maintenance action is taken based on specific basis, e.g., regular time. In that case, the preventive maintenance approach is called TBM (Time Based Maintenance). If the maintenance action is taken based on not specific time but the condition of machine, then we call it as CBM (Condition Based Maintenance) approach. The CBM might be like TBM as in its goal is to prevent system abnormality ahead of time before abnormality happens. However, the CBM approach is different from the TBM. It focuses on the prediction of degradation process of the system, which depends with the understanding that most abnormalities do not happen promptly, and typically there are some kinds of degradation process from normal states to abnormalities (Fu et al., 2004). Hence, unlike breakdown maintenance and TBM, the CBM focuses on not only fault detection and diagnostics of components but also degradation monitoring, failure prediction, and maintenance, the scope of which is very similar with that of PHM.

Although the conceptual scope of CBM is very similar to today's PHM, early CBM studies mainly focused on condition monitoring and optimal decision making for maintenance. That is, studies related to diagnosis and prognosis were limited. Since then, CBM has evolved into CBM+ from the military domain with the addition of a lifecycle concept. Today, PHM or CBM + that focuses more on fault diagnosis and residual life prediction, and lifecycle health management of core facilities/equipment are in the spotlight. The PHM empowers us to recognize and tackle issues ahead of time before system damage happens. In industry systems, any damage can prompt serious results. In this regard, the PHM is an exceptionally appealing technique for the manufacturing industry operating high-valued physical facilities/equipment.

With recent advances in modern technology, industrials and researchers are advancing toward upgraded maintenance support systems that target improving reliability and availability of critical engineering assets while reducing overall costs. Therefore, the role of maintenance has changed from a "necessary evil" to a "profit contributor" (Javed, 2014). Under the new environment, we can accumulate the machine status and usage data connected with usage conditions, failure, maintenance or service events, and so on. These data empower us to analyze the degradation status of the machine in a more exact way. Using accumulated data gives us new challenging issues for improving the efficiency of maintenance operations and diminishing the quality issues connected with the machine. If manufacturing defects are found, their causes could be identified by analyzing data about past operations, environmental conditions, and historical defects with several PHM results such as diagnostics and prognostics information of relevant machines, e.g. degradation status, remaining useful life, etc. That is, the PHM becomes the key technology for achieving the ZDM system.

To achieve the goal of ZDM, it is prerequisite to learn how to control the quality during manufacturing operations. For this purpose, machine interactions and production characteristics should be considered. The quality of products depends on the condition of the production system and the used equipment (Lindström et al., 2020a). Hence, we could know that advanced maintenance strategy such as PHM and ZDM are closely related with each other. Wang (2013) mentioned the general functional requirements of ZDM, which are very similar to the procedure of PHM: 1) automatic capture, cleaning and formatting of relevant data using intelligent sensors system; 2) automatic signal processing, filtering and feature extraction; 3) data mining and knowledge discovery for diagnosis and prognosis; 4) provision of clear and concise defect information and advice supplied to the user; 5) self-adaption and optimization control. Negandhi et al. (2015) addressed that a predictive maintenance and quality solution could also detect anomalies within processes, compare parts against their master, and conduct in-depth root cause analysis, which leads to improving part quality and reduce recalls. **Figure 1** depicts the overview of PHM in ZDM system. In this vein, it is necessary to look specifically at what PHM is and how it relates to ZDM.

3 ADVANCED MAINTENANCE APPROACH: PHM

PHM is an emerging engineering discipline which links studies of failure mechanisms (corrosion, fatigue, overload, etc.) and lifecycle management (Javed, 2014). Chen et al. (2012) mentioned it as an approach for system lifecycle support. It seeks to reduce unnecessary maintenance actions throughout real-time monitoring, eventually extend the service cycle of an engineering asset. As of late, PHM has arisen as one of the vital enablers for accomplishing efficient system-level maintenance and bringing down lifecycle costs need (Vichare and Pecht, 2006; Zhang et al., 2009).

So far since the maintenance of facilities has depended on population-specific reliability characteristics, it is difficult to maintain more accurate individual maintenance of facilities that inevitably have different degradation characteristics for each work environment. In this regard, PHM technology, which diagnoses and predicts failures in more detail in consideration of the deterioration characteristics of individual machine, is receiving a lot of attention.

According to Javed (2014), abbreviation PHM comprises of two elements:

1. Prognostics refers to a prediction/forecasting/extrapolation process by modeling fault progression, based on current state assessment and future operating conditions;
2. Health management refers to a decision-making capability to intelligently perform maintenance and logistics activities based on diagnostics/prognostics information.

As can be seen from the above, in general, the PHM system ought to have the capability of anomaly detection, fault diagnostics, fault prognostics, and health management. According to Zhang et al. (2009), implementation of PHM can resolve the accompanying three issues: 1) what is healthy condition of the observed machine, 2) if the machine is not sound, where does the degradation or anomaly happen, and 3) when the observed machine is going to fail or degrade to the point which its performance becomes unacceptable and maintenance action ought to be initiated.

There are several definitions of PHM in previous works. For example, the IEEE reliability society (www.phmconf.org) defines PHM as "a system engineering discipline focusing on detection, prediction, and management of the health and status of complex engineered systems". Furthermore, according to Sheppard et al. (2009), PHM could be defined as "a maintenance and asset management approach utilizing signals, measurements,

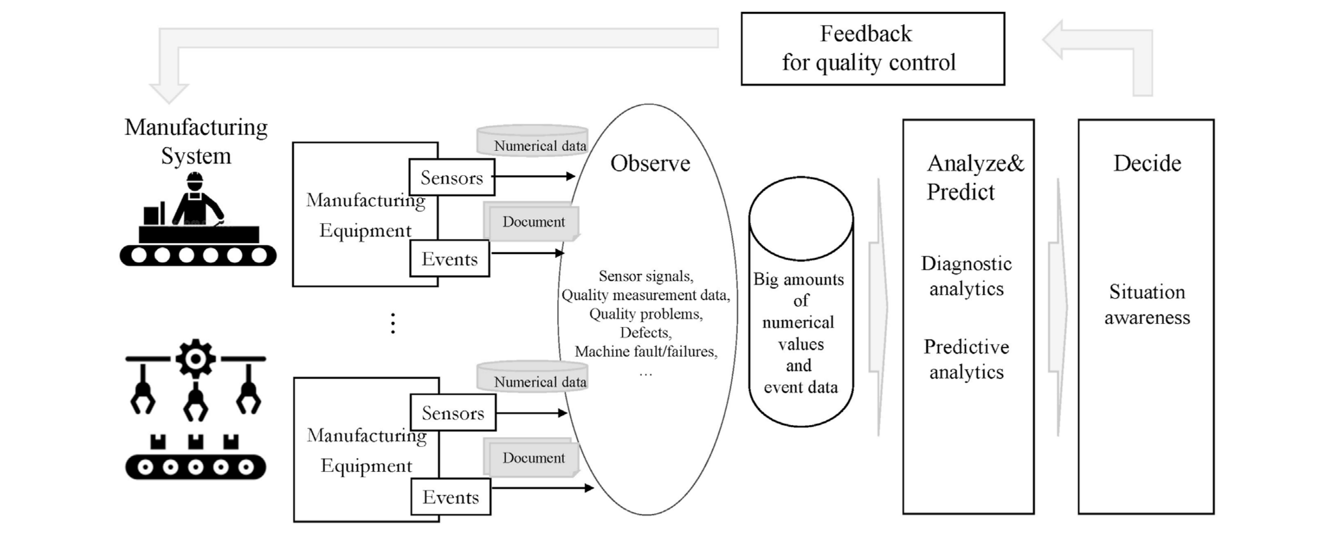

FIGURE 1 | PHM in ZDM.

models, and algorithms to detect, assess, and track degraded health, and to predict failure progression". According to Chen et al. (2012), PHM comes from the US DoE (Department of Energy) and the US DoD (Department of Defense). In the JSF (Joint Strike Fighter) program of US DoD, the name PHM was adopted (Jun 2018). Since then, prognostics technology has become an area of flourishing international research (Sun et al., 2012). With respect to PHM term, there are a few similar terms used interchangeably in the previous literature: e.g., predictive maintenance, prognostics, and CBM. Among them, the most well-known terminology is CBM. Over the last decade, CBM has evolved into the concept of PHM, because of its broader scope (Javed, 2014). In November 2002, the US deputy under secretary of defense for logistics and materiel readiness released a policy called CBM+ (Condition-Based Maintenance plus) (Vichare and Pecht, 2006). CBM + addresses an effort to move unscheduled corrective equipment maintenance of new and legacy systems to preventive and predictive approaches that plan maintenance in light of the evidence of need (Jun 2018), which is similar with the concept of PHM.

3.1 Purpose and Benefits of PHM

The motivation behind PHM is to augment the functional availability and safety of the engineering asset, e.g., manufacturing facility/equipment. Eventually the PHM can improve security, reliability, availability and mission success, and support a better ability to plan for maintenance events, which leads to reduce the operation and maintenance cost (Jinyu et al., 2009; Sheppard et al., 2009; Das et al., 2011).

PHM technologies can evaluate and measure the degree of deviation or degradation from an expected normal working condition (i.e. health) by incorporating sensor data and prediction models that enable *in-situ* assessment of the degree of deviation or degradation of the system from an expected normal working condition (i.e. the system's health or reliability) (Vichare et al., 2006). The accurate remaining life of the equipment obtained as a result of the prediction of the PHM is essential information for making an effective maintenance plan. Based on this, a series of maintenance plans must be set up and properly dealt with before the machine/equipment breaks down to ensure the integrity of the product. PHM could provide us with several benefits in all product lifecycle activities including design and development, production and construction, operations, logistics support on maintenance, phase out, and disposal. In particular, when coupled with autonomic logistics, PHM can improve mission-critical system reliability and availability, and reduce logistics delay time, on-demand repair actions and sparing, and life-cycle costs (Chen et al., 2012). Utilizing PHM technologies, the companies can catch unexpected performance variations during the engineering asset's lifetime. This is particularly useful in high-tech sectors, e.g., aerospace, military, etc., where operational costs have become a significant source of revenue generation (Teixeira et al., 2012).

According to Vichare et al. (2006); Zhang et al. (2009); Luna (2009); Sun et al. (2012); Javed (2014)'s works, the benefits of PHM could be summarized as in **Table 2**(Jun 2018). As you see in **Table 2**, many of the quality domain benefits of PHM must be directly tied to ZDM aims.

3.2 Procedure and Standards for PHM

PHM usually requires a long-term effort in order to implement several steps needed for the PHM procedure. **Figure 2** briefly shows the overall procedure for PHM from sensing to doing predictive maintenance, which consists of data gathering step including sensing, signal processing, and condition monitoring, data analyzing part containing diagnosis and prognosis, and health management step including decision making and predictive maintenance action. The PHM can be done by 1) gathering machine status data with failure and quality event data;

TABLE 2 | Benefits of PHM.

Domain	Benefits of PHM
Quality	Maintain effectiveness through timely repair actions Increase system operations reliability and mission availability Avoid consequences of failure by advance warning of failures Extend life/Reduce maintenance frequency Optimize resource use Decrease unnecessary maintenance actions Improve system safety (predict to prevent negative outcomes) Improve qualification and assisting in the design and logistical support of fielded and future systems Improve decision making to prolong life time of a machinery
Cost	Reduce LCC (Life-Cycle Costs) by decreasing inspection costs, downtime, and inventory Reduce operational costs to optimized maintenance
Delivery	Reduce lead time Minimize unscheduled maintenance Extend maintenance cycles

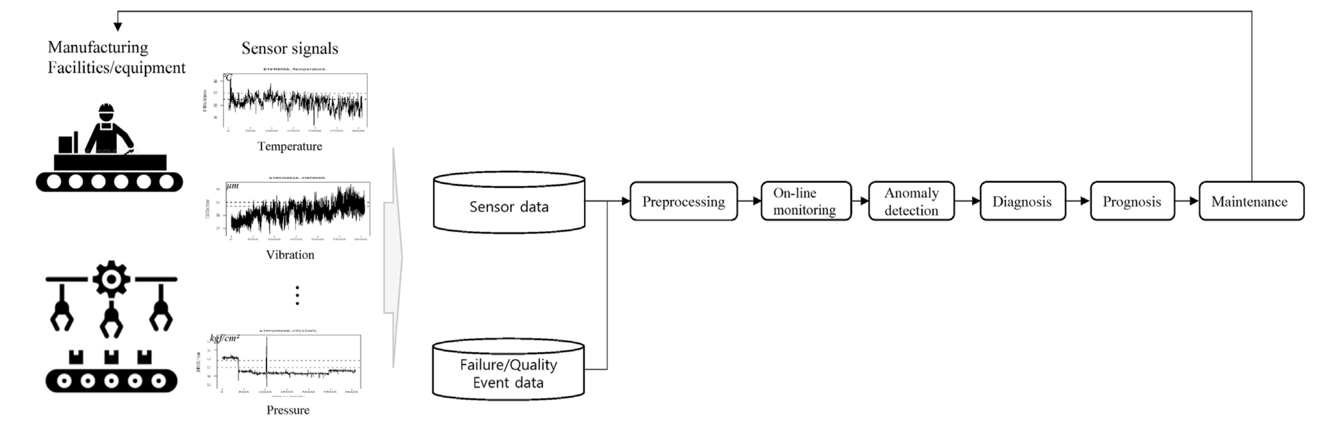

FIGURE 2 | PHM process.

2) data preprocessing and on-line monitoring; 3) anomaly detection; 4) making a diagnosis of a machine status if necessary; 5) predicting the time of machine abnormality; and 6) executing appropriate maintenance actions such as repair, replace, and disposal based on reasonable decision making by estimating maintenance costs which depend on the deterioration level and maintenance schedule. Consequently, to implement the PHM approach, it is required to resolve several research issues connected with data gathering, analyzing, decision, and actions.

Regarding relevant standards for PHM, Vogl et al. (2014a,b) conducted a review of PHM-related standards relevant to manufacturing systems. In their work, they addressed several existing standards for each PHM step. In particular, they mentioned the ISO 17359 (condition monitoring and diagnostics of machines-general guidelines) as the relevant PHM standard of manufacturing domain. According to Vogl et al. (2014a,b), ISO 17359 outlines the condition monitoring procedure for a general manufacturing process, factors influencing condition monitoring, a list of issues affecting equipment criticality, and a table of condition monitoring parameters for various machine types. Furthermore, although it is not a PHM architecture, there is the OSA-CBM (Open Standard Architecture Condition Based Maintenance) architecture for CBM. The OSA-CBM is designed by MIMOSA (Machinery Information Management Open System Alliance) which is an organization engaged in the development of the standards for CBM. MIMOSA is a not-for-profit trade association devoted to developing and empowering the adoption of open information standards for operations and maintenance in manufacturing, fleet, and facility environments. The OSA-CBM is a standard for information flow to realize an end-to-end CBM system. According to MIMOSA OSA-CBM, there are six layers expected to execute the idea of CBM: 1) Data Acquisition, 2) Data Manipulation, 3) State Detection, 4) Health Assessment, 5) Prognostics Assessment, and 6) Advisory Generation. These layers are very similar to the PHM procedure. Although there are some relevant standards for implementing the PHM in manufacturing systems, diagnostics and prognostics standards are still lacking according to Vogl et al. (2014a,b).

4 REVIEW ON PREVIOUS WORKS RELATED TO ZDM AND PHM

So far there have been several previous works related to ZDM. Most of the previous works are mainly based on the results of the ZDM projects that have been carried out in recent years. According to Eger et al. (2018a), several EU projects such as MUPROD, IFACOM, MEGAFIT and MIDEMMA have demonstrated how to achieve near zero defect level in different manufacturing systems. For example, Myklebust (2013) introduced the IFaCOM (Intelligent Fault Correction and self-Optimizing Manufacturing systems) project and addressed the concept of ZDM focusing on maintenance. They focused on a part and plant lifecycle approach to achieve the best possible practice to ZDM. Eger et al. (2018a) also introduced the ForZDM project targeting at developing and demonstrating a next generation ZDM strategy capable of dynamically achieving the production and quality targets grounding on an integrated quality and production control solution for multi-stage systems. For the ZDM in multi-stage manufacturing systems, they have highlighted multi-scale modeling, CPS, big data and data analytics as key enabling technologies. In their other work (Eger et al., 2018b), they also introduced the knowledge capturing platform for the multi-stage production system in ZDM, which consists of 1) correlation analysis, 2) part variation modeling, and 3) advanced monitoring methods. Furthermore, Leitão et al. (2018) presented the main principles of a multi-agent CPS aiming the application of ZDM in multi-stage production systems based on the GO0D MAN EU project. They introduced the MAS (Multi-Agent System) architecture that allows the distributed data collection and the balancing of the data analysis for monitoring and adaptation among cloud and edge layers. May and Kiritsis (2019) provided a holistic framework and a comprehensive set of integrated strategies for achieving zero-defects manufacturing via a novel ZDM platform in the era of Industry 4.0. In their work, they mentioned the five multi-stage production based strategies: Z-Defect, Z-Predict, Z-Prevent, Z-Repair, and Z-Manage. Lindström et al. (2020b) addressed the requirements for change and desired effects from ZDM, with an Industry 4.0 perspective, concerning production in the manufacturing and process industries, based on an in-depth qualitative case study comprising six companies. Magnanini et al. (2020) proposed a MES (Manufacturing Execution System) centered reference architecture and related software modules for ZDM, based on ForZDM EU project.

In addition, Psarommatis et al. (2020a) have conducted an extensive literature review of 280 research articles covering the broad scope of ZDM including product quality, defect, and so on, from 1987 to 2018. Based on the review, they identified and highlighted four distinctive strategies for ZDM, i.e. detection, repair, prediction, and prevention. They classified four ZDM strategies into two categories: triggering factors and actions, respectively. Among four strategies, detection and prediction are the strategies that correspond to diagnosis and prognosis in PHM technologies. In their other work (Psarommatis et al., 2020b), they have carried out an extensive literature survey on the quality improvement methodologies. They analyzed the quality improvement tools used in manufacturing, the critical factors and benefits of implementation of these methodologies, and to investigate how they are related to ZDM. However, the scope of their study did not directly include ZDM studies. Psarommatis (2021) also proposed a methodology for designing a manufacturing system for achieving ZDM in terms of DT (Digital Twin) technology. To this end, they defined ZDM control parameters and proposed the methodology for creating the DT model of a manufacturing system. They analyzed how much each ZDM control parameter is affecting the performance of each ZDM strategy. The proposed methodology has been applied to a real-life industrial use case in the semiconductor domain. In their work, they mentioned that one of the core features of ZDM is the use of prediction technologies. Powell et al. (2021) addressed not only product-based and process-based approaches but also the people-oriented one as a third dimension to ZDM and extracted practical insights to present a framework for digitally enhanced quality management. Mourtzis et al. (2021) presented the design and development of a DT-based framework to optimize the equipment design for ZDM. The proposed framework includes data acquisition, data processing, and simulation. Recently, Powell et al. (2022) also provided a state-of-the-art perspective of ZDM throughout providing critical (systematic) and structured review on ZDM. In their work, they classified the most prominent subject areas of ZDM in terms of 1) scope (single-, multiple-, or system-level); 2) focus (product-, process-, or people-centricity); 3) type (theoretical or applied); 4) hierarchical level (strategic, tactical, or operational); and 5) key enabling technologies. Psarommatis and Kiritsis (2022) also dealt with detection and repair-based ZDM strategies. They developed a hybrid DSS (Decision Support System) to recognize defects and then automate the necessary decision-making processes based on data-driven and knowledge-based approaches. For the evaluation, a case study had been performed in the semiconductor domain. Caiazzo et al. (2022) introduced an extensive overview of the current trends in the fairly broad domain of ZDM research field from 2018 to 2020. In their work, they investigated the most frequently used research methods for each ZDM strategy, i.e. detection, repair, prediction, and prevention, respectively. From their survey results, we could see that most ZDM-related studies focus on AI/ML techniques related to detection, prediction, prevention, etc., and the proportion of studies discussing direct linkage with quality control and quality management for achieving the zero-defect was found to be relatively small.

Table 3 shows the summary of previous works on ZDM. As can be seen from the previous studies of ZDM examined so far, ZDM studies have been mainly conducted recently, and thanks to the development of various ICTs, they are presented as a result of research projects to build a next-generation manufacturing system. Also, it can be seen that most studies are being attempted to define and classify the characteristics of ZDM academically in terms of framework, infrastructure,

TABLE 3 | Previous works on ZDM.

Previous Works	Keywords	Main Features	Related Project	Category
Myklebust (2013)	Part and plant lifecycle approach for ZDM	Enterprise model architecture for plant-product model of ZDM	IFaCOM	Framework
Eger et al. (2018a)	ZDM solution for multi-stage manufacturing systems	ZDM and CPS for multi-stage production system	ForZDM	Infrastructure
Eger et al. (2018b)	Knowledge capturing platform for ZDM	Knowledge capturing platform (correlation analysis, part variation modeling, and advanced monitoring methods) in multi-stage production system for ZDM	ForZDM	Infrastructure
Leitão et al. (2018)	Multi-agent CPS for ZDM	CPS, cloud/edge computing with MAS architecture for ZDM in multi-stage manufacturing	GO0D MAN	Infrastructure
May and Kiritsis (2019)	ZDM framework and strategies in multi-stage production	Five multi-stage production based strategies: Z-Defect, Z-Predict, Z-Prevent, Z-Repair, and Z-Manage	Z-Fact0r	Fraemwork
Sesana and Moussa (2019)	AR and AI technologies for ZDM	AR and AI solution to support human workers for ZDM	QU4LITY	Infrastructure
Lindström et al. (2020b)	Requirement analysis for ZDM	Requirements for change and desired effects from ZDM, based on an in-depth qualitative case study comprising six companies	–	Requirement analysis
Magnanini et al. (2020)	MES centered reference architecture for ZDM	MES software modules for ZDM	ForZDM	Fraemwork
Psarommatis et al. (2020a)	Extensive literature review of 280 research articles on ZDM	Four ZDM strategies: detection, repair, prediction, and prevention	–	Review
Psarommatis et al. (2020b)	Extensive literature survey on the quality improvement methodologies for ZDM	Tools of quality improvement, enabling factors, benefits, barriers to implementation for ZDM	–	Review
Mourtzis et al. (2021)	Design and development of a DT-based framework to optimize the equipment design for ZDM	DT-based framework including data acquisition, data processing, and simulation	MARKET4.0	Framework
Powell et al. (2021)	ZDM framework for digitally enhanced quality management	Addressing not only product-based and process-based approaches but also the people-oriented one	QU4LITY	Framework
Psarommatis (2021)	DT based methodology for designing a manufacturing system for ZDM	Presenting ZDM strategies control parameters, ZDM performance map, and proposing a methodology for creating the digital twin model of a manufacturing system	Z-Fact0r	Framework Methodology
Psarommatis and Kiritsis (2022)	Detection and repair-based ZDM strategies, hybrid DSS framework for ZDM	Hybrid DSS to recognize defects and then automate the necessary decision-making processes based data-driven and knowledge-based approaches	Z-Fact0r	Framework Case study
Caiazzo et al. (2022)	Extensive overview of the current trends in the ZDM field from 2018 to 2020	Investigating the most frequently used research methods for each ZDM strategy, i.e. detection, repair, prediction, and prevention	–	Review
Powell et al. (2022)	Systematic and structured review on ZDM	Classifying ZDM subject area in terms of scope, focus, type, hierarchical level, and key enabling technologies	–	Review

methodology, and so on. Overall, expanding the research scope of ZDM, it can be noticed that there are still a number of a number of case studies or studies on certain approaches that have implemented various aspects of ZDM.

Regarding PHM technology, there are some research works dealing with the architecture or framework or methodology. For example, Kunche et al. (2012) reviewed and discussed the architectures and architectural framework proposed for various PHM applications. The reviewed frameworks coordinate various functionalities of the PHM system including data acquisition, signal processing, feature extraction, anomaly detection, diagnostics, prognostics and decision support. He and Ma (2012) reviewed the history of PHM and analyzed the main elements of general PHM system. Based on them, they proposed the PHM system architecture for electronic equipment. Lee et al. (2014b) carried out a comprehensive review of the PHM field. They introduced a systematic PHM design methodology, 5S methodology, for converting data to prognostics information. They additionally introduced a systematic methodology for conducting PHM as applied to machinery maintenance. Vogl et al. (2014b) mentioned the general PHM system development process and associated standards. Ning et al. (2016) presented a cloud-based PHM framework with maximizing OEE (Overall Equipment Effectiveness) as ultimate goal. The cloud-based PHM system is compliance to OSA-CBM standard, including data acquisition, state detection, health assessment, prognostics assessment, and advisory generation. Each component contains a variety of algorithms (part) in the framework. In addition, Xia and Xi (2019) classified the PHM decision making layer into the following: 1) machine-specific diagnosis and prognosis, 2) machine-level maintenance scheduling, and 3) system-level maintenance optimization.

TABLE 4 | Previous works on advanced maintenance in ZDM.

Previous Works	Keywords	Maintenance Related	Advanced Maintenance in ZDM
Ferretti et al. (2013)	Monitoring system for ZDM, Overview of possible direct/indirect actions for ZDM	Consideration of planned and preventive maintenance	Not applicable
Myklebust (2013)	Part and plant lifecycle approach for ZDM	Addressing the concept of ZDM focusing on maintenance	Conceptual framework
Wang (2013)	Data mining approach for ZDM (IFDAPS framework)	General functional requirements of ZDM (IFDAPS framework) mentioned in this study is very similar to those of PHM	Conceptual framework
Dreyfus and Kyritsis (2018)	Predictive maintenance, ZDM, Production scheduling	Framework for combining predictive maintenance, automatic scheduling and ZDM	Integration of scheduling and maintenance
Fusko et al. (2018)	Designing proactive maintenance processes	Three zero program (1 ~ 4 phases). Phase 4 (prediction of lifetime) is closely related to prognosis of PHM	Conceptual framework
Schafer et al. (2019)	Predictive Six Sigma	Transforming steps from descriptive to predictive Six Sigma using data mining and machine learning techniques for the zero defect	Indirect link to ZDM
Lee et al. (2019)	Predictive quality management	Predictive quality management based on an extensive literature review on quality management and introduction of five industry cases	Indirect link to ZDM
Lindström et al. (2019)	Main pillars for intelligent and sustainable ZDM	Monitoring of process parameters, on-line predictive maintenance	Conceptual framework
Lindström et al. (2020a)	Initial model for ZDM with an Industry 4.0 perspective	Addressing the relation to condition monitoring and fault detection	Conceptual framework
Psarommatis et al. (2021)	Predictive maintenance, ZDM, Production scheduling	Identifying the relations among predictive maintenance, ZDM, and production scheduling	Quantitative approach

In terms of existing research on various PHM technologies, there have been also lots of research works from anomaly detection to diagnostic or prognostic maintenance methods in various application domains. This study does not deal with the review on the PHM research works for each PHM step. Instead, we briefly review a number of methodological studies related to how the PHM technology can be applied to the manufacturing system. For example, Pecht (2012) introduced an assessment of the state of practice in PHM of information and electronics rich systems. He presented a fusion prognostics approach, which consolidates or "fuses together" the model-based and data–driven approaches, to enable markedly better prognosis of remaining useful life. To represent the implementation of the fusion approach to prognostics, he carried out a case study of a printed circuit card assembly. Lee et al. (2014a) mentioned the 'product and process quality'as one of five distinctive issues to be solved for being intelligent machines in the CPS-enabled manufacturing and service innovation. They addressed that diagnostic and prognostic algorithms are too machine or application-specific, so there are aspects that are difficult to apply in new situations, which are due to the following two reasons: 1) lack of a closely coupled human-machine interaction, 2) lack of adaptive learning and full utilization of available information. Shin et al. (2018) also presented a PHM framework giving a guideline for PHM application to manufacturing systems. They have performed a survey to gather the current situations with respect to maintenance approaches and system failures handling in the field. They mentioned the PHM-enabled manufacturing systems as smart manufacturing system. As briefly reviewed above, the existing studies related to PHM mainly focused on a specific machine level, and it seems that there are relatively few studies related to the manufacturing system level, especially ZDM.

In the meantime, several studies have been conducted on how to apply advanced maintenance strategies/methods such as PHM or predictive maintenance to implement ZDM. **Table 4** summarizes them. For example, Myklebust (2013) addressed the concept of ZDM focusing on maintenance, but stayed at the level of mentioning the framework, and the specifics were insufficient. Wang (2013) presented a general framework of ZDM (IFDAPS: intelligent fault diagnosis and prognosis system) and addressed how to apply data-mining approaches in order to achieve zero-defect in manufacturing. The IFDAPS is a framework for ZDM and has overall PHM functionality. They mentioned that ZDM could be carried out by controlling the process parameters in real time and by the utilization of intelligent processing diagnosis and prognosis, and proactive controls on processes, production systems and sub-systems incorporated in the production lines/cells. However, even in their study, it was not easy to understand how the results of the research method were specifically and directly related to the achievement of zero defect. Ferretti et al. (2013) made an overview of possible actions which could be implemented for ZDM. Their study referred to planned and preventive maintenance rather than predictive maintenance strategies as an indirect way to achieve ZDM. Furthermore, Fusko et al. (2018) dealt with a research work of designing proactive maintenance processes for Industry 4.0. They have carried out practical field research survey from automotive industry in Slovak and Czech Republic that identifies the current state in manufacturing factories and their readiness for Industry 4.0. They proposed the fifteen phases for efficient maintenance processes in a factory with the concept of three zero program requirements: 1) Zero accidents, 2) Zero defects, and 3) Zero failure. However, there is a limitation in that the ZDM implementation method is relatively abstract. Dreyfus and Kyritsis (2018) addressed the framework for combining predictive maintenance, automatic scheduling, and ZDM. To this end, they proposed a framework consisting of product-centered tuning assistant, machine-centered predictive maintenance, and production-centered automatic scheduling. Their study is meaningful in that they discussed how to take the link with production scheduling to achieve ZDM using advanced maintenance. Schafer et al. (2019) proposed steps to be taken to transform from descriptive to predictive Six Sigma for the zero defect goal within production lines. However, there was also a limit to the specific methodology for implementing ZDM. Lee et al. (2019) dealt with predictive quality management based on an extensive literature review on quality management. They also introduced and analyzed five industry cases (Rolls-Royce, Hyundai Motors, BOSCH, John Deere, and Clova) to illustrate how service and operational efficiencies can be improved through predictive maintenance. According to their work, BOSCH, the world's number one automotive parts company, is actively implementing predictive maintenance and quality control through a software tool it developed, the "Nexeed Production Performance Manager." However, their study was limited to the introduction of the application cases of predictive maintenance, so there was a limit to grasp a specific method for implementing ZDM.

Recently, Lindström et al. (2019) addressed main pillars for intelligent and sustainable ZDM achieved through combination and integration of online predictive maintenance, monitoring of process parameters and continuous quality control. Despite the fact that their study specified the components for adopting ZDM using advanced maintenance, the method they used was relatively insufficient. Lindström et al. (2020a) also investigated an initial model for ZDM with an Industry 4.0 perspective, based on empirical data collected from five manufacturing companies. The proposed initial model in their work utilized a cost function where the operation and condition of a production process are reflected. However, their study can be said to be somewhat abstract in relation to maintenance in ZDM implementation. Psarommatis et al. (2021) have investigated the key control parameters for identifying the relations among ZDM, maintenance, and production scheduling. They have performed the simulations to investigate the effect of identified seven key parameters (predictive accuracy, prediction horizon, horizon standard deviation, reaction time, maintenance cost, maintenance time, maintenance effectiveness) on production scheduling, and gave some useful insights when considering predictive maintenance on ZDM based on simulation results. Their study is meaningful in that it quantitatively considered the relationship between predictive maintenance and production scheduling to implement ZDM.

5 DISCUSSION AND OUTLOOK

In **Section 4**, we mostly examined previous research works that directly addressed ZDM, including those that primarily addressed the advanced maintenance technique for ZDM implementation. As the result, as Psarommatis (2021) mentioned, it could be noticed that most previous ZDM works, which dealt with advanced maintenance, have the restriction of giving a detailed method for designing quality assurance policies for ZDM. Although many previous studies dealt with ZDM, PHM, and quality assurance problem in manufacturing, most of them were dealt with individually, and in particular, there were not many studies that dealt with ZDM and advanced maintenance policy including PHM together. As can be seen from the above section, there have been existing studies that have studied the relationship between ZDM and advanced maintenance (predictive maintenance, PHM, etc.), and linkage with framework and production scheduling. However, it can be seen that there are not many specific methods or case studies on how the advanced maintenance method can specifically achieve zero defect. Many ZDM-related studies are still in the concept and framework definition stage, and even if we look closely at maintenance-related studies among the papers that have studied ZDM, qualitative comments about their relevance and importance are mainly made from the framework and process perspective. There were not many studies dealing with a more specific quantitative analysis method. The following points can be inferred as the reason that there are not many studies that have specifically studied the relationship between advanced maintenance and ZDM research. First, ZDM and PHM technologies are the latest technologies/concepts that are being studied for their feasibility based on recently developed ICT technologies. Since it is still in the early stages of applying new concepts and new technologies, there will not be many research cases, and it may be too early to derive a generalized methodology. Second, since the technical scope of ZDM and PHM is very vast, it is difficult to present a specific research methodology by tying these two concepts together. Nevertheless, advanced maintenance techniques such as PHM are one of the essential technologies required to implement ZDM, so research on how the process, components and architecture of PHM are related to the framework of ZDM from an architectural point of view desperately needed. For example, as described in **Table 5**, since there is a common intersection between the PHM architecture and the ZDM strategy, more detailed studies on this part are needed. In addition, more specific research is needed on applying the detailed layers of PHM originally made for fault diagnosis and health management of equipment to ZDM element, e.g., health assessment for product quality management or process quality management.

The application of PHM to manufacturing systems is very challenging since manufacturing systems have become more complicated (Jun 2018). It is even more difficult to apply PHM to ZDM. There are several difficulties in applying the PHM to ZDM as follows. First, to implement the PHM into ZDM, from sensor data acquisition, data preprocessing, online monitoring, fault diagnosis, fault prediction, maintenance decision making, etc., professional knowledge in the multi-disciplinary field is required. In addition, it requires specialized knowledge and experience on how the condition of the facility or machine equipment is related to the quality of the product and process, and on how to reduce the generation and propagation of defects. However, there are few experts in the manufacturing system field who have the convergence technology of PHM to see through these various fields of knowledge and implement ZDM.

TABLE 5 | PHM layers and ZDM strategies.

PHM Layers	ZDM strategy (Psarommatis et al., 2020a)	
Data acquisition	-	-
Data manipulation	-	-
State detection	Detect	Triggering factors
Health assessment	Detect	
Prognostics assessment	Predict	
Advisory generation (Prescriptive maintenance)	Prevent/Repair	Actions
	Repair	
	Detect-Repair	
	Detect-Prevent	
	Predict-Prevent	

According to Fusko et al. (2018), many factories are not ready for transforming the standard maintenance into an intelligent maintenance like PHM. As you know, PHM is definitely not a single technique and requires very complex and various interdisciplinary research techniques (Jun 2018), which leads to take a lot of time and endeavors for PHM implementation in ZDM. In particular, SMEs (Small and Medium-sized Enterprises) have difficulty in applying PHM due to the lack of internal expertise, time, and resources for research and development (Shin et al., 2018).

Second, several advanced manufacturing paradigms such as mass customization, reconfigurable manufacturing, additive manufacturing, and so on, need different types of manufacturing system architectures. Hence, there is a difficulty in that the PHM system must be applied in accordance with the characteristics of these various types of manufacturing systems. Because product quality and zero defect implementation features differ depending on the type of manufacturing system, study on these topics should come first. Furthermore, as Xia and Xi (2019) also mentioned, since there are various layers to make decisions regarding failure of major equipment in the manufacturing system (e.g., component level, machine level, system level), this results in the difficulties of applying PHM solutions to diagnosis and prognosis. According to Aivaliotis et al. (2019), utilisation of PHM solutions at the machine level is still a lot of confined by the absence of solutions to collect, connect and control data/information from sensors and to join them through efficient digital models for the provision of important health assessment and prediction results for optimal maintenance allocation. To make matters worse, since the effects on product quality and process quality will be different for each hierarchical layer of the manufacturing system, there will be an increasing number of issues to tackle in order to apply PHM to ZDM. In addition, considering the recent characteristics of manufacturing facilities, where electrical/electronic components are increasing, PHM studies, which mainly monitor, diagnose, and predict the deterioration of machinery-oriented facilities, have still the limitations in applying diagnosis and prognosis solutions to the facilities or equipment with electrical/electronic components.

Finally, the PHM system requires a large amount of normal/abnormal data due to its nature. Therefore, it takes a lot of money and time to build the data. However, it is not easy to analyze the PHM construction cost and its effects. According to Malinowski et al. (2019), the potential cost and effectiveness of PHM implementation are uncertain and arbitrary. In addition, it is necessary to precisely define and accumulate the data sets required to achieve the purpose of ZDM using PHM. However, many manufacturers still do not have data sets related to this, so many preparations are needed to apply PHM to ZDM.

6 FUTURE RESEARCH WORKS FOR APPLYING PHM TO ZDM

As you could see in **Table 6**, there are still many issues to be solved in order to achieve the goal of ZDM by making the PHM technology well integrated into the manufacturing system, which could be considered future research issues. For example, we could think of the followings in terms of PHM steps:

6.1 Data Acquisition

From a technological perspective, ZDM, quality management, and PHM leverage data-driven technologies (e.g., IIoT, Big Data, ML, and AI) (Errandonea et al., 2020). In order to monitor, diagnose, and predict the state of a manufacturing facility or equipment in an exact way, it is necessary to make a decision based on data collected directly or indirectly. To achieve the zero-defect, it is very important to identify the correlation between direct measurement data (vibration, sound, temperature, current, etc.) from the sensor, as well as indirect data such as workplace environment/operation data, and feedback data corresponding to product or process quality. Hence, first of all, the research on selection and collection of related data for achieving ZDM is of utmost importance and required. Furthermore, data quality and data resolution issues must be investigated in data collecting. In order to achieve the zero defect rate of product or process quality, research should be done on what kind of state data is necessary for equipment, which data are useless, and what level of resolution of sensor data should be. Also, we could think of the studies on where to store and process the collected data will be more effective from the overall system point of view, considering cloud computing or edge computing technologies.

TABLE 6 | Challenging issues for applying PHM to ZDM.

PHM Steps	Challenging Issues in ZDM	Applicable IoT/ML/AI Technologies and Methods
Data acquisition	Data selection related to product/process quality Data quality issue Data resolution issue Data storage/processing location	Sensor technologies DCS, SCADA/Network technologies Cloud, edge computing
Data manipulation	Product/Process quality features extraction Data imbalance problem	Sensor data fusion Feature engineering Data augmentation
State detection	Product/Process quality definition Online monitoring interval Integration with SQC, SPC	Statistics, data mining methods Anomaly detection algorithms Defective automatic detection technology
Health assessment	Identifying the relation between machine health and product/process quality	Classification algorithms
Prognostics assessment	Product/Process quality prediction method based on machine health prediction	Prediction algorithms
Advisory generation	Knowledge capturing framework/method for ZDM	Prescriptive maintenance Decision support system
	Situation awareness and response methods for controlling quality	Expert system Knowledge DB, Situation awareness
Total integration	General framework or standard for PHM to ZDM	Knowledge DB CPS, digital twin
	System-level approach, Necessity of system tuning	Expert system Augmented reality

6.2 Data Manipulation

After proper data collection, it is necessary to select key features that are directly related to product/process quality to achieve ZDM. For this, it is necessary first to define product quality/process quality, and to conduct research on factors that can influence these qualities. Also, in most cases, there will be much more normal data than abnormal data related to defects, so studies related to data augmentation technology are also needed to solve this data imbalance problem.

6.3 State Detection

In the state detection stage, first of all, in order to define a state, a clear definition of the quality/defect of the product and process must be preceded. In addition, research works on how to set up the online monitoring interval for more effective state detection, or integration with quality control chart methods and state detection methods based on data from sensors are needed to be done.

6.4 Health Assessment

In the health assessment stage, it is necessary to study the correlation analysis between the specific type of the failure mode of machinery and the quality of the product or process. These studies will be needed for each of the various hierarchical layers of the manufacturing system. Thus, it is necessary to develop a general methodology that is not limited to a specific machine or unit process, expanded to component, subsystem, and system-level.

6.5 Prognostics Assessment

In applying PHM technology, one of the most interesting things is related to prediction or prognostics. As a result of prognostics, it is feasible to estimate the RUL (Remaining Useful Life) of equipment, and then to execute proactive maintenance on the equipment to reach zero defects. Thus, in the prognostics assessment stage, it is necessary to study the methodology that can predict and control the quality of products and processes based on the results of predicting the performance of machinery. Many machine learning approaches can be employed as appropriate research methods to study the intricate relationship between the prediction outcomes of equipment and the quality of products or processes, and this result can be applied.

6.6 Advisory Generation

In the advisory generation stage, we should think of how to answer the question of what action to take specifically to achieve zero-defect of the product and process based on the identified state of the machine and equipment and its predicted performance. Research in this area is called prescriptive maintenance. For the prescriptive maintenance, it is necessary to study the technology to recognize the status of machine facilities, products, and processes based on the collected data, as well as how to deal with them appropriately. Research on connection and integration with production scheduling is also needed. And in order to derive appropriate decision-making and feedback, research on technologies to extract, store, and utilize relevant knowledge, e.g. knowledge capturing framework, situation awareness, etc., is also necessary.

6.7 Total Integration

To integrate PHM technology into ZDM, the following research concerns are also required.: First, a general framework or standard is needed to apply PHM technology to ZDM for each type of manufacturing system. As Psarommatis et al. (2020a) mentioned that there was the missing standard and clear definition of terms related to ZDM, a standard model and architecture should be introduced to ensure interoperability of the PHM system in ZDM. This should allow hardware, software, and middleware frameworks to interact with each other. As Myklebust (2013) already also addressed, a detailed lifecycle oriented product model and a plant or enterprise model should be created and carried out in a coordinated manner. In spite of the fact that there are some previous relevant works, generally, state-of-the-art platforms for predictive maintenance and quality management give restricted capabilities for mitigating the fragmentation of industrial data accordingly hindering interoperability (Errandonea et al., 2020). This can be said to be the reason why research on such general frameworks or standards is necessary. Second, rather than developing PHM technologies in ZDM specialized for specific machinery or processes, a more system-oriented methodology is needed. As Mobley (2002) mentioned, most PHM approaches treat target system as isolated unit system and not as part of a coordinated system. Therefore, no work is made to decide the impact of system variables (process parameters, e.g., flow rate, temperature, load, speed, etc.) on the individual component. Today's manufacturing systems have more complex structure having multiple components. However, known PHM algorithms or methods are difficult to generalize because they are application or component specific. PHM methods and practices have been persistently improved for the last decades: however, PHM is conducted at equipment level-one piece of equipment at a time, and the developed prognostics approaches are application or equipment specific (Kobbacy and Murthy, 2008). Thus, to get the practical benefit of PHM approach in ZDM, it is necessary to develop the research work on applying PHM into not only one piece of equipment but also an integrated system level (Shin and Jun 2015). Furthermore, research on methodologies that can achieve the goal of ZDM sustainably by continuously and dynamically tuning the system from the overall system perspective is required. Once established PHM technologies must be made in a form that is periodically updated in consideration of the dynamically changing manufacturing environment. In order to guarantee the zero-defect capability of manufacturing system, it is necessary to periodically tune them based on the data collected in real time. For this purpose, it is necessary to define and develop the framework or processes for operating PHM based ZDM under the dynamic manufacturing environment. The research must also focus on augmenting and analyzing data using CPS or digital model-based simulation technology.

7 CONCLUSION

In this study, PHM was treated as one of the advanced maintenance policy methods to be applied to ZDM. Throughout the study, we have briefly reviewed the concept, definition, purpose and benefits, procedure, and standards of PHM. Furthermore, we reviewed previous studies on ZDM, including studies that attempted to apply PHM or advanced maintenance techniques to ZDM. In addition, the limits of these studies were examined, as well as research subjects to consider when applying PHM to ZDM. Although this study did not include significant research on quality improvement, zero defect, or advanced maintenance techniques throughout the manufacturing system, it could serve as a foundation for future studies on the merger of PHM and ZDM.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

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