

Advancing Autonomous Fabs

A PM Automation and Standardization Strategy

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Acknowledgement

This white paper reflects the collective insights and technical discussions of the SEMI Autonomous Fab Working Group (Afab WG). The following companies contributed through active participation, expertise sharing, and industry alignment efforts.

Leading Semiconductor Manufacturers

- Intel
- Samsung Electronics
- SK hynix

Global Equipment Suppliers

- Hitachi High-Tech
- Lam Research
- Tokyo Electron

Korean Equipment Manufacturers

- Global ZEUS
- WONIK IPS

Automation & Robotics

- Cymechs
- Robots & Design
- Yaskawa Electric

Software, Data & AI

- Doople
- Linkgenesis, Inc.
- Miracom Inc.
- Vamos AI

Foreword

The development of this white paper has been guided by the activities of the SEMI Autonomous Fab Working Group (Afab WG), a global, pre-competitive platform established to address structural challenges in semiconductor manufacturing automation. The Afab WG brings together semiconductor manufacturers, equipment suppliers, and technology partners across major manufacturing regions to identify common barriers that cannot be effectively resolved by individual companies alone. In particular, the transition toward Autonomous Semiconductor Fabs has highlighted the need for coordinated approaches to preventive maintenance automation, data interoperability, robotics integration, and equipment design—areas where fragmented efforts have proven insufficient.

This white paper also reflects the broader participation of related industry organizations and associations that contribute complementary perspectives from policy, standardization, and industrial ecosystems. Their involvement underscores the recognition that PM automation is not merely a technical optimization issue, but an industry-wide transformation challenge that requires alignment across manufacturing practices, standards development, and collaborative governance. By consolidating insights from these collective activities, this document aims to provide a credible and actionable foundation for advancing PM automation through standardization and cross-sector cooperation.

Executive Summary

The semiconductor industry is entering a critical transition phase toward Autonomous Semiconductor Fabs, driven by escalating process complexity, increasing equipment costs, and heightened demands for operational stability. In this environment, preventive maintenance (PM) is no longer a peripheral operational function but a central determinant of equipment availability, productivity, and manufacturing resilience. As fabs scale and processes advance, reliance on labor-intensive, experience-based maintenance practices is becoming increasingly unsustainable.

This white paper examines PM automation as a foundational enabler for autonomous semiconductor manufacturing. Based on an industry-wide survey conducted in 2025, complemented by in-depth interviews and technical trend analysis, the study captures both the industry's strong consensus on the necessity of PM automation and the structural challenges that continue to limit its large-scale adoption. Rather than focusing solely on individual technologies, this paper addresses PM automation as a system-level transformation

requiring coordination across equipment design, data infrastructure, robotics, logistics, and standardization frameworks. Survey results indicate that while PM automation is widely recognized as essential, most companies currently target a collaborative automation model in which systems and robots perform the majority of PM tasks with limited human intervention. Fully unmanned maintenance is generally viewed as a longer-term objective. The primary motivation for PM automation is clear: reducing equipment downtime and improving uptime, which were consistently identified as the most important performance goals and evaluation metrics. However, despite this alignment in objectives, implementation remains constrained. Many respondents anticipate a development horizon of close to a decade, citing resource burdens, uncertainty in return on investment, and the absence of industry-wide standards as key barriers.

A central finding of this study is that the obstacles to PM automation are predominantly structural rather than technological. Equipment architectures are still largely designed around manual maintenance assumptions, limiting robot accessibility and automation feasibility. Maintenance-related data—such as equipment status variables, component usage history, and PM execution records—remain fragmented and inconsistently exposed, undermining the reliability and scalability of predictive maintenance (PdM) models. In addition, physical infrastructure elements, including component logistics, packaging, and handling methods, are largely unprepared for automated operation, despite broad recognition of their importance.

The analysis further highlights that PM automation cannot be effectively realized through isolated, company-specific optimization efforts. As maintenance activities increasingly influence fab-level performance, interoperability across equipment, robots, data systems, and logistics platforms becomes a prerequisite rather than an option. Standardization therefore emerges as a critical enabler. The survey reveals unanimous agreement on the necessity of standardization, with particular emphasis on interface compatibility, data traceability, and the reduction of duplicated development across the supply chain.

In response to these findings, this white paper proposes a structured set of key technology standardization areas spanning the entire PM automation lifecycle. These include automation-oriented equipment design criteria, robot and platform interface standards, communication protocols and data models, component handling and packaging specifications, PM component modularization, cleanliness and safety requirements, PM–PdM–host system integration scenarios, and digital twin frameworks for data-driven decision-making. Collectively, these areas form a common technical language intended to support scalable automation and cross-vendor interoperability.

Ultimately, this white paper positions PM automation not as a single technology initiative, but as an ecosystem-level challenge requiring pre-competitive collaboration and coordinated standardization. By aligning technical priorities, sharing operational insights, and establishing common frameworks, the semiconductor industry can move beyond fragmented pilot efforts and lay a sustainable foundation for autonomous manufacturing. This document is intended to serve as a starting point for that collective effort, supporting future standardization activities, joint research initiatives, and practical implementation pathways toward Autonomous Semiconductor Fabs.

Highlights

PM automation is a critical enabler for Autonomous Semiconductor Fabs.

As process complexity and equipment costs continue to rise, labor-intensive and experience-based maintenance practices are becoming increasingly unsustainable. PM automation is essential to improving equipment uptime, operational stability, and manufacturing resilience.

Industry consensus is strong, but large-scale adoption remains limited.

Industry survey results show unanimous agreement on the necessity of PM automation. However, most implementations remain at pilot or localized levels, with collaborative automation—rather than fully unmanned maintenance—viewed as the near-term target.

Structural barriers outweigh technological limitations.

The primary challenges to PM automation are not the absence of advanced technologies, but structural constraints such as automation-unfriendly equipment design, fragmented maintenance data, incompatible interfaces, and insufficient readiness of logistics and packaging infrastructure.

Standardization is the key to scalability.

Without common standards for equipment accessibility, data models, communication protocols, component handling, and safety requirements, PM automation efforts risk duplication and limited interoperability across vendors and fabs.

PM automation is an ecosystem-level challenge.

Effective PM automation requires coordination across equipment manufacturers, device makers, component suppliers, robotics vendors, and software providers. Isolated optimization within individual organizations cannot deliver fab-wide impact.

This white paper identifies priority standardization areas.

The paper proposes a structured set of key technology standardization areas spanning equipment design, robotics interfaces, data and communication frameworks, component logistics and modularization, cleanliness and safety, PM-PdM-host integration, and digital twin environments.

Collaboration enables sustainable progress.

Pre-competitive, industry-wide collaboration is essential to align technical priorities, reduce duplicated investment, and establish a shared foundation for autonomous manufacturing.

1. Introduction

The semiconductor industry is undergoing a structural transition driven by continued process scaling, increasing equipment sophistication, and rapidly expanding capital investment. As manufacturing complexity grows, maintaining stable equipment availability, yield, and process reliability has become a strategic priority rather than an operational concern. In advanced semiconductor fabs, particularly those operating 300 mm wafer platforms and beyond, the impact of equipment downtime is no longer linear; the failure or stoppage of a single tool can propagate across the production line, disrupting throughput, scheduling, and logistics at the fab level.

Preventive maintenance (PM) plays a critical role in sustaining equipment performance and mitigating unplanned downtime. However, PM practices in most fabs remain heavily dependent on manual execution, experience-based decision-making, and equipment-specific procedures. As fabs scale and diversify, this approach increasingly exposes structural limitations. Variations in PM procedures, data formats, component handling methods, and maintenance timing across equipment types and vendors complicate coordination, introduce inefficiencies, and constrain the ability to systematically optimize maintenance at the fab level.

In response to these challenges, PM automation emerges as a key enabler for improving equipment uptime and operational stability, as well as a foundational element for the transition toward Autonomous Semiconductor Fabs. Despite growing recognition of its importance, PM automation efforts across the industry remain fragmented. Many initiatives are confined to pilot projects or isolated implementations within individual companies, often lacking common interfaces, shared data models, or standardized physical and digital infrastructures. This fragmentation limits scalability and increases the risk of duplicated investment.

This white paper addresses these challenges by examining PM automation from an industry-wide perspective. It analyzes PM automation as a system-level transformation that spans equipment design, data interoperability, robotics integration, component logistics, and standardization frameworks, rather than focusing solely on individual technologies. Drawing on an industry survey conducted by Afab WG in 2025, in-depth interviews, and a review of relevant technical developments, the paper identifies structural barriers to adoption and outlines priority areas where standardization can enable scalable and sustainable automation.

The objective of this white paper is threefold. First, it aims to establish a common understanding of PM automation, scope, target levels, and practical constraints, across the semiconductor manufacturing ecosystem.

Second, it seeks to translate field-level challenges into clearly defined standardization and pre-competitive research topics. Finally, it provides a strategic reference to support coordinated industry action toward autonomous manufacturing, serving as a foundation for future standardization activities, collaborative initiatives, and implementation roadmaps.

2. PM Automation and the Evolving Industry Landscape

2.1 Preventive Maintenance: Definition and Role

In semiconductor manufacturing, preventive maintenance (PM) is a planned intervention performed to sustain equipment reliability, process stability, and productivity. Unlike corrective maintenance, which responds to failures after they occur, PM is scheduled to mitigate the risk of unplanned downtime by maintaining tools within defined operating and control limits. In high-volume manufacturing environments, the quality and consistency of PM execution directly influence equipment availability, yield stability, and cycle time performance.

PM also functions as a system-level control activity rather than a simple routine task. Because semiconductor fabs operate highly interdependent toolsets and auxiliary systems, PM affects not only individual equipment performance but also upstream and downstream operations, including scheduling, logistics, and workforce planning. As PM requirements grow in complexity and variability, reducing PM duration and minimizing execution variability become increasingly important for fab-level performance.

2.2 Why PM Automation Matters

PM automation is increasingly recognized as a prerequisite for improving fab resilience and supporting the transition toward Autonomous Semiconductor Fabs. While traditional PM practices have relied on fixed schedules based on time, cycles, or wafer counts, modern fabs operate under diverse and dynamic process regimes where degradation behavior is not fully captured by static rules. As a result, maintenance decisions require greater responsiveness to real-time conditions, and execution requires higher consistency and repeatability.

PM automation enables three outcomes that are difficult to achieve through manual approaches alone:

1. **Condition-aware decision-making:** It uses equipment and process signals to determine when and what maintenance is required.
2. **Consistent and verifiable execution:** It reduces variability driven by human dependency and improving reproducibility.
3. **Integrated operational coordination:** It links maintenance decisions to scheduling, logistics, and

resource constraints to reduce fab-wide disruption.

Industry feedback indicates that the primary barriers to scaling PM automation are not the absence of advanced algorithms, but structural constraints such as inconsistent equipment accessibility, fragmented data structures, incompatible interfaces, and insufficient alignment across logistics, packaging, and robotics integration. These constraints highlight why standardization is central to enabling PM automation at scale.

2.3 Evolution of PM Automation: From Monitoring to Orchestration

PM automation has evolved from basic monitoring and diagnostic automation to more integrated and autonomous maintenance systems. Early stages focused on equipment condition monitoring and fault detection. More recent efforts integrate predictive capabilities to support condition-based maintenance and to optimize maintenance timing in coordination with production schedules. The longer-term trajectory extends further toward automation of maintenance execution and orchestration, where maintenance tasks can be planned, supplied, and validated through coordinated interactions among equipment, software platforms, logistics systems, and robots.

This evolution reinforces a key point for this white paper: PM automation is not a single technology deployment. It is an end-to-end capability that depends on interoperability across data, interfaces, physical handling, and operational governance. Technical literature demonstrates rapid progress across many enabling technologies; however, scaling these capabilities across diverse fabs and equipment ecosystems requires common specifications and shared reference architectures.

2.4 Predictive Maintenance (PdM) as the Intelligence Layer

Predictive maintenance (PdM) plays a central role in enabling effective PM automation by providing the intelligence needed to determine optimal intervention timing. PdM uses equipment signals, process logs, and condition indicators to detect degradation patterns, estimate failure risk, and guide maintenance decisions. In practice, PM automation and PdM are mutually reinforcing: PdM triggers maintenance actions, and maintenance outcomes feed back into PdM models for continuous improvement.

For the purposes of this white paper, PdM should be understood as the **decision layer** of PM automation, supporting when to intervene and how to prioritize actions, while automation and standardization frameworks ensure that those decisions can be executed reliably and consistently across equipment, vendors, and fab environments.

Note: Detailed literature reviews and representative technical examples supporting Sections 2.1–2.4 are provided in the Technical Annex (Appendix), as this white paper focuses on industrial-scale adoption and standardization strategy.

3. Survey Results and Industry Insights

This chapter summarizes the key findings of an industry survey on Semiconductor Preventive Maintenance (PM) Automation conducted between July and August 2025. The survey was jointly promoted by the Autonomous Fab Working Group (Afab WG) under SEMI Korea and the Korea Semiconductor Industry Association (KSIA). Responses were collected from a broad range of stakeholders across the semiconductor supply chain, including device manufacturers, equipment and component suppliers, robotics companies, and software vendors.

Rather than assessing PM automation as an abstract or theoretical concept, the survey focuses on capturing the industry's current level of preparedness, perceived challenges, and areas of active consideration. The results presented in this chapter provide a factual snapshot of how PM automation is currently understood, prioritized, and reflected in practice across different sectors of the industry.

3.1 Survey Design and Respondent Characteristics

[Table 1] Survey Respondent Characteristics

(Unit : People, %)

Category		Cases	Percentage
Total		79	100.0
By Industry Segment	Device Manufacturing	15	19.0
	Wafer Manufacturing	4	5.1
	Equipment and Sub-systems supplier	38	48.1
	Robot Manufacturer	10	12.7
	Fab Infrastructure and Services	3	3.8
	Materials supplier	2	2.5
	Software supplier	7	8.9

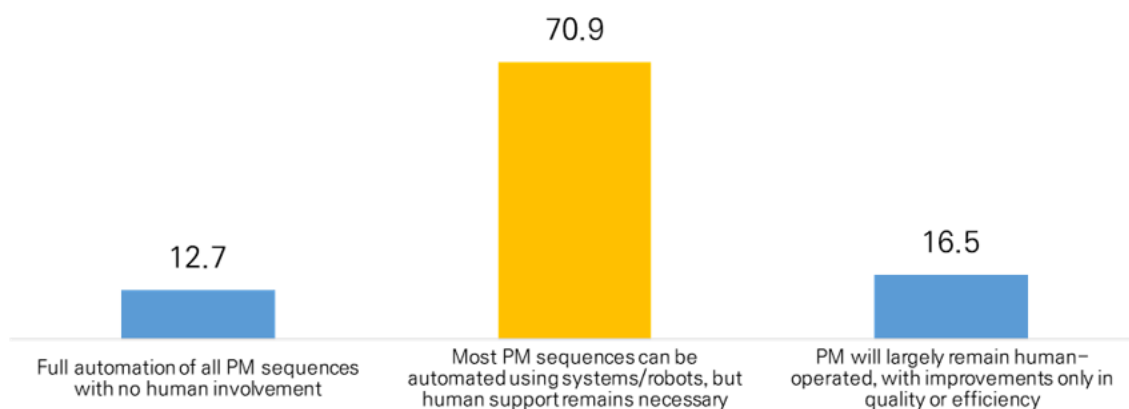
The online survey was conducted over a period of 56 days, from July 6 to August 31, 2025, and received responses from a total of 79 participants representing domestic and international companies within the semiconductor industry supply chain. Survey questions addressed topics including the definition and target level of PM automation, robot application scope, automation of PM component transfer, potential for PM component modularization, and requirements related to communication protocols and interfaces.

Analysis of respondents by company sector shows that equipment and sub-system suppliers accounted for the

largest share at 48.1% (38 respondents), followed by device manufacturers at 19.0% (15 respondents), robot manufacturers at 12.7% (10 respondents), and software suppliers at 8.9% (7 respondents).

Regarding the definition of PM automation, 70.9% of respondents described it as a level where most PM procedures can be executed using systems or robots, while some degree of human involvement remains necessary. In contrast, only 12.7% defined PM automation as complete execution of all PM procedures without human intervention.

With respect to the expected timeframe to reach the target level of PM automation, 49.4% of respondents indicated approximately 10 years, and the average estimated time was calculated at 8.23 years.



[Figure 5] Definition of PM Automation

The most frequently cited primary objective of PM automation was reducing downtime, followed by reducing maintenance costs, enhancing worker safety, and improving data accuracy and traceability. In line with this objective, equipment uptime was selected as the most important key performance indicator (KPI) for evaluating PM automation performance, accounting for 45.6% of responses.

[Table 2] Number of Cases by Company Sector for PM Automation Definition

(Unit : People, %)

Category		Cases	Full automation of all PM sequences with no human involvement	Most PM sequences can be automated using systems/ robots, but human support remains necessary	PM will largely remain human-operated, with improvements only in quality or efficiency
Total		79	12.7	70.9	16.5
By Industry Segment	Device Manufacturing	15	26.7	73.3	-
	Wafer Manufacturing	4	25.0	50.0	25.0
	Equipment and Sub-systems supplier	38	7.9	65.8	26.3
	Robot Manufacturer	10	10.0	80.0	10.0
	Fab Infrastructure and Services	3	-	66.7	33.3
	Materials supplier	2	-	100.0	-
	Software supplier	7	14.3	85.7	-

[Table 3] Primary Goals (Top Priority) Sought Through PM Automation

(Unit : People, %)

Category		Cases	Reduce down-time	Improve safety	Improve data accuracy and traceability	Lower maintenance costs	Extend equipment lifespan
Total		79	38.0	24.1	20.3	13.9	3.8
By Industry Segment	Device Manufacturing	15	33.3	13.3	33.3	20.0	-
	Wafer Manufacturing	4	50.0	-	-	-	50.0
	Equipment and	38	39.5	23.7	18.4	18.4	-

	Sub-systems supplier						
	Robot Manufacturer	10	50.0	40.0	-	-	10.0
	Fab Infrastructure and Services	3	33.3	66.7	-	-	-
	Materials supplier	2	-	-	100.0	-	-
	Software supplier	7	28.6	28.6	28.6	14.3	-

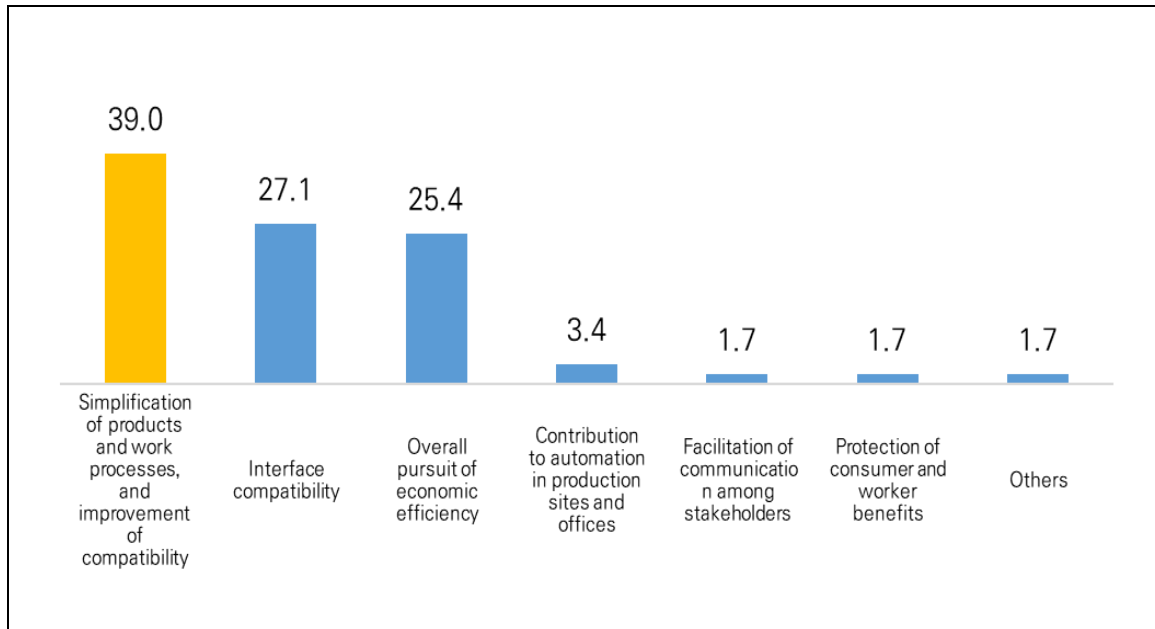
Note: Given the limited number of cases, the results should be interpreted with caution.

3.2 Standardization Needs Identified by the Survey

All respondents (100.0%) to the Korean-language survey indicated that standardization activities related to PM automation are necessary. When asked about the primary purpose of standardization, the most common response was simplifying products and work processes while enhancing compatibility (39.0%), followed by securing interface compatibility (27.1%).

Sector-level analysis shows that, among device manufacturers, interface compatibility was selected as the primary purpose of standardization by 50.0% of respondents.

(Unit : %)

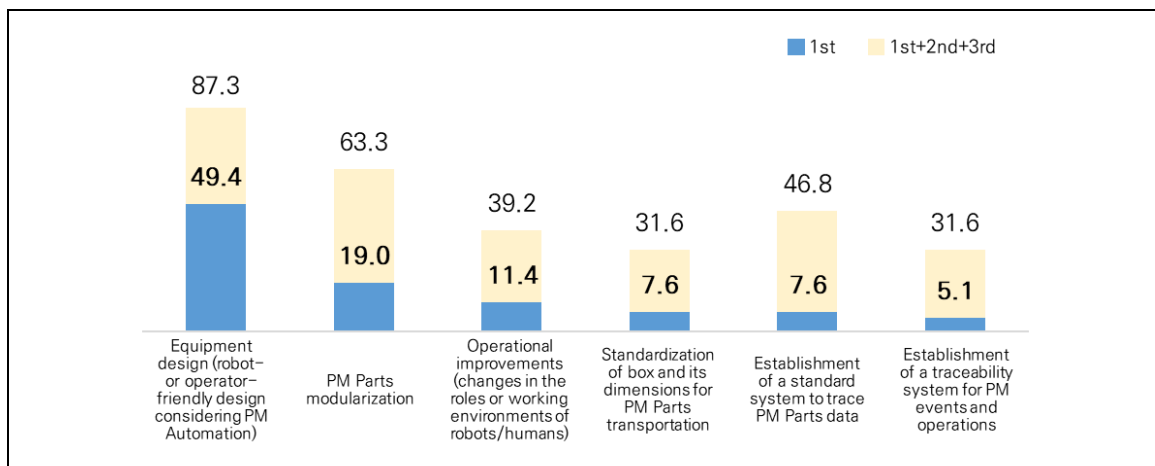


[Figure 6] Primary Purpose of Standardization

3.3 Equipment Design and Robot Application for PM Automation

3.3.1 Equipment Design and Hardware Considerations

(Unit : %)



[Figure 7] Hardware Improvement Items for PM Automation

When respondents were asked to identify the most urgent hardware improvement items for PM automation, equipment design facilitating automation ranked highest, with a combined response rate of 87.3% across the top three priority selections.

When asked to identify tasks for robot application for PM, respondents most frequently identified PM part replacement (50.6%), followed by bolt and nut tightening/loosening (39.2%) and inspection of tightening quality (36.7%). Mobile collaborative robots were the most commonly considered robot type, accounting for 59.5% of responses.

[Table 4] Tasks Requiring Robot Introduction (Multiple Responses)

(Unit : People, %)

Category		Cases	PM parts replacement	Bolt/ nut fastening & removal	Verify correct assembly	Vacuum chamber cleaning	Others
Total		79	50.6	39.2	36.7	31.6	21.5
By Industry	Device Manufacturing	15	73.3	66.7	20.0	60.0	46.7
	Wafer Manufacturing	4	50.0	25.0	25.0	-	25.0

Segment	Equipment and Sub-systems supplier	38	42.1	34.2	42.1	28.9	18.4
	Robot Manufacturer	10	70.0	50.0	20.0	20.0	10.0
	Fab Infrastructure and Services	3	100.0	33.3	-	-	-
	Materials supplier	2	-	-	100.0	50.0	-
	Software supplier	7	14.3	14.3	71.4	28.6	14.3

Note: Given the limited number of cases, the results should be interpreted with caution.

3.3.2 Robot Platform and Arm Configuration

With respect to the need for a common robot platform for PM automation, 54.4% of respondents answered "Yes," while 38.0% indicated that the necessity depends on the specific application environment. When asked about robot arm configuration, most respondents (50.6%) chose multiple arms optimized for specific tasks. However, for device manufacturing and wafer manufacturing, finger-type end-effectors suitable for diverse tasks accounted for more than half of the responses.

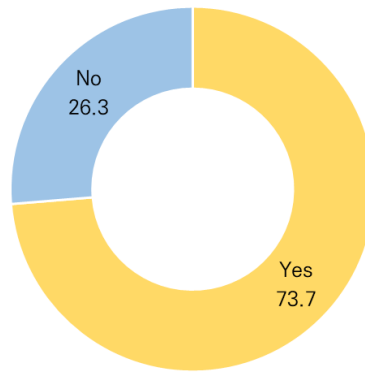
[Table 5] Arm configurations suitable for PM tasks from the final robot design perspective

(Unit : People, %)

Category		Cases	A single arm type customized for the specific task	Multiple arms customized for the specific task	Multi-tasking fingers for various operations
Total		79	20.3	50.6	29.1
By Industry Segment	Device Manufacturing	15	6.7	40.0	53.3
	Wafer Manufacturing	4	25.0	25.0	50.0
	Equipment and Sub-systems supplier	38	23.7	50.0	26.3
	Robot Manufacturer	10	20.0	70.0	10.0
	Fab Infrastructure and Services	3	-	66.7	33.3
	Materials supplier	2	100.0	-	-
	Software supplier	7	14.3	71.4	14.3

3.4 Communication Protocols and Data Tracking Requirements

(Unit : %)

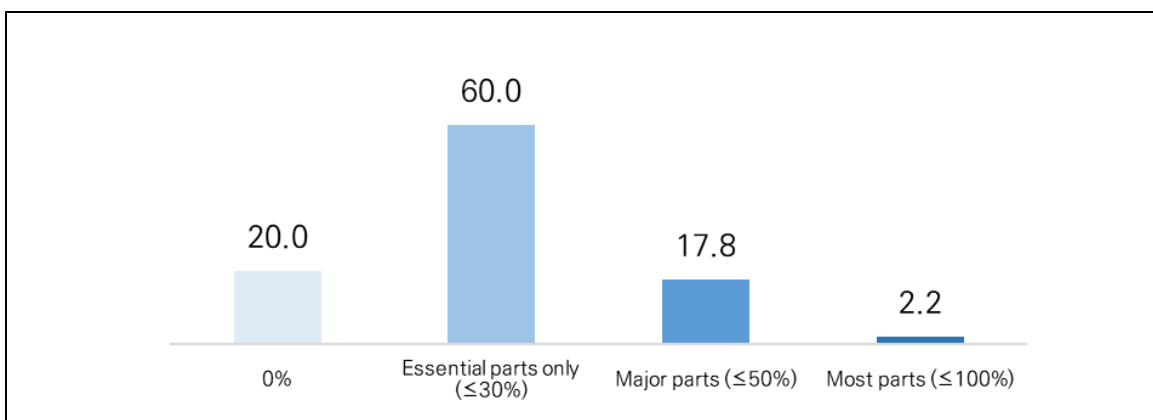


[Figure 8] Need for a Dedicated Communication Protocol for PM Automation

A strong demand for standardized communication and data frameworks was observed across the survey results. Overall, 73.4% of respondents indicated that a dedicated communication protocol is necessary for PM automation. This requirement was particularly pronounced among software suppliers (100.0%) and device manufacturers (86.7%).

The issue of PM part data tracking, establishing standardized systems for tracking PM parts recorded a combined response rate of 46.8% across the top three hardware improvement priorities. When asked about the current status of PM part lifespan or condition tracking beyond wafer count or RF timer metrics, 60.0% of respondents indicated that such tracking is limited to essential components representing 30% or fewer number of total parts.

(Unit : %)

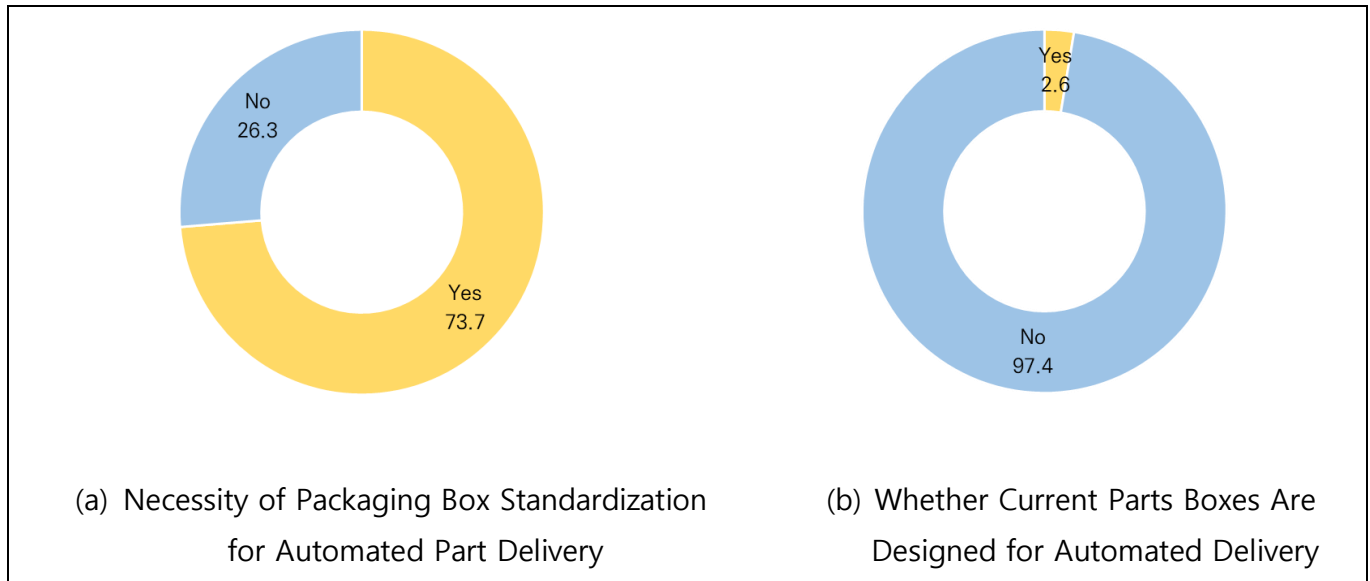


[Figure 9] Percentage of Parts Whose Lifespan or Status Can Be Determined Under Other Conditions

Despite current limitations, 55.6% of respondents indicated that development efforts related to unsupported component lifespan information are planned.

3.5 PM Component Transfer Automation and Modularization

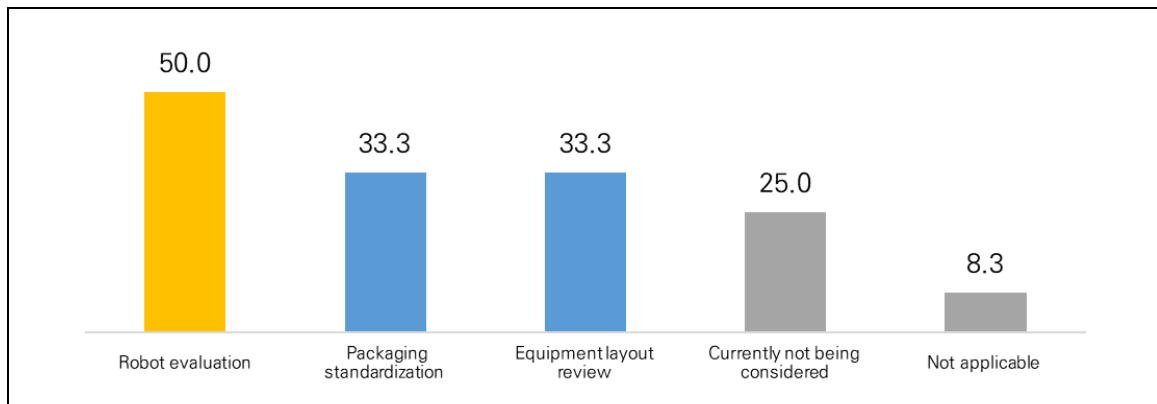
(Unit : %)



[Figure 10] Survey Results on Component Boxes for Automated Component Delivery

A substantial gap was identified between perceived requirements for automated component transfer and the current state of infrastructure. Among equipment and sub-system suppliers, 73.7% indicated that standardization of packaging boxes for automated component delivery is necessary. However, 97.4% reported that their current component boxes are not designed for automated delivery and instead rely on standard fab boxes.

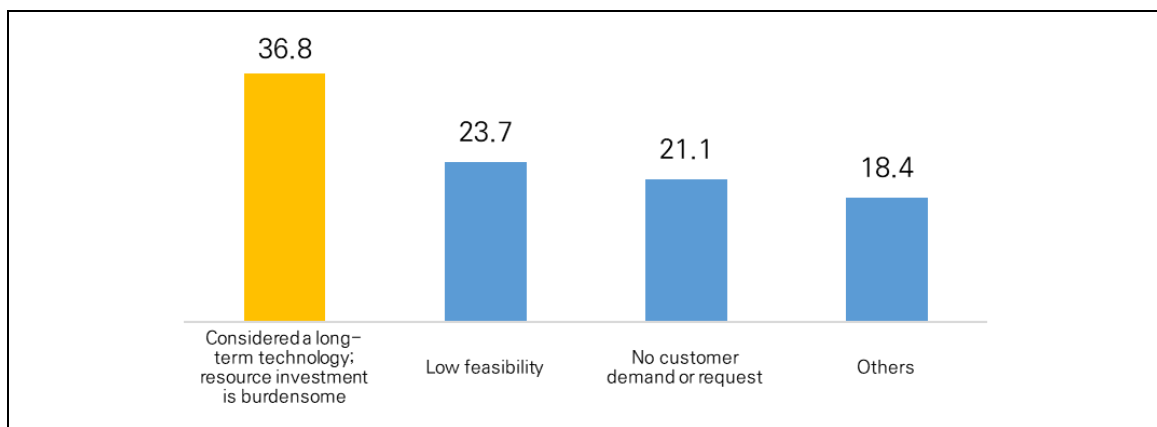
Regarding current operational practices, 63.2% indicated that component boxes are selected and used individually depending on the part. Additionally, 68.4% of respondents stated that they are not currently considering automated component delivery.



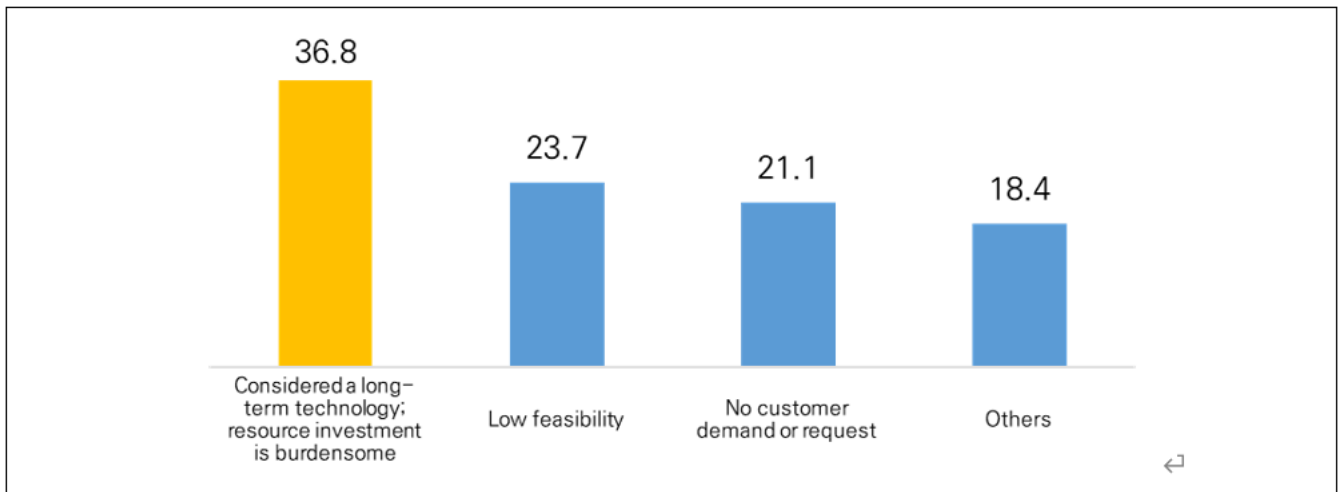
[Figure 11] Preparations for Automated Component Delivery within the Fab (Multiple Responses)

With respect to PM part modularization, 55.3% of equipment and sub-system suppliers indicated that they have development plans or are currently developing modularized PM parts. PM part modularization ranked as the second most important hardware improvement item after equipment design considering automation, with a combined top three priority response rate of 63.3%.

(Unit : %)



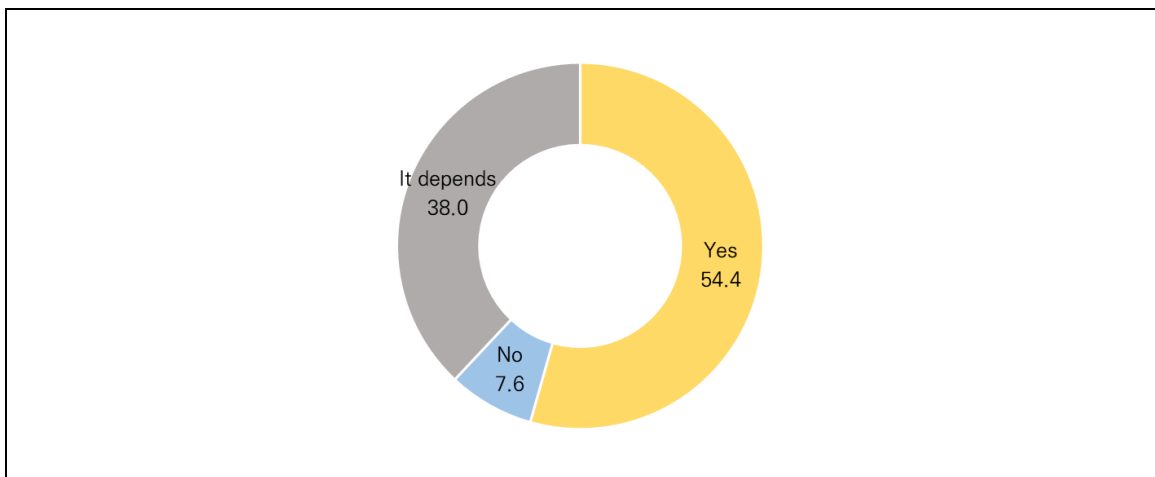
(Unit : %)



[Figure 12] Major Obstacles in PM Part Modularization Development

3.6 Additional Standardization Topics

(Unit : %)



[Figure 13] Need for Common Robot Platforms for PM

Survey responses also highlighted additional standardization topics related to cleanliness evaluation, robot operation methods, and host-based PM automation scenarios. A total of 84.8% of respondents indicated that standards for cleanliness evaluation methods are necessary, with consistent responses observed across all industry sectors.

Preferences for robot operation methods were evenly split between multiple robots performing specialized tasks and a single robot performing most tasks, each accounting for 43.0% of responses. Sector-specific differences were observed across respondent groups.

Regarding the development of host-based PM automation scenarios, 46.7% of respondents from equipment and software suppliers indicated that no development plans are currently in place, while 35.6% reported that such development efforts are underway.

Finally, 84.7% of respondents had a positive response towards further standardization of current technologies or future technologies under development that go beyond PM automation.

4. Analysis of the Current Status and Limitations in the Semiconductor Industry

Across the semiconductor industry, PM automation is increasingly viewed as a key enabler for reducing the inefficiencies and variability associated with labor-dependent maintenance and for enabling more consistent and timely execution of maintenance tasks. The findings show broad agreement on the importance of PM automation. At the same time, they highlight multi-layered limitations that slow implementation, including gaps in standardization, insufficient data accessibility and usability, physical constraints in equipment design, immaturity in end-to-end automation scenarios, and the burden of long-term investment.

4.1 Industry Perspective on Standardization

Survey results indicate unanimous agreement on the need for standardization activities (100% among Korean-language survey respondents). Respondents described standardization not merely as technical integration, but as a prerequisite for interoperability across equipment, systems, and operations. In particular, device manufacturers most frequently emphasized “interface compatibility” as a primary objective, reflecting the complexity of operating heterogeneous toolsets and software systems in a single fab environment.

Interview results reinforced this view. Participants repeatedly noted that the lack of semiconductor-specific standardization, particularly in robotics integration and related interfaces, creates friction during early implementation stages. One interviewee observed that semiconductor environments require robotics standards that reflect cleanroom constraints, tool access characteristics, and fab operational requirements, and that the absence of such standards delays preparation for automated component transfer. Another participant emphasized that without shared infrastructure-level standards, system-wide automation (e.g., alignment with 300 mm AMHS operations) becomes difficult to scale beyond isolated deployments.

Despite this shared recognition, stakeholders noted that R&D investments still tend to focus on company-specific PM solutions, while cross-industry standardization efforts remain limited in their institutional momentum and coordinated execution.

4.2 Target PM Automation Level and Adoption Status

While full automation is often described as an eventual direction, survey responses show that the most widely accepted target level is cooperative automation, a model in which systems or robots execute most procedures while some human intervention remains (70.9%). In addition, “equipment uptime” was most frequently selected as the primary KPI for evaluating PM automation outcomes (45.6%), indicating that availability improvement remains the dominant driver.

Interview feedback suggested that the industry is still in an early-to-intermediate stage of implementation, with significant progress in sensing and diagnostics but limited maturity in the “core execution” stage of robot-based maintenance. Several interviewees described current readiness as being concentrated around “sensing → diagnosis,” with the integrated loop of “prediction → action → verification” not yet broadly realized in practice. Physical constraints were frequently cited as a reason for this gap.

4.3 Equipment Design and Physical Readiness for Automation

Survey respondents most frequently ranked “equipment design facilitating automation” as the top improvement priority (87.3% across combined top three selections), suggesting that current equipment architectures remain fundamentally optimized for human access rather than robot execution.

Interview participants echoed this constraint, pointing out that many high-frequency tasks, such as chamber opening & closing operations, remain difficult to automate due to the need for redesign at both the equipment and line-layout level. In multiple cases, respondents characterized robot deployment as requiring more than add-on integration, instead involving structural redefinition of access, layout, and maintenance interfaces. These results indicate that limitations in PM automation are often rooted in hardware architecture and physical accessibility, rather than in software capability alone.

4.4 Data Availability and PdM Integration Challenges

A recurring limitation identified in the interviews was the perceived reliability and practical trustworthiness of PdM outputs. One interviewee summarized the challenge as a trust gap: predictive models are difficult to validate operationally, especially in environments where failures are rare but costly.

Participants also highlighted challenges in data quality, collection cycles, and log usability. In some cases, interviewees noted that even basic visibility into what portion of equipment data is exposed through common data streams (e.g., SVID) is not always clearly established at the field level. Others emphasized that maintenance organizations are often not equipped with the workflow and capability to directly access and utilize data sources efficiently, noting that data extraction and analysis capabilities are not yet embedded as a standard competency in PM engineering roles.

From an organizational execution perspective, interviews also identified coordination limitations. In some cases, PdM initiatives were described as being assigned primarily to software functions without sufficient integration across planning, ownership, and operational execution teams, which can reduce the effectiveness of implementation even when enabling technologies exist.

These interview findings align with survey results highlighting the need for standardized PM parts data tracking systems (46.8% across combined top-three priority selections) and broader communication and interface standardization requirements discussed in Chapter 3.

4.5 Logistics, Packaging, and Component Handling Readiness

Interview participants similarly emphasized that logistics automation constraints are not primarily driven by robot capability, but by the absence of standardized supporting infrastructure (e.g., packaging specifications, handoff rules, and fab interface readiness). This suggests that achieving scalable parts-transfer automation requires coordinated standardization of the physical handoff layer, not only the robotics layer.

4.6 Summary of Cross-Industry Limitations

Overall, while the semiconductor industry shows high consensus on the necessity and long-term direction of PM automation, implementation is constrained by multiple structural limitations, including:

- insufficient standardization for interoperability across equipment, robots, and systems,
- equipment designs and physical layouts that limit automation accessibility,
- limited data visibility, usability, and organizational capability for PdM-driven decision-making,
- immature end-to-end automation scenarios integrating PdM, PM execution, and verification,
- gaps in logistics readiness, including packaging and physical handoff infrastructure,
- and limited cross-organizational coordination to drive standardization as a shared activity.

These findings suggest that PM automation should be approached not as an isolated technology deployment, but as a system-level transformation that requires aligned standardization, physical infrastructure readiness, and coordinated execution across stakeholders.

Taken together, the survey findings and interview insights indicate that the primary challenges facing PM automation are not isolated technical shortcomings, but systemic issues spanning equipment design, data interoperability, physical logistics, and cross-organizational alignment. While individual companies continue to advance enabling technologies, such as sensing, robotics, and predictive analytics, the absence of shared specifications and reference frameworks limits scalability beyond localized or pilot-level implementations. These observations suggest that the transition toward intelligent and autonomous maintenance cannot rely solely on

incremental technology adoption. Instead, it requires a coordinated approach to standardization that aligns physical interfaces, data structures, operational scenarios, and environmental requirements across the semiconductor manufacturing ecosystem. Building on this analysis, the following chapter identifies key technology standardization items that can serve as a common foundation for accelerating PM automation and supporting the industry's longer-term transition toward autonomous fabs.

5. Proposed Key Technology Standardization Areas for PM Automation

Building on the analysis presented in Chapter 4, this chapter proposes key technology standardization areas required to enable scalable and interoperable PM automation across the semiconductor manufacturing ecosystem. The survey results and in-depth interviews consistently indicate that PM automation cannot be realized through isolated technologies or company-specific solutions alone. Instead, effective adoption depends on alignment across multiple layers, including equipment design, robotics, data communication, logistics infrastructure, and system-level orchestration.

The standardization areas outlined in this chapter are intended to define a common structural framework rather than detailed implementation specifications. They aim to provide shared reference points that allow equipment manufacturers, device makers, robotics suppliers, software vendors, and infrastructure operators to coordinate development efforts, reduce redundant investment, and improve interoperability. By establishing a common technical language across these domains, the proposed areas support the industry's transition from localized automation initiatives toward intelligent, autonomous maintenance operations.

5.1 Scope and Approach to Standardization

PM automation spans a broad lifecycle, from equipment design and maintenance execution to data-driven decision-making and system-level coordination. As such, standardization must be approached holistically, addressing both physical and digital interfaces rather than individual technologies in isolation.

The scope of standardization proposed in this chapter focuses on:

- defining common assumptions and interface boundaries,
- enabling interoperability across heterogeneous equipment and systems,
- and supporting long-term scalability across fabs and supply chains.

Rather than prescribing specific solutions, the proposed areas identify where standardization can most effectively reduce friction and accelerate adoption while allowing flexibility for technological evolution.

5.2 Equipment Design Standards Considering Automation

Survey results identified equipment design considering automation as the most urgent hardware improvement area for PM automation. This reflects the reality that many semiconductor tools remain fundamentally designed for manual access, inspection, and replacement.

Standardization in this area should address equipment design considerations that enable automated or robot-assisted PM, such as accessibility of maintenance points, consistency in fastener and interface structures, and provision of sufficient workspace for automated tools. Establishing common design principles at this level reduces the need for tool-specific adaptations and supports scalable deployment of automation solutions.

By aligning equipment design assumptions across manufacturers, these standards can improve compatibility with robotics and automation platforms while reducing repetitive redesign efforts.

5.3 Robot and Platform Interface Standards for PM Operations

Robots are increasingly considered for PM tasks such as component replacement, fastening operations, and inspection. However, the absence of common interfaces between robots and equipment limits broader adoption.

Standardization in this area should focus on defining consistent interaction mechanisms between robots and equipment, including positioning references, task authorization sequences, and status exchange. Rather than specifying robot form factors, standards should define interface requirements that allow diverse robot platforms, such as mobile collaborative robots or fixed installations, to integrate using common protocols.

These standards enable flexibility in robot selection while supporting interoperability and reducing integration complexity across different fabs and equipment types.

5.4 Communication Protocol and Equipment/Component Data Model Standards

Effective PM automation relies on reliable data exchange among equipment, robots, and higher-level systems. Survey responses showed strong demand for standardized communication protocols and data models to support this integration.

Standardization in this area should define common data structures for PM-relevant information, including equipment status, maintenance events, and component lifecycle data. Clear definitions of required and optional data fields can support predictive maintenance while addressing concerns related to data ownership and security.

Establishing consistent communication and data models enables seamless integration across vendors and supports the development of interoperable PdM and PM automation solutions.

5.5 Standards for PM Component Handling, Logistics, and Packaging

Physical logistics was identified as a significant gap between PM automation requirements and current infrastructure readiness. While automated component transfer is widely recognized as necessary, packaging and handling practices often remain incompatible with automation systems.

Standardization in this area should address packaging specifications, identification methods, and handling requirements that enable automated transport and delivery of PM components. Aligning these physical standards with data tracking systems further supports coordinated logistics and scheduling.

By reducing variability in component handling, these standards help unlock the benefits of automation across maintenance workflows.

5.6 Standards for PM Component/Module Structure and Replaceability

PM component modularization has been recognized as an important enabler of automation, particularly for frequently replaced parts. However, development efforts remain fragmented and are often constrained by long-term investment considerations.

Standardization should provide guidance on modular design principles that support automated replacement, such as consistent attachment methods, alignment features, and embedded identification. These standards can reduce mechanical variability and improve predictability in maintenance execution.

By supporting modularization at the industry level, standardization can improve compatibility between components, equipment, and automation systems.

5.7 Standards for Cleanliness, Environment, and Safety in PM Automation

Introducing automation into PM activities raises additional considerations related to cleanliness control, environmental exposure, and safety, especially in cleanroom environments where maintenance involves opening equipment and handling contaminants.

Standardization in this area should define evaluation methods and operational criteria for maintaining cleanliness and safety during automated PM tasks. This includes interfaces between automation systems and environmental controls, as well as safety considerations for human–robot collaboration.

Clear standards in this domain support consistent implementation across fabs and reduce uncertainty in compliance and risk management.

5.8 PM–PdM–Upper System Integration Scenario Standards

Survey and interview findings indicate that PM automation is often implemented in isolated segments, with

limited integration into higher-level systems such as MES or host platforms.

Standardization in this area should define reference scenarios that link PdM outputs, PM execution, and system-level coordination. By outlining common event flows and interaction points, these standards support alignment between predictive analytics and physical maintenance actions.

Such integration scenarios provide a foundation for scalable automation and improve coordination across equipment, logistics, and scheduling systems.

5.9 Digital Twin Framework Standardization for Data-Driven Maintenance

Digital twin technologies are emerging as a key enabler of intelligent manufacturing and maintenance. In the context of PM automation, digital twins support simulation, validation, and optimization of maintenance strategies before execution.

Standardization in this area should focus on defining common data representations, interfaces, and modeling assumptions that allow digital twins to interoperate with equipment, PdM systems, and automation platforms. By enabling consistent integration across tools and vendors, these standards support broader adoption of data-driven maintenance and autonomous operations.

6. Conclusion and Industry Implications

Summary of Key Findings

This white paper examined preventive maintenance (PM) automation as a foundational enabler for the transition toward Autonomous Semiconductor Fabs. Drawing on industry-wide survey results, in-depth interviews, and technical analysis, the findings confirm a broad consensus on the importance of PM automation for improving equipment uptime, operational stability, and manufacturing resilience. At the same time, they indicate that large-scale adoption remains limited, with most initiatives still concentrated at the pilot or localized implementation level.

Across the analysis, the primary barriers to PM automation were identified as structural rather than purely technological. These include variability in equipment design assumptions, fragmentation of maintenance-related data, limited interoperability across communication interfaces, and incomplete integration with robotics and logistics systems. Together, these factors constrain scalability and limit the long-term impact of isolated automation efforts.

Implications for PM Automation and Standardization

The findings suggest that PM automation cannot be effectively advanced through incremental or tool-specific optimization alone. As maintenance increasingly affects fab-level performance, interoperability across equipment, data, and operational systems becomes a fundamental requirement.

In this context, standardization plays a central role in enabling PM automation to evolve from experimental deployment to sustainable, fab-wide adoption. Establishing common frameworks for equipment accessibility, maintenance data representation, communication interfaces, component handling, safety considerations, and digital representations can reduce integration complexity, mitigate investment risk, and support compatibility across vendors and fabs.

Industry Implications and the Role of Collaboration

The transition toward Autonomous Semiconductor Fabs extends beyond individual technologies or organizational boundaries. PM automation spans multiple domains—including equipment engineering, maintenance operations, data interoperability, robotics integration, logistics infrastructure, and safety management—making it an ecosystem-level challenge.

Industry-wide, pre-competitive collaborative platforms provide a practical mechanism for addressing these challenges. Such platforms enable stakeholders to identify shared requirements, align technical priorities, and coordinate standardization efforts in a neutral setting. Without this form of collaboration, PM automation initiatives are likely to remain fragmented, resulting in duplicated investment and delayed adoption.

Way Forward

To support the scalable adoption of PM automation, continued engagement in coordinated, standards-oriented activities is essential. Participation in collaborative working structures, joint pilot programs, and standardization discussions can help clarify development priorities, improve interoperability, and strengthen the foundation for long-term automation initiatives.

By collectively addressing the structural enablers of PM automation, the semiconductor industry can move beyond isolated automation experiments and establish a more sustainable pathway toward autonomous manufacturing operations.

[Appendix]

Appendix 1. Technical Background of Preventive Maintenance (PM)

This appendix provides foundational technical background on preventive maintenance (PM) concepts that support the discussions in Chapters 1 and 2, where PM is positioned as a core operational function and a prerequisite for automation. It elaborates on classical PM objectives, execution characteristics, and operational impacts that are referenced in the main text but not discussed in detail.

A1.1 Definition, Objectives, and Operational Impacts of PM

In the semiconductor industry, preventive maintenance (PM) is a planned maintenance activity performed to sustain equipment reliability and productivity. PM is typically initiated based on statistically derived parameters such as average time or usage, to determine when maintenance should be conducted before equipment enters a “risk zone” in which the probability of random failure increases (A. A. Kalir et al., 2017). Most semiconductor manufacturing equipment is maintained according to schedules based on time, cycle, or wafer usage established through statistical analysis and executed on a regular basis (M. E. Cholette et al., 2013).

PM increases overall operational reliability by enabling planned unproductive downtime instead of risking unexpected downtime caused by sudden equipment failures (J. A. Ramírez-Hernández et al., 2010).

PM plays a critical role in enhancing equipment availability and reliability in semiconductor manufacturing facilities. Properly applied PM contributes to improved productivity and throughput and helps justify the substantial capital investments required for advanced fabs. PM activities are commonly used in conjunction with equipment health monitoring (EHM) systems to monitor equipment condition in real time. PM plays a critical role in enhancing equipment availability and reliability in semiconductor manufacturing facilities. Properly applied PM contributes to improved productivity and throughput and helps justify the substantial capital investments required for advanced fabs. PM activities are commonly used in conjunction with equipment health monitoring (EHM) systems to monitor equipment condition in real time.

A1.2 PM Duration, Variability, and Splitting Strategies

As PM activities increase in complexity, they often require more tasks and longer execution times, which can negatively affect cycle time (CT) at both the toolset and fab levels. To mitigate these effects, strategies that divide a long PM into shorter, more frequent PM tasks, commonly referred to as PM splitting, have been proposed. PM splitting reduces CT by offsetting variability in equipment operation and PM duration, even though additional setup times may slightly reduce overall equipment availability.

Research shows that PM splitting provides particularly strong CT improvement when equipment performance or PM duration exhibits high variability relative to the average (coefficient of variation). This benefit arises because splitting reduces fluctuations in effective processing time. Furthermore, when PM activities are imperfect and prone to failure, requiring subsequent repair work, PM splitting increases the probability of successful PM completion and reduces expected repair time. As a result, the advantages of splitting become more pronounced under realistic operating conditions (A. A. Kalir, 2013).

Simulation studies incorporating high toolset loading conditions (e.g., 95%) demonstrate that PM splitting may provide limited or no benefit when setup times are excessive. Conversely, under conditions of moderate setup time and high variability, PM splitting remains effective in improving CT. These findings highlight the importance of balancing setup costs, availability impacts, and variability reduction when designing PM strategies.

A1.3 PM Quality, Human Factors, and Work Standardization

The quality of PM execution can vary significantly depending on the skill and experience of maintenance personnel, leading to substantial differences in equipment performance and productivity. High-quality PM work is essential for preserving or restoring equipment to its initial operating condition. Empirical studies have shown that the number of plasma etching defects decreased and productivity increased significantly when PM was performed by specific technicians (M. Kagaya et al., 2017).

To better understand and standardize high-quality maintenance practices, research has explored the use of optical motion sensors to record maintenance worker movements, such as wiping actions during wet cleaning. These movements can be converted into time-series three-dimensional coordinate data, enabling the extraction of key indicators associated with effective PM execution. This approach provides a quantitative basis for identifying best practices and supports the development of standardized work procedures.

Such findings demonstrate the necessity of work standards and execution consistency to eliminate device defects caused by variability in PM quality. They also provide foundational data for predictive maintenance and more efficient PM execution by reducing dependence on individual experience and tacit knowledge.

Appendix 2. Environmental, Safety, and Contamination Considerations Related to PM

This appendix supports the discussion in Chapter 4 and Section 5.7, which identifies environmental, cleanliness, and safety constraints as structural factors limiting PM automation. It provides technical context on contamination mechanisms and mitigation measures relevant to PM execution in cleanroom environments.

A2.1 AMC, Corrosive Gas Emissions, and Cleanroom Risks

Preventive maintenance plays a critical role in controlling contamination within semiconductor manufacturing environments. Airborne Molecular Contaminants (AMCs) can cause metal corrosion on integrated circuits in cleanroom environments and lead to wafer scrap (B.-J. Wu et al., 2010). During PM activities, wipers are often used to simulate chloride ion (Cl^-) molecular contamination, which can be utilized for monitoring cleanroom microcontamination levels.

In metal etching processes, uncontrolled hydrogen chloride (HCl) gas emissions generated during PM, such as outgassing or fumes can reach concentrations as high as 343 ppmv. These emissions can cause corrosion of wafers and process tools, posing risks to both yield and equipment integrity. Consequently, PM-related contamination control is a critical aspect of maintaining cleanroom reliability and safety.

A2.2 PM-Related Mitigation Measures

To mitigate contamination and safety risks associated with PM, various engineering controls have been implemented. PM hoods are used to contain contaminants within a controlled environment during maintenance operations. Additionally, replacing critical exhaust components, such as the central ring of the fore line on an annual basis, helps prevent exhaust gas leakage and reduces corrosion risks.

These mitigation measures highlight the interdependence between PM execution quality, environmental control, and equipment safety, reinforcing the need for standardized PM procedures that incorporate contamination management considerations.

Appendix 3. Condition-Based Maintenance (CBM) and Equipment Health Monitoring (EHM)

This appendix complements Section 2.4 and Chapter 4, where CBM and EHM are discussed as enabling layers for PM automation. It summarizes established CBM and EHM frameworks to provide technical grounding for the intelligence layer referenced in the main text.

A3.1 CBM Frameworks and Practical Limitations

Condition-Based Maintenance (CBM) represents a paradigm shift from fixed-schedule PM to maintenance decisions based on actual equipment condition. CBM converts raw data related to equipment status and performance into actionable information that guides maintenance interventions (M. E. Cholette et al., 2013). However, widespread adoption of CBM in semiconductor manufacturing has been limited by incomplete understanding of complex process physics and the difficulty of accurately predicting degradation using available sensor data alone.

A3.2 EHM, SPC, and Equipment Health Index (EHI)

Equipment Health Monitoring (EHM) frameworks commonly utilize Statistical Process Control (SPC) to monitor numerous state variable identifiers (SVIDs) and aggregate them into integrated metrics such as an Equipment Health Index (EHI). By detecting abnormal equipment state changes in real time, EHI frameworks allow engineers to decompose hierarchical indicators and identify root causes through Out-of-Control Action Plans (OCAP) (C.-Y. Lee et al., 2019).

EHI is typically implemented through data preprocessing, SPC, and analytic hierarchy process (AHP) methods. It integrates variables such as idle time, material usage rate, and defect counts into a unified hierarchical structure, enabling rapid detection and diagnosis of abnormal equipment conditions.

Appendix 4. Prognostics and Failure Prediction Technologies

This appendix provides technical background supporting Sections 2.3 and 2.4, which describe the evolution of PM automation toward predictive and intelligence-driven approaches. It reviews representative prognostics and failure prediction techniques that underpin PdM capabilities referenced in the main text.

A4.1 Data-Driven Prognostics Methods

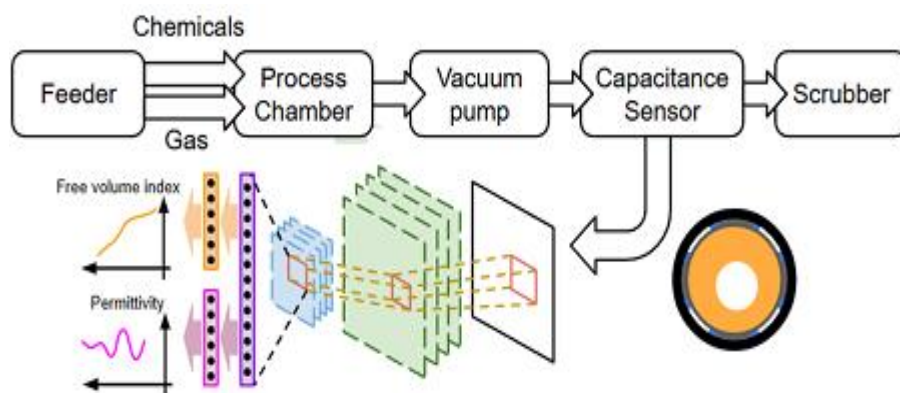
Prognostics technology predicts when equipment will fail to perform its intended function, enabling proactive planning of PM schedules. When mechanism-based modeling is impractical due to process complexity, data-driven approaches are commonly applied. One such method integrates Auto-associative Regression (AR) and Gaussian Process (GP) models (L. Zhu, 2024).

In this approach, the AR model learns normal-state behavior and calculates residuals between observed data and predicted normal values. These residuals serve as indicators of degradation magnitude. A GP model is then used to predict degradation trends and provide probabilistic inference, including prediction confidence intervals, even with limited data availability.

A4.2 Residual Monitoring and In-Situ Diagnostics

Electrical capacitance tomography (ECT) combined with convolutional neural networks (CNNs) has been developed to detect residue buildup inside semiconductor exhaust pipelines in a non-destructive manner (M. Jeon et al., 2025). This approach enables early detection of blockages and supports condition-based maintenance strategies.

In-situ sensors such as spectral ellipsometers (SE) are also widely used to monitor, diagnose, and control plasma etching equipment. By compensating for process drift through real-time measurement and analysis, these sensors contribute to enhanced process stability and maintenance effectiveness (S. Maung et al., 1994).



[Figure A4-1] Residual Gas Monitoring Techniques in Semiconductor Processes (M. Jeon et al., 2025)

Appendix 5. Maintenance Scheduling and Operational Optimization

This appendix supports Chapter 4 and Section 5.8, where limitations in end-to-end PM execution and system-level coordination are discussed. It introduces representative scheduling and optimization models that inform the integration of PM automation with operational decision-making systems.

A5.1 PM Scheduling Models

PM scheduling in semiconductor manufacturing is a complex optimization problem involving interdependencies among tasks, work-in-process (WIP) levels, labor availability, and time windows. Hierarchical modeling frameworks have been proposed to address this complexity. In such frameworks, upper-layer models capture probabilistic failure processes and demand patterns, while lower-layer mixed-integer programming (MIP) models schedule PM tasks to maximize availability and throughput while minimizing costs (J. A. Ramírez-Hernández et al., 2010).

A5.2 Integrated Dispatching and PM Optimization

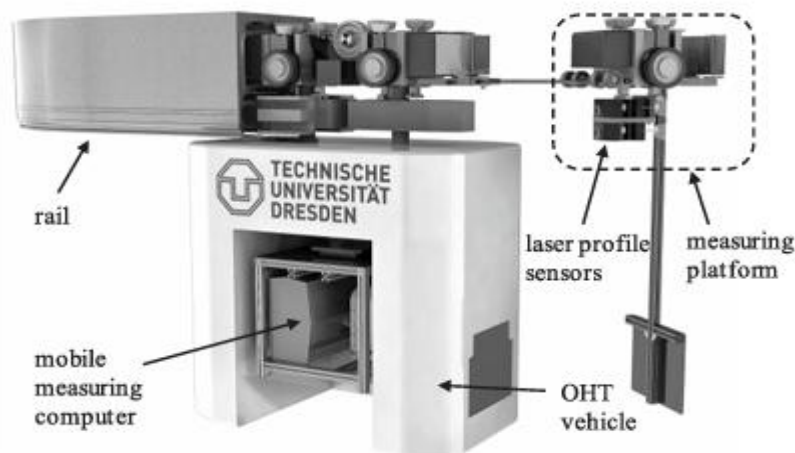
The Decomposed Dynamic Dispatching and Preventive Maintenance (D-DDPM) framework enables simultaneous optimization of dispatching and PM decisions in large-scale systems (B. Zhang et al., 2023). By decomposing the global problem into single-machine subproblems, this approach ensures computational scalability while incorporating equipment health considerations into operational decision-making.

Appendix 6. Robotics and Physical Automation for PM Execution

This appendix complements Sections 3.3 and 5.3, which discuss robot application and physical readiness for PM automation. It provides technical examples of robotics and automation systems that enable execution-layer PM automation referenced in the main text.

A6.1 Diagnostic and Inspection Robotics

Robotic systems have been developed to inspect overhead transport system (OHT) rail networks in 300 mm fabs. Trailer-based inspection platforms equipped with optical sensors scan rail networks at millimeter resolution, generating three-dimensional models and automatically detecting defects such as cable holder warping (A. Zhakov et al., 2020).



[Figure A6-1] Monitoring system for OHT rail networks (A. Zhakov et al., 2020)

A6.2 Automated Part Supply and Replacement

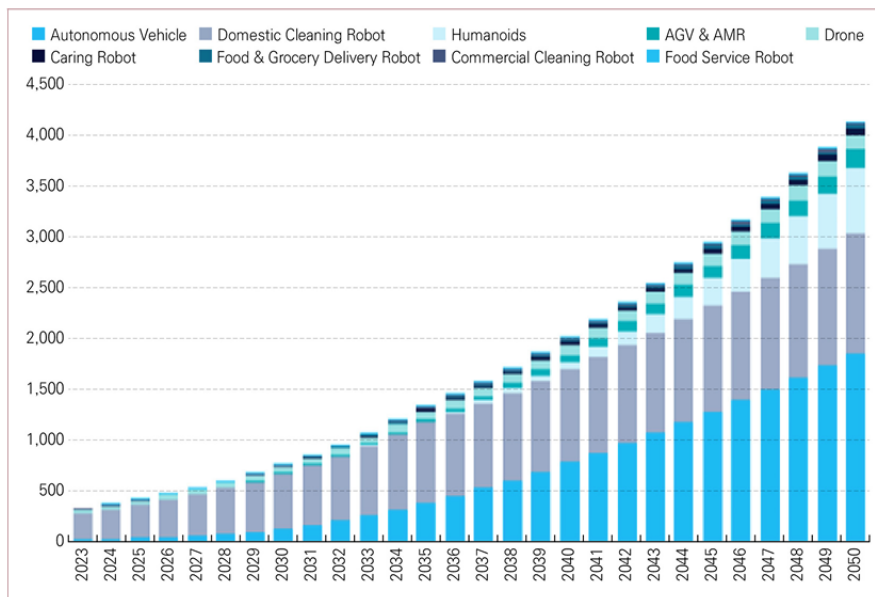
Autonomous Mobile Robots (AMRs) are increasingly used to supply replacement parts during PM activities. These systems link predictive diagnostic results with inventory and scheduling data, identify parts using RFID or vision systems, and determine optimal transport routes and timing based on autonomous scheduling algorithms.

A6.3 Collaborative Robots and Maintenance Execution

Collaborative robots (Cobots) are being deployed to perform maintenance tasks alongside human workers. Using vision-based alignment and force-torque sensors, Cobots can replace periodically worn components such as filters, O-rings, motors, and belts with high precision. These systems reduce worker exposure to hazards and significantly shorten maintenance duration.

A6.4 PM Orchestration Platforms and Digital Twins

Integrated PM orchestration platforms combine cloud and edge computing to coordinate diagnostic results, spare-part logistics, robotic execution, and verification processes. These platforms derive replacement priorities, perform task simulations in digital twin environments, and automatically generate quality verification reports, enabling more reliable and efficient PM execution.



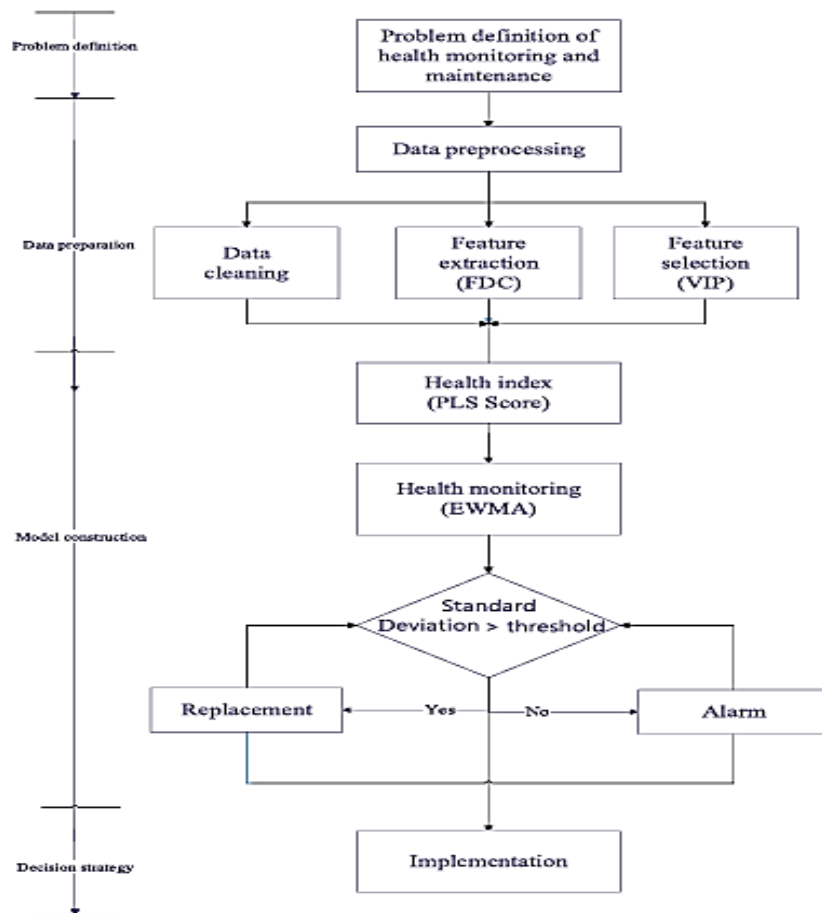
[Figure A6-2] AI Robot Diffusion Outlook (Lee Seung-hwan, 2025, re-cited)

Appendix 7. Predictive Maintenance (PdM) Technology Landscape

This appendix consolidates detailed technical literature and representative research examples supporting the discussion of PM automation and PdM in Chapter 2. The content is preserved to provide technical depth and evidence, while the main body of the white paper focuses on industrial adoption and standardization strategy.

This appendix reviews 50 key PdM-related papers published in IEEE journals up to 2025 to examine the evolution of PdM technologies over the past 25 years. The analysis covers sensing- and signal-processing-based diagnostics, machine learning-driven prediction algorithms, digital twin-linked platforms, and edge-AI architectures. Beyond simple technology classification, this review provides a structured overview of core PdM trends, application domains, and their potential convergence with automated PM systems.

A7.1 Supporting Technologies for Data Preprocessing and Health Indicator Extraction



[Figure A7-1] PLS-based equipment condition monitoring technique (C. -F. Chien et al., 2020)

The first step in improving PdM effectiveness is transforming raw sensor and process data into analyzable forms and extracting meaningful indicators that represent equipment condition. The large volume of State Variable Identifier (SVID) data collected in semiconductor manufacturing environments often suffers from multi-collinearity, necessitating the use of dimensionality

reduction and feature selection techniques such as Principal Component Analysis (PCA) and Partial Least Squares (PLS) (Y. J. Cruz et al., 2025).

For example, in data-driven fault prediction for silicon carbide MOSFETs (SiC MOSFETs), PCA is applied to reduce data dimensionality, suppress noise, and construct robust anomaly indicators for real-time implementation. PLS is used to extract feature scores from SVID data and Fault Detection and Classification (FDC) parameters to build equipment health models, particularly in environments where fault events are rare (C.-F. Chien et al., 2020).

The Health Index (HI) is a core PdM component designed to comprehensively evaluate real-time equipment condition. Hierarchical Equipment Health Index (EHI) frameworks integrate data preprocessing, Statistical Process Control (SPC), and Analytic Hierarchy Process (AHP) techniques to aggregate large numbers of SVIDs into a single metric and support root-cause tracing through hierarchical decomposition when anomalies occur (S.-X. Kao et al., 2023).

Dynamic Time Warping (DTW) has also been applied to diagnose positioning errors in wire bonding equipment by extracting relevant information from streaming time-series data and separating normal and defective patterns (P. Li et al., 2019). Similarly, modified Piecewise Linear Approximation (PLA) methods have been proposed to extract contamination-related features from dry etching process traces, forming a basis for remaining useful life (RUL) prediction.

Synthetic data generation techniques address data sparsity and imbalance issues in PdM model training. For example, Generative Adversarial Networks (GANs) have been used to generate synthetic reliability data for semiconductor laser PdM applications, improving model performance when real failure data are limited (K. Abdelli et al., 2022). Similar benefits have been reported for RUL prediction models trained on augmented SiC MOSFET datasets.

Virtual Metrology (VM) predicts equipment condition using process data without physical measurement and is regarded as a core enabling technology for PdM. VM-based Baseline Predictive Maintenance (BPM) constructs healthy baseline models that serve as reference points for fault detection and prediction. Techniques such as Keep Important Sample (KIS) and Dynamic Moving Window (DMW) are applied to maintain concise and healthy datasets, ensuring model robustness (Y.-S. Hsieh et al., 2013).

A7.2 RUL Prediction Using Deep Learning and Advanced Machine Learning

The ultimate objective of PdM is accurate residual useful life (RUL) prediction, which is increasingly addressed using deep learning models capable of capturing nonlinear and complex degradation behavior. Recurrent Neural Networks (RNNs) and their variants are widely used for time-series modeling.

Long Short-Term Memory (LSTM) networks mitigate gradient vanishing issues inherent in RNNs and have been applied to RUL prediction for SiC MOSFETs and lithium-ion batteries. Gate Recurrent Units (GRUs), with simpler architectures, are also used for performance degradation prediction in laser equipment. Attention-based GRU models further enhance prediction accuracy by emphasizing highly relevant features, while Bi-directional LSTM (BiLSTM) models improve prediction accuracy as additional health information becomes available (A. Vaccaro et al., 2023).

Temporal Convolutional Networks (TCNs) offer a computationally efficient alternative to recurrent architectures. The TCLSTM model combines TCN-based feature extraction with LSTM and attention layers, achieving low prediction errors in ion mill

etching RUL prediction and outperforming conventional deep learning models (C.-Y. Hsu et al., 2022).

Graph-based models such as Spatio-Temporal Graph Convolutional Networks (STGCNs) capture interactions among electrical attributes and temporal dependencies. Electrical-STGCN architectures address oversmoothing issues through novel kernel functions and enable effective condition estimation in industrial PdM applications (Y. Jiang et al., 2022).

Classical machine learning approaches remain relevant in PdM. Random Forest (RF) and Bayesian Ridge Regression (BRR) models have been combined in two-stage pipelines to classify equipment states and predict degradation trajectories for SiC MOSFETs, balancing computational efficiency and prediction uncertainty quantification (C. L. Kahraman et al., 2024). RF-based approaches are also used to reduce availability variability and increase mean time between failures (MTBF) in complex chamber process tools.

A7.3 Probabilistic Models and Bayesian-Based Estimation Techniques

Probabilistic models play a key role in quantifying uncertainty and tracking nonlinear degradation processes. Particle Filters (PFs) and their variants support online RUL updates by continuously incorporating new measurements, even under non-Gaussian conditions (G. A. Susto et al., 2012).

Hybrid approaches combining Cox's Proportional Hazards (PH) models with Continuous-Time Markov Chains (CTMCs) enable efficient estimation of conditional reliability and mean remaining life (MRL) by jointly considering component age and degradation state (C. L. Kahraman et al., 2024).

Maintenance timing optimization based on probabilistic predictions has also been demonstrated to reduce expected costs by balancing unplanned failure losses and premature replacement costs. Such approaches have been successfully applied to plasma etching equipment maintenance planning (S. Umeda et al., 2021).

Few-shot learning frameworks, such as Fuzzy Few-Shot Learning (FFSL), address PdM challenges in data-scarce environments. By training on limited abnormal data and incorporating fuzzy similarity measures, these models enable effective maintenance decision-making even under uncertainty (H.-H. Huang et al., 2024).

A7.4 Transfer Learning and Domain Adaptation Techniques

Transfer learning techniques address generalization and data scarcity challenges by enabling models trained on one tool or process to be adapted to others. A two-stage TCN-DANN approach combines Temporal Convolutional Networks with Domain-Adversarial Neural Networks to extract tool-invariant features and fine-tune models for fault modes with limited data (C. Liu, L. Zhang et al., 2021).

A7.5 Intelligent Automation and Other Element Technologies

Intelligent Factory Automation (iFA) systems integrate Predictive Maintenance (IPM) functions to support Zero-Defect Manufacturing objectives. These systems leverage e-diagnostics frameworks that collect Equipment Engineering (EE) data and perform online failure prediction. Recently, Large Language Models (LLMs) have been identified as a potential future direction for managing manufacturing complexity and enhancing PdM-driven maintenance optimization (Y. J. Cruz et al., 2025).

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[List of Abbreviations]

A

AHP – Analytic Hierarchy Process

AI – Artificial Intelligence

AMHS – Automated Material Handling System

ANN – Artificial Neural Network

API – Application Programming Interface

AR – Auto-associative Regression

AR–GP – Auto-associative Regression–Gaussian Process

Afab WG – Autonomous Fab Working Group

AS–RS – Automated Storage and Retrieval System

C

CBM – Condition-Based Maintenance

CDM – Capacity Decomposition Model

CNN – Convolutional Neural Network

CoA – Certificate of Analysis

COSAR – Council of Semiconductor Advanced Research

CT – Cycle Time

CB / TB – Condition-Based / Time-Based

D

D-DDPM – Decomposed Dynamic Dispatching and Preventive Maintenance

dEWMA – double Exponentially Weighted Moving Average

DT – Digital Twin

E

ECT – Electrical Capacitance Tomography

EHl – Equipment Health Index

EWMA – Exponentially Weighted Moving Average

F

FDC – Fault Detection & Classification

G

GP – Gaussian Process

H

HMM – Hidden Markov Model

HTI – Hotelling T-squared Index

Host – Host System

I

ICT – Information and Communication Technology

IDM – Integrated Device Manufacturer

IGBT – Insulated Gate Bipolar Transistor

M

MDP – Markov Decision Process

MES – Manufacturing Execution System

MIP – Mixed Integer Programming

ML – Machine Learning

MM – Maintenance Module

O

OEE – Overall Equipment Effectiveness

OHT – Overhead Hoist Transport / Overhead Transport System

P

PdM – Predictive Maintenance

PM – Preventive Maintenance

PoC – Proof of Concept

R

R2R – Run-to-Run Control

RUL – Remaining Useful Life

RRVM – Robust Relevance Vector Machine

ROI – Return on Investment

S

SE – Spectral Ellipsometer

SEMI – Semiconductor Equipment and Materials International

SMA / SMI – Smart Manufacturing Initiative

SPC – Statistical Process Control

SVID – System Variable ID

T

TMSE – Target Mean Square Error

V

VEWMA – Variable EWMA (Modified EWMA)

VM – Virtual Metrology

PM Automation/Standardization Strategy for the Transition to Autonomous Fab in Semiconductors