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Demand Analysis and Effectiveness Evaluation of Digital Twin System for Semiconductor Equipment Operation and Maintenance

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Abstract: With the improvement of the precision of semiconductor equipment, the traditional equipment operation and maintenance (O&M) mode is difficult to meet the real-time and predictive monitoring requirements of wafer manufacturing equipment, while existing digital twin systems for equipment lack demand-oriented design. Therefore, this study takes scanning electron microscope (SEM) equipment as the research object and proposes a demand analysis framework of digital twin system based on "Affinity Diagram (KJ) Method + Analytic Hierarchy Process (AHP)". Firstly, summarized specific requirements for the digital twin system of SEM equipment through the Affinity Diagram Method. Then, the AHP was used to quantify the priority and determine the importance and priority of the requirements. The system was built and applied according to the results of requirement analysis. Through practical application and data verification, it is confirmed that the digital twin system established based on this method has achieved remarkable results in equipment O&M management and cost reduction. This study provides a scientific requirement analysis method for the design of digital twin systems for semiconductor equipment, and offers practical reference for the intelligent O&M upgrading of the industry.

1. Introduction

As the pearl on the crown of modern industry, the O&M of semiconductor manufacturing equipment faces extremely strict requirements due to the unique characteristics of the industry, and it has also become a frontier for the research and implementation of advanced O&M technologies.

The traditional O&M mode relies heavily on engineers' experience, leading to lagging equipment fault response and excessively long MTTR, resulting in huge capacity losses [1]. On the other hand, preventive maintenance with fixed cycles is prone to over-maintenance or insufficient maintenance, which not only leads to excessive unnecessary working hours and spare parts costs, but also causes some faults that should be found in advance in preventive maintenance to occur during equipment production, resulting in losses of products and capacity [2]. These double pain points force the O&M mode to transform to "data-driven and prediction-first"[3].

Digital twin technology, which constructs virtual mappings of physical entities, enables key intelligent O&M functions including real-time monitoring, fault early warning, and predictive maintenance [4]. However, most current research on digital twin systems focuses on technical implementation such as 3D modeling and data integration, lacking demand-oriented design based on O&M scenarios and user needs. This leads to insufficient matching between system functions and actual business pain points, and limited implementation effects [5]. In the field of semiconductor equipment, existing research on O&M management tools mostly focuses on technical implementation, lacking in-depth exploration of how user needs guide system design, resulting in failure to solve actual O&M pain points after implementation. This highlights the necessity of demand orientation in the development of digital twin systems for semiconductor equipment [6].

To address this gap and translate user needs into actionable system design, this paper proposes a combined requirement analysis framework of "KJ Method + AHP". Through multi-expert participation in requirement collection, induction and quantitative ranking, a requirement priority list is formed, and an SEM equipment digital twin system is built based on this. Finally, the application effect of the system is verified through on-site data.

The main contributions of this study are as follows:

(1) Proposing a structured requirement analysis method for digital twin systems of semiconductor equipment.

(2) Building a digital twin system based on requirement priorities and realizing engineering implementation.

(3) Verifying the comprehensive benefits of the digital twin system in improving O&M efficiency and reducing costs through key performance indicator comparison.

2. Demand Analysis Methodology for Digital Twin System

The effectiveness of digital twin technology in industrial application scenarios depends on the virtualization method of physical entities and the realization degree of engineers' usage requirements. While to improve these situations through digital twins, it is necessary to systematically and accurately respond to the core needs of different roles: field engineers need to grasp the dynamic changes of multiple equipment parameters in real time to quickly locate faults, technical experts need to conduct in-depth analysis of data correlations to explore the root causes of faults, and management personnel need to quantify O&M benefits to optimize resource allocation.

But the traditional requirement investigation method is mainly interview, it has obvious limitations. On the one hand, the investigation results are fragmented, with vague expressions and overlapping contents, which are difficult to sort out structurally in the later stage. On the other hand, the subjective judgments of different respondents may lead to their subjective needs deviating from the actual priorities. As a result, the system development results deviate from the core needs and fail to achieve the expected use effect.

To overcome these limitations and address the specific technical characteristics of SEM equipment, we employed a combined "KJ Method + AHP" approach to construct a structured requirement analysis framework. The former is used as a qualitative analysis tool to generalize scattered and disordered original expert requirements into a logically clear hierarchical system, while the latter is used as a decision-making tool integrating qualitative and quantitative analysis. Through weight calculation and comparison, it converts the subjective needs of many experts into quantifiable priority data. The integration of these two tools creates a coherent analytical process, moving from qualitative induction to quantitative ranking. This overall technical route is depicted in Figure 1.

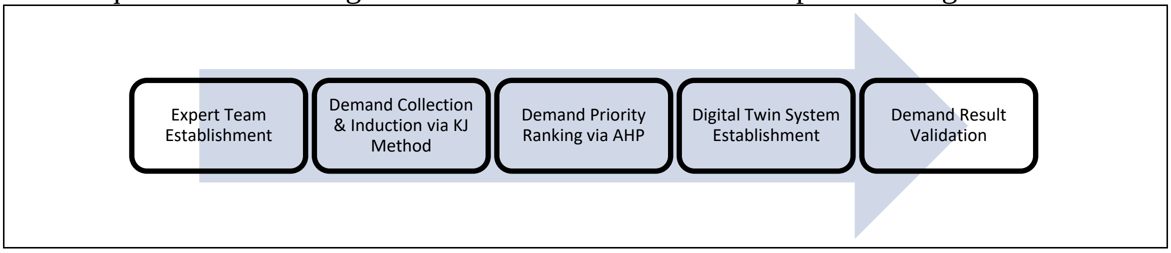

Figure 1: Technical Route.

3. Requirement Collection and Induction Based on Affinity Diagram (KJ) Method

3.1. Expert Team Establishment

To ensure that the obtained requirements are as representative as possible, we selected 34 employees of company engaged in SEM equipment-related work to form an expert team, covering all participants in the entire SEM equipment O&M process (Table 1).

Table 1: Expert Team Information.

Expert Type	Number	Demand Contribution Focus
Field Engineers	18	Practical pain points in equipment services
Technical Experts	6	Technical support requirements
Engineering Supervisors	6	Team management requirements
Management	3	Cost and benefit requirements
Equipment R&D Staff	3	System implementation requirements

3.2. Two-Round Requirement Collection

Table 2: Structured Summary of Requirements Using KJ Method.

Goal Layer (A)	Criterion Layer (C)	Alternative Layer (P)
Construction of Digital Twin System	C1: Real-Time Status Monitoring	P1: High-Frequency Data Collection
		P2: Multi-Parameter Linkage Analysis
		P3: Health Status Dashboard
	C2: Intelligent Fault Diagnosis	P4: Automatic Fault Root Cause Analysis
		P5: Fault diagnosis knowledge base and case matching recommendation
		P6: Interactive interface supporting remote expert collaborative diagnosis
	C3: Maintenance Decision Optimization Demand	P7: Key component remaining useful life (RUL) prediction and replacement reminders
		P8: Predictive maintenance trigger mechanism based on actual equipment status
		P9: Automatic generation and optimized ranking of maintenance task lists
	C4: Data & Management Demand	P10: Data security and hierarchical permission management mechanism
		P11: Data interface with customers' existing MES/EAP systems
		P12: Electronic recording of all O&M activities and automatic report generation

Based on the team status, we booked two online meetings to complete requirement collection and induction. Through the KJ Method, we consolidated the system requirements proposed by 34 experts and organized the following structured requirement statistics (Table 2).

4. Requirement Priority Ranking Based on Analytic Hierarchy Process

4.1. Determination of Weight Coefficients of Evaluation Indicators at All Levels

In the functional priority ranking of the twin system construction, a questionnaire survey was conducted among 34 experts to score and compare the criterion layer C1-C4 and the alternative layer P1-P3, P4-P6, P7-P9, P10-P11 with each other. This paper uses a 1-9 ratio scale to score the pairwise compared factors. The pairwise comparison result of factors "i" and "j" is recorded as "a_{ij}", and the scale is shown in the Table 3 below.

Table 3: Scale Assignment and Interpretation of Judgment Matrix.

Expert Judgment	Scale	Expert Judgment	Scale
Absolutely Important a_{ij}	9	Intermediate Value a_{ij}	1/2
Intermediate Value a_{ij}	8	Slightly Less Important a_{ij}	1/3
Very Important a_{ij}	7	Intermediate Value a_{ij}	1/4
Intermediate Value a_{ij}	6	Obviously Less Important a_{ij}	1/5
Intermediate Value a_{ij}	5	Intermediate Value a_{ij}	1/6
Intermediate Value a_{ij}	4	Very Less Important a_{ij}	1/7
Slightly Important a_{ij}	3	Intermediate Value a_{ij}	1/8
Intermediate Value a_{ij}	2	Absolutely Less Important a_{ij}	1/9
Equally Important a_{ij}	1		

The pairwise comparison matrix A_{nn} established through the evaluation indicators is as follows:

$$A_{nn}=\begin{bmatrix} 1 & a_{12} & a_{1..} & a_{1n} \\ a_{21} & 1 & a_{2..} & a_{2n} \\ a_{..1} & a_{..2} & 1 & a_{..n} \\ a_{n1} & a_{n2} & a_{n..} & 1 \end{bmatrix} \tag{1}$$

After the questionnaire survey, the collected questionnaires were sorted out to obtain the judgment matrix of each expert on the criterion layer C and the alternative layer P.

4.2. Calculation of Indicator Layer Weights

Indicator weight calculation is one of the core calculation links of the Analytic Hierarchy Process. The weight vector (denoted by W) quantitatively describes the relative importance of each factor in the final decision. converting the decision-maker's subjective and qualitative comparative judgments into objective and quantitative values. In this study, the root mean square method is used to calculate W. For an n-order judgment matrix A, the calculation formula of the weight vector W is:

$$W_i=\frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}},\quad i=1,2,...n \tag{2}$$

4.3. Consistency Test of Judgment Matri

When experts conduct pairwise comparisons between indicators, they are often affected by personal experience, cognitive habits and other factors, and the constructed judgment matrix may have logical inconsistency. Therefore, after constructing the judgment matrix using the AHP, conducting a consistency test is an important step to ensure the reliability of the analysis.

This study completes this test by calculating three core indicators: the maximum eigenvalue (λ_{max}), consistency index (CI) and consistency ratio (CR). According to Saaty's judgment standard (Table 4), when the CR value is less than 0.1, it is considered that the consistency degree of the judgment matrix is within an acceptable range, and the weight calculation result is reliable and has reference value;

The calculation formula of the consistency index used is:

$$CI = \frac{\lambda_{max} - n}{(n-1)} \tag{3}$$

Among them, λ_{max} represents the maximum eigenvalue of the judgment matrix, and its calculation formula is:

$$\lambda_{max} = \sum_{i=1}^{n} \frac{\lfloor AW \rfloor_i}{nW_i} \tag{4}$$

The expression of CR is:

$$CR = \frac{CI}{RI} \tag{5}$$

Table 4: Average Random Consistency Index of the Judgment Matrix RI.

Matrix Order (n)	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

4.4. Weight Calculation and Priority Ranking

In the decision-making process of the Analytic Hierarchy Process, it is necessary to integrate multiple valid expert judgment matrices into a unified comprehensive judgment matrix that can represent group consensus through the key step of "aggregation matrix",and ensuring the objectivity and scientificity of the decision-making results.

In Section 4.3, all expert-submitted judgment matrices have been subjected to consistency test through calculation, and valid matrices meeting CR<0.1 have been screened out. The geometric mean method is used to aggregate the 5 groups of valid judgment matrices of the criterion layer and alternative layer, and the calculation formula is as follows:

$$A_{ij} = \left(\prod_{k=1}^{k} a_{ij}^{k} \right)^{1/k} \tag{6}$$

(K represents the matrix data that has passed the consistency test)

Python was used to aggregate the 22 matrices of the criterion layer requirement dimensions:

$$C = \begin{bmatrix} 1 & 2.19 & 2.72 & 2.6795 \\ 0.46 & 1 & 1.13 & 1.19 \\ 0.37 & 0.88 & 1 & 1.18 \\ 0.33 & 0.84 & 0.85 & 1 \end{bmatrix} \tag{7}$$

According to the formula, weight and consistency analysis were conducted on the aggregation matrix, and the results are as Table 5:

Table 5: Weight Calculation Results of Criterion Layer.

Indicator	Weight W	λ_{max}	CI	CR
C1	0.46	4.01	0.001	0.001<0.1
C2	0.20			
C3	0.18			
C4	0.16			

Similarly, the matrices of the 4 alternative layers that passed the consistency test were aggregated and weighted, and the final results are summarized as Table 6:

Table 6: Summary of the Final Weight Calculation Results.

Goal Layer (A)	Criterion Layer (C)	Weight	Alternative Layer (P)	Local Weight	Global Weight	Priority Ranking
A	C1	0.46	P1	0.31	0.14	2
			P2	0.48	0.22	1
			P3	0.21	0.10	4
	C2	0.20	P4	0.48	0.10	3
			P5	0.29	0.06	8
			P6	0.22	0.04	9
	C3	0.18	P7	0.52	0.09	5
			P8	0.37	0.07	7
			P9	0.11	0.02	12
	C4	0.16	P10	0.54	0.09	6
			P11	0.25	0.04	10
			P12	0.21	0.03	11

Through this method, we obtained a clear priority for system requirement development in terms of results. In terms of process, we also scientifically obtained requirements that can cover most SEM equipment O&M personnel. Therefore, based on the weight ranking of the functional layer, the management decided to prioritize the development of the top five ranked P2, P1, P4, P3, and P7.

5. Application Effect Evaluation

After clarifying system requirement priorities, this study built a digital twin model for SEM equipment in domestic FABs. The system’s core goal is to create an intelligent graphical O&M platform that synchronizes with physical SEM equipment, turning user needs into actionable, focused solutions. Its architecture follows a "data-driven, model-supported, intelligence-oriented" design and uses digital twin technology to connect the data perception-to-decision execution process. See Figure 2 for the implementation framework.

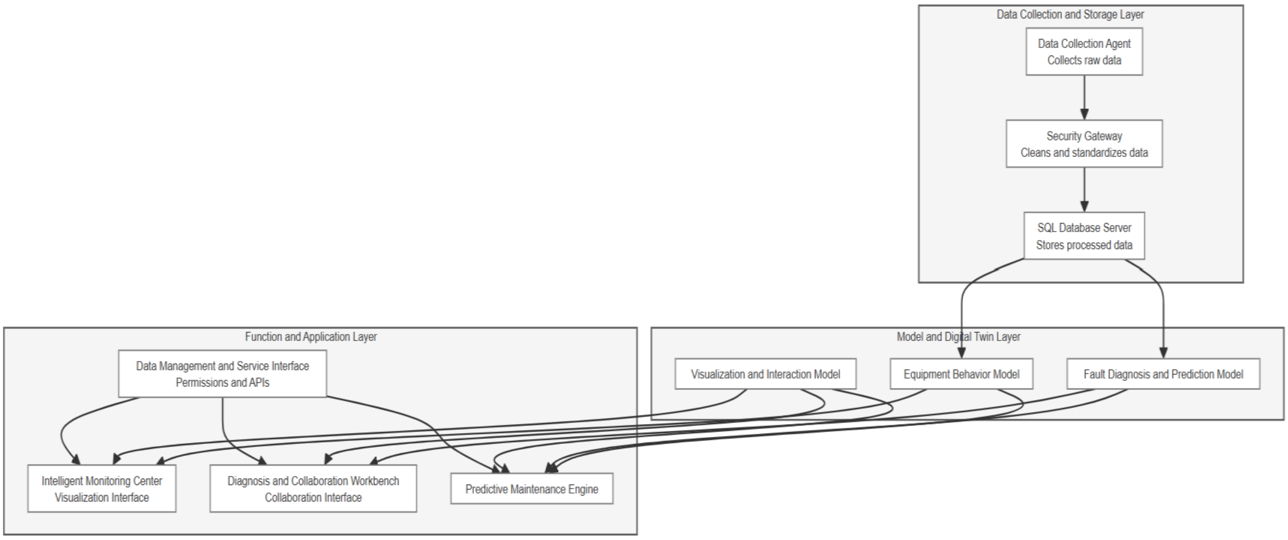

Figure 2: Digital Twin System Functional Architecture Diagram.

We selected an SEM tool at the customer's FAB for a 7 months application verification period (from early May to late November 2025) and compared its O&M data with data before the system implementation. Figure 3 clearly shows the resulting changes:

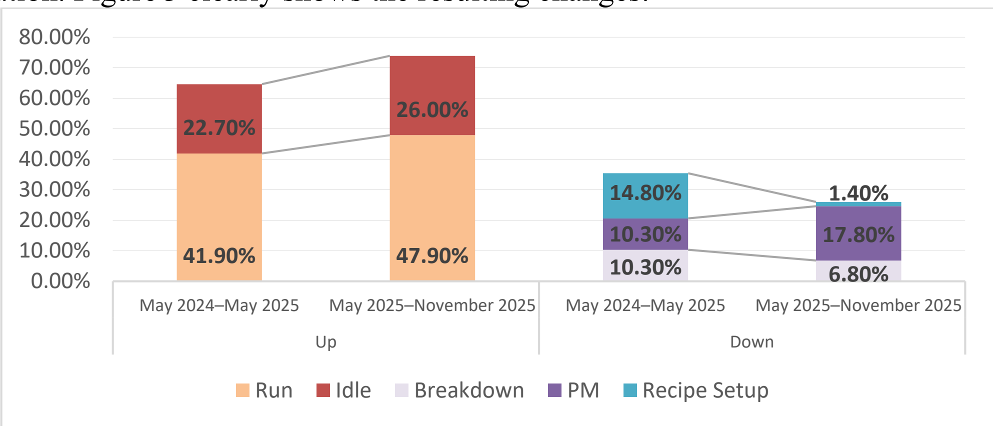

Figure 3: Percentage Comparison of Equipment Status Quantities.

After data calculation, the comparison of key indicators is shown in Table 7:

Table 7: Comparison of Key Indicators.

Indicator	May 2024–May 2025	May 2025–Nov. 2025	Change Rate
MTTR (hours)	5.74	3.85	-32.90%
MTBF (hours)	272.79	986.11	261.50%
Downtime Ratio	49.90%	36.40%	-13.50%
Total O&M Cost (￥)	231,98	152,82	-34.10%
Labor Cost	116,45	84,58	-27.40%
Spare Parts Cost	104,24	75,03	-28.00%

These results directly answer the research questions posed earlier. The quantifiable improvements in MTBF, MTTR, and cost demonstrate that the system, built upon prioritized requirements, successfully brought measurable efficiency gains and cost savings. This validates the core premise that a demand-oriented digital twin can effectively connect with business pain points and unify management benefits with technical value.

6. Conclusions

This study successfully developed and validated a digital twin system for SEM equipment O&M, driven by a user-centric requirement analysis framework that integrates the KJ Method and the AHP. The proposed framework effectively bridging the common gap between technical implementation and actual business pain points in intelligent management systems development. Providing a replicable reference for similar studies in the field.

The findings of this study demonstrate a strong causal link between the rigor of requirement analysis and the effectiveness of application outcomes. Specifically, the highly weighted requirements correspond directly to the key functionalities needed to address traditional O&M bottlenecks. The implementation of these functionalities is the primary driver behind the observed improvements in equipment O&M management. Therefore, requirement analysis serves as the essential precursor and guarantor of application effectiveness, while the realized outcomes, in turn, validate and fulfill the purpose of the requirement analysis.

Despite these promising results, this work has limitations that outline clear pathways for future research. First, the generalizability of the "KJ+AHP" framework requires validation by applying it to other types of semiconductor or industrial equipment. Second, the system's intelligence, currently based on rule and model-driven approaches, can be advanced by integrating AI techniques like deep learning for more adaptive prediction and decision-making. Finally, achieving seamless data-model-decision linkages through deeper integration with factory-level systems (e.g., MES, EAP) is crucial for unlocking further gains in overall O&M efficiency.

In summary, this research provides a validated, practical methodology and a case study for demand-driven digital twin development in semiconductor equipment O&M. Future efforts should focus on extending the methodology's scope, enhancing system intelligence, and promoting cross-platform integration to fully realize the transformative potential of digital twin technology in advanced manufacturing.

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