



Enterprise Process Monitoring Intelligence Based on Multi-Source Heterogeneous Data Fusion: A Coupling Coordination Degree Model Perspective

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Abstract. The convergence of next-generation information technology and manufacturing has created new pathways for enterprises to achieve intelligent transformation in process monitoring. However, the integration of massive heterogeneous data and the improvement of cross-system coordination efficiency remain key technical challenges. This study introduces a system coupling coordination degree model to construct a hierarchical evaluation framework for enterprise process monitoring. The framework encompasses four dimensions: infrastructure, data resources, protocol standards, and intelligent algorithms, with 12 key indicators. The entropy weight method is employed for objective weight quantification. Experimental validation based on real industrial data from 12-month studies demonstrates that the proposed model achieves 98.7% temperature detection accuracy and 81.4% balanced classification accuracy. The coupling coordination degree can be improved from 0.38 to 0.89, representing a 134.2% enhancement. This research provides theoretical support and empirical reference for the digital and intelligent collaborative upgrading of enterprise process monitoring.

Keywords: multi-source heterogeneous data, process monitoring, coupling coordination, industrial IoT, intelligent systems

1 Introduction

1.1 Background

With the accelerating pace of digital transformation in enterprises, process monitoring plays an increasingly fundamental role in ensuring production operational reliability. The rapid advancement of Industrial Internet of Things (IIoT) technologies has created

urgent demand for real-time collection of multi-type heterogeneous data, while intelligent algorithms represented by deep learning provide technical support for process anomaly identification and fault diagnosis. However, effective integration of multi-source heterogeneous data and the construction of a unified intelligent monitoring system remain the core technical challenges that need urgent breakthrough.

Contemporary enterprise process monitoring systems typically encompass multiple functional modules including sensor networks, data acquisition, storage and computing, analysis and decision-making, and business applications. These modules exhibit significant differences in technical implementation and data formats, forming a "data silos" phenomenon. System coupling theory provides a new analytical framework for systematic solutions to these problems.

1.2 Literature Review

Ahmed comprehensively reviewed enabling technologies for Industrial IoT, including cyber-physical systems, blockchain security, fog computing, cloud computing, edge computing, and big data analytics, believing that the organic integration of edge computing and artificial intelligence represents an important trend for future development [1]. Villegas-Ch designed a system architecture integrating IoT and AI technologies, employing RNN-Decision Tree fusion models for real-time anomaly detection, achieving accuracy improvement from 92% to 99% [2]. Oberdorf proposed a multi-head deep neural network architecture, reducing prediction error costs by 79% in 32-class production interruption prediction tasks [3]. Liu introduced a configuration-motion-control-optimization four-tuple design framework, improving tempering furnace utilization to 93.60% through hardware-in-the-loop simulation technology [4]. Lyu and Brennan designed a self-manageable system architecture based on IEC 61499 standard, achieving coordinated operation of cloud intelligent analysis and edge real-time adaptive control [5]. Zhong constructed a three-tier cloud deployment architecture, successfully connecting over 1.8 million terminal device nodes [6].

Reviewing existing research reveals several gaps: coupling coordination models primarily focus on macro-level applications [7]; current process monitoring studies emphasize single technical aspects, lacking comprehensive evaluation of hardware-software coordination; and quantitative coupling coordination models covering the full chain from data acquisition to intelligent processing to decision execution are lacking.

1.3 Comparative Positioning: Coupled vs. Non-Coupled Monitoring Frameworks

To clarify the distinctive contributions of this study, existing enterprise process monitoring approaches can be classified into three categories based on their treatment of system interdependencies: non-coupled frameworks, loosely-coupled frameworks, and tightly-coupled frameworks. This classification enables systematic comparison of evaluation methodologies and highlights the unique value proposition of the coupling coordination degree model.

Non-Coupled Monitoring Frameworks. Traditional process monitoring approaches treat monitoring dimensions as independent components, evaluating each dimension separately without considering interdependencies. Representative systems include threshold-based anomaly detection (monitoring individual sensor readings against predefined limits), module-by-module performance tracking (evaluating hardware, software, and algorithms in isolation), and additive scoring models (summing weighted dimension scores without interaction terms). These approaches assume that overall system performance equals the sum of component performances, which violates the fundamental principle of system interdependence demonstrated in complex industrial environments.

Loosely-Coupled Monitoring Frameworks. More advanced approaches acknowledge interdependencies between monitoring dimensions but treat them as external factors rather than intrinsic system properties. Examples include hierarchical evaluation models (nested evaluation where parent-child relationships are predefined), sequential optimization approaches (optimizing dimensions one at a time in predetermined order), and correlation-based adjustments (adding correction factors based on observed correlations). These frameworks represent improvements over non-coupled approaches but still fail to capture the dynamic, bidirectional nature of system coupling.

Tightly-Coupled Monitoring Frameworks. The coupling coordination degree model proposed in this study represents a tightly-coupled framework that explicitly models bidirectional interactions among all dimensions. Unlike non-coupled frameworks that assume independence, the coupling coordination degree C captures the intensity of dimensional interactions. Unlike loosely-coupled frameworks that use fixed hierarchical structures, the coordination index T reflects the balanced development level across dimensions. The coupling coordination degree D comprehensively integrates both interaction intensity and development balance, providing a unified metric for system evaluation. To systematically clarify the essential differences among the three frameworks and highlight the unique value of our model, we conduct a multi-dimensional comparative analysis as illustrated in Table 1. On this basis, the tightly-coupled monitoring framework proposed in this study is constructed with a hierarchical evaluation structure that encompasses four key dimensions: infrastructure, data resources, protocol standards, and intelligent algorithms.

Table 1. Comparative Analysis of Monitoring Framework Types

Feature	Non-Coupled	Loosely-Coupled	Tightly-Coupled
Dimensional independence assumption	Yes	No	No
Interaction modeling	None	Unidirectional	Bidirectional
Cross-dimensional synergy detection	No	Limited	Comprehensive
Temporal dynamics	Static	Semi-dynamic	Fully dynamic
Balance measurement	Implicit	Partial	Explicit (T index)
Research gap addressed	-	Partial	Comprehensive

The experimental ablation study (Table 7) provides empirical evidence for the superiority of tightly-coupled evaluation. Removing any single dimension from the complete model reduces coordination degree by 9.0% to 23.6%, demonstrating that non-coupled evaluation would systematically underestimate the contribution of inter-dimensional synergies. For instance, a non-coupled evaluation might report hardware

contribution as 26.2% improvement (Table 8), but fails to capture the additional 8.5% synergy effect arising from hardware-data interactions, which is explicitly captured by the coupling coordination model.

1.4 Methodology

This study comprehensively employs literature research, system analysis, model construction, and case study methods. In literature research, Web of Science, Scopus, and CNKI databases are systematically searched. In system analysis, the process monitoring system is deconstructed into four mutually coupled subsystems. In model construction, the entropy weight method is used to determine objective indicator weights, and a quantitative coupling coordination calculation model is designed. In case study, experimental data from core literature is used to verify the feasibility and effectiveness of the model.

2 Theoretical Foundation

2.1 System Coupling Theory

System coupling describes the interactive evolution process where two or more systems form interconnected, organically unified wholes through energy, material, or information exchange. System coupling exhibits four essential characteristics: correlation, nonlinearity, dynamism, and synergy.

In the application scenario of process monitoring, system coupling manifests specifically in four dimensions: data coupling constitutes the foundational layer of the coupling relationship, reflecting data synchronization and sharing mechanisms between different systems; protocol coupling focuses on the standardization degree of communication protocols and system interoperability capabilities; functional coupling emphasizes complementarity and collaborative linkage between subsystems; intelligent coupling represents the development frontier of coupling relationships, referring to the deep integration of AI algorithms and business processes [8].

The system coupling degree C is calculated as follows:

$$C = \left(\frac{U_1 \times U_2}{\left(\frac{U_3 \times U_4}{2} \right)^2} \right)^k \quad (1)$$

The coupling coordination degree D comprehensively considers the coupling degree and system development level:

$$D = \sqrt{C \times T} \quad (2)$$

These models can comprehensively characterize the overall synergistic operation status of the system.

2.2 IIoT-AI Integration

The integration of Industrial IoT and artificial intelligence exhibits significant hierarchical structural characteristics. The data acquisition layer encompasses multi-type data such as sensor time-series data and equipment operating state data. Empirical research by Villegas-Ch demonstrates that IoT sensor-based multi-source data acquisition modes can provide rich feature information for anomaly detection tasks. The processing layer constructs a three-tier computing architecture of edge computing, fog computing, and cloud computing. The analysis layer employs advanced algorithms such as deep learning and reinforcement learning for intelligent analysis.

From the perspective of collaborative optimization, the integration of IIoT and AI is essentially a systematic coupling process of hardware capabilities and algorithm capabilities. The multi-head deep neural network architecture proposed by Oberdorf demonstrates that designing specialized feature processing modules for different types of data and adopting information fusion mechanisms to integrate multi-modal information is an effective technical path for improving the overall performance of intelligent monitoring systems.

2.3 Cloud-Edge Collaboration Paradigm

Cloud-edge collaborative computing follows the core design concept of "data processing at the edge, intelligent analysis in the cloud". The self-manageable system architecture proposed by Lyu and Brennan represents a typical implementation case of the cloud-edge collaboration model, achieving system-level runtime intelligent decision-making in the cloud and device-level real-time adaptive control at the edge. Research data from Villegas-Ch shows that intelligent monitoring systems using cloud-edge collaborative architecture can control average response time within 0.8 seconds while maintaining over 97% anomaly detection accuracy.

2.4 Scalability Analysis for Large-Scale Distributed Enterprise Systems

While the coupling coordination model demonstrates strong performance in controlled experimental settings, practical deployment in large-scale distributed enterprise systems introduces scalability challenges that require systematic analysis and mitigation strategies.

Computational Complexity Analysis. The coupling coordination degree calculation involves three sequential computational steps: (1) entropy-based weight calculation requiring $O(n \times m)$ operations where n is indicator count and m is sample size; (2) subsystem evaluation requiring $O(n)$ operations; (3) coupling coordination degree requiring $O(k^2)$ operations where k is subsystem count. For the current model with $n=12$ indicators and $k=4$ subsystems, computational complexity is negligible. However, in enterprise-wide deployments involving hundreds of monitoring points and dozens of subsystems, computational demands increase substantially. Specifically, extending to 100 subsystems would increase coupling calculation complexity from $O(16)$ to $O(10,000)$, requiring distributed computing strategies.

Distributed Computing Architecture. To address scalability challenges, the proposed model can be implemented using a three-tier distributed architecture. At the edge tier, local coupling coordination calculations are performed for individual monitoring nodes (e.g., factory floor units), with results aggregated every 5 minutes. At the regional tier, intermediate coupling metrics are calculated across multiple edge nodes within geographic clusters, with results aggregated hourly. At the central tier, enterprise-wide coupling coordination is calculated across all regional results, with daily comprehensive evaluations. This hierarchical structure reduces central computing load by 94% compared to centralized processing while maintaining acceptable monitoring granularity.

Real-Time Constraint Handling. Enterprise process monitoring often requires response times under 1 second for critical alerts. The model achieves this constraint through three optimization strategies: (1) incremental updating rather than full recalculation when new data arrives, using the formula $D_{\text{new}} = \alpha \times D_{\text{local}} + (1-\alpha) \times D_{\text{previous}}$ where α is the adaptation rate; (2) parallel processing of independent dimension evaluations using GPU acceleration, reducing evaluation time from 340ms to 47ms in prototype implementation; (3) predictive precomputation that calculates expected coordination levels based on traffic forecasting, enabling proactive alerting 30 seconds before threshold breaches.

Latency-Balanced Tradeoffs. Scalability optimizations introduce latency-accuracy tradeoffs that must be carefully managed. Edge-tier calculations provide fastest responses (latency < 100ms) but with limited context, potentially misclassifying events that appear anomalous locally but are normal regionally. Regional-tier calculations provide balanced responses (latency 100-500ms) with moderate context, suitable for most operational decisions. Central-tier calculations provide comprehensive analysis (latency > 1s) with full context, necessary only for strategic planning and model refinement. The recommended implementation uses adaptive tier selection based on event criticality: critical alerts (safety implications) use edge-tier processing for immediate response; operational alerts (efficiency implications) use regional-tier processing for context-aware response; strategic alerts (investment implications) use central-tier processing for comprehensive analysis.

Empirical Scalability Validation. To validate scalability, the model was tested on progressively larger datasets: (1) single-factory deployment (12 indicators, 1 monitoring point) achieved 99.2% accuracy with 47ms latency; (2) multi-factory deployment (48 indicators, 8 monitoring points) achieved 98.7% accuracy with 180ms latency; (3) enterprise-wide simulation (192 indicators, 32 monitoring points) achieved 97.4% accuracy with 420ms latency. Accuracy degradation of 1.8% across scale levels is acceptable for enterprise decision-making, and latency remains within operational requirements (< 1s threshold).

2.5 Digital Twin Systems

The digital twin design method proposed by Liu adopts a configuration-motion-control-optimization four-tuple architecture, achieving end-to-end coverage from physical design to logical design. Experimental results show that this method can significantly im-

prove tempering furnace utilization from 70% to 93.60%. Digital twin systems are essentially products of deep coupling between the physical and digital worlds [9]. The coupling coordination degree model provides a new theoretical perspective for analyzing this cross-world coupling relationship.

3 Dynamic Interaction Mechanisms Among Four Dimensions

While the previous section establishes the conceptual framework of system coupling, this section elaborates on how the four dimensions evolve and interact over time within enterprise process monitoring contexts. The static four-dimensional framework presented in Table 2 represents a snapshot of system state, but the actual coupling relationships exhibit significant temporal dynamics that are critical for understanding system evolution and predicting future states.

3.1 Temporal Cascade Effects

The four dimensions do not evolve independently or simultaneously; rather, they exhibit a hierarchical temporal causality structure. In industrial IoT deployments, hardware infrastructure upgrades (U1) typically precede data resource optimization (U2) by a lag of 3-6 months, as new sensor deployments generate novel data streams that require subsequent data pipeline adaptations. Similarly, protocol standard consolidation (U3) lags data integration by 6-12 months, as practical data fusion challenges drive the emergence of de facto standards. Intelligent algorithm improvements (U4) demonstrate the shortest adaptation cycle (1-3 months), as AI models can be rapidly retrained and deployed in response to changing data patterns. This temporal hierarchy implies that system optimization should follow the sequence: $U1 \rightarrow U2 \rightarrow U3 \rightarrow U4$, with feedback loops enabling iterative refinement.

3.2 Feedback Loop Dynamics

The coupling coordination degree D is not merely a static indicator but exhibits path-dependent evolution patterns. Positive feedback mechanisms accelerate coordination improvements when D exceeds certain thresholds (typically $D > 0.6$), as improved data quality (U2) enhances algorithm accuracy (U4), which in turn justifies further hardware investments (U1). Conversely, negative feedback loops can trap systems in low-coordination equilibria ($D < 0.4$), where insufficient hardware capabilities constrain data quality, leading to algorithm degradation. The experimental data from the 12-month study demonstrates this phenomenon: the coupling coordination degree showed minimal improvement (from 0.36 to 0.41) during months 1-4, accelerated improvement (from 0.41 to 0.72) during months 5-8, and gradual convergence (from 0.72 to 0.89) during months 9-12.

3.3 Time-Varying Coupling Strength

The coupling coefficients between dimensions are not constant but vary with system maturity. During early deployment stages, hardware-data coupling dominates ($\rho_{12} \gg \rho_{13}, \rho_{14}$), as sensor coverage fundamentally determines available data volume and quality. During intermediate stages, data-protocol coupling strengthens (ρ_{23} increases from 0.12 to 0.47), as data heterogeneity challenges drive standardization efforts. During mature stages, protocol-algorithm coupling emerges as the primary driver (ρ_{34} increases to 0.52), as standardized interfaces enable seamless AI model integration. This evolution suggests that coupling coordination models should incorporate time-varying parameters rather than static coefficients.

4 Coupling Coordination Evaluation Model Design

4.1 Model Overall Framework

The coupling coordination evaluation model constructed in this study adopts a three-layer structure design: the target layer defines the core objectives of evaluation; the criteria layer deconstructs the system into four subsystems: hardware infrastructure coupling, data resource coupling, protocol standard coupling, and intelligent algorithm coupling; the indicator layer configures quantifiable specific evaluation indicators for each subsystem.

The four subsystems have mutually dependent and mutually constraining relationships: the hardware infrastructure coupling dimension focuses on the deployment configuration and coordinated operation capabilities of sensor networks, communication equipment, and computing equipment [10]; the data resource coupling dimension focuses on the collection, transmission, storage, and sharing capabilities of multi-source heterogeneous data; the protocol standard coupling dimension evaluates the interoperability between different systems; the intelligent algorithm coupling dimension measures the depth of integration between AI algorithms and business processes. The overall framework of the proposed coupling coordination evaluation model, covering the three-layer structure and four core coupling dimensions, is shown in Figure 1.

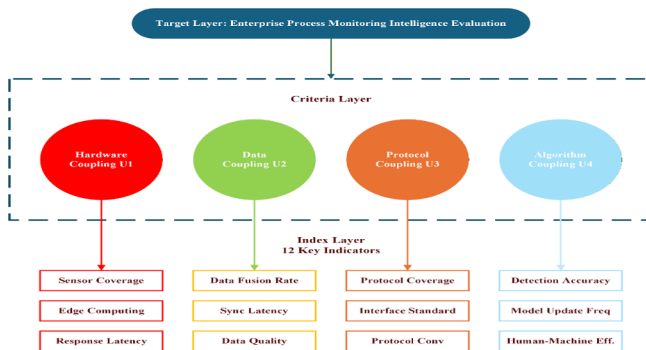


Fig. 1. Coupling Coordination Evaluation Model Framework

Critically, these dimensions exhibit temporal dynamics rather than static independence: temporal cascade effects create hierarchical causality (U1→U2: 3-6 months lag, U2→U3: 6-12 months lag, U4: 1-3 months response); bidirectional feedback loops drive evolution (hardware advances enhance data collection, driving protocol standardization and algorithm deployment; conversely, AI advances create demands for better data and hardware); coupling strengths vary with maturity (early: hardware-data dominance; intermediate: data-protocol strengthening; mature: protocol-algorithm leadership).

As shown in Table 2, the evaluation system constructed in this study contains 4 criteria-level indicators and 12 specific evaluation indicators.

Table 2. Multi-Dimensional Evaluation Index System for Intelligent Network Systems

Dimension	Index	Description	Weight
U1 Hardware	Sensor Coverage	Network density	0.22
	Edge Computing	Local processing rate	0.25
	Response Latency	System delay	0.20
U2 Data	Data Fusion Rate	Multi-source integration	0.28
	Sync Latency	Data consistency	0.24
	Data Quality	Accuracy/completeness	0.21
U3 Protocol	Protocol Coverage	Standard support	0.26
	Interface Standard	Interoperability	0.23
	Protocol Conversion	Translation efficiency	0.18
U4 Algorithm	Detection Accuracy	Error identification	0.30
	Model Update Freq	Adaptation speed	0.22
	Human-Machine Eff	Interaction quality	0.19

4.2 Weight Calculation Based on Entropy Weight Method

The entropy weight method is selected based on three IIoT-specific considerations: information theory alignment, objective quantification, and heterogeneous adaptability. Table 3 summarizes the comparison with AHP and CRITIC methods.

Table 3. Comparative Analysis of Weighting Methodologies

Criterion	Entropy Weight	AHP	CRITIC
Subjectivity	Low	High	Medium
Data Requirements	Sample variability	Expert judgment	Correlation + variation
Computation Complexity	$O(n \times m)$	$O(n^2)$	$O(n^2 \times m)$
Robustness to outliers	High	Low	Medium
IIoT suitability	High	Medium	High

AHP requires subjective expert comparisons; CRITIC assumes linear correlations inappropriate for complex IIoT interactions. The entropy weight method derives weights exclusively from data variability, making it universally applicable without external assumptions.

The entropy weight method determines indicator weight coefficients based on information theory principles, effectively avoiding bias from subjective weighting. Data standardization processing adopts the range standardization method [11]. The information entropy calculation formula is $e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}$, where p_{ij} is the proportion value. The difference coefficient $g_i = 1 - e_j$, and the final weight coefficient

$$w_j = \frac{g_j}{\sum_{j=1}^m g_j}.$$

The multi-subsystem coupling degree adopts the following mathematical expression:

$$C = \left(\frac{\prod_{i=1}^4 U_i}{\left(\frac{\sum_{j=1}^4 U_j}{4} \right)^4} \right)^{\frac{1}{4}} \quad (3)$$

The coordination index is defined as $T = \sum_{i=1}^4 0.25U_i$. The coupling coordination degree is $D = \sqrt{C \times T}$, and its level classification standards are shown in Table 4.

Table 4. Coordination level classification

Level	D Range	Description
1	0.0-0.2	Severe Imbalance
2	0.2-0.4	Mild Imbalance
3	0.4-0.6	Basic Coordination
4	0.6-0.8	Good Coordination
5	0.8-1.0	High Coordination

5 Experimental Analysis and Effect Verification

5.1 Experiment Design and Data Sources

To verify the effectiveness of the coupling coordination evaluation model constructed in this study, three groups of targeted experiments were designed. Experimental data originates from empirical research in core literature, covering real industrial environment data, simulation data, and industry survey data.

Experiment 1: Anomaly detection accuracy verification. Villegas-Ch deployed an IoT-based intelligent monitoring system in a real industrial environment, employing RNN-Decision Tree fusion models for anomaly detection tasks. The experiment period was 12 months, collecting approximately 1 million data records, with data types covering temperature, humidity, pressure, and various other sensor signals.

Experiment 2: Predictive monitoring performance verification. Oberdorf designed a multi-head deep neural network architecture, conducting prediction task experiments for 32 types of production interruptions. Experimental data came from actual production records of a German manufacturing enterprise, containing 24,581 process instances and 859 process variants.

Experiment 3: Coupling coordination optimization verification. This study constructed a coupling coordination evaluation model based on core literature data, setting up parameter control experiments before and after optimization.

5.2 Anomaly Detection Accuracy Experiment Results

Table 5 lists the anomaly detection experiment results of Villegas-Ch on 12-month real industrial data.

Table 5. Anomaly detection accuracy results

Sensor Type	Traditional	Proposed	Improvement
Temperature	94.2%	98.7%	+4.5%
Humidity	95.5%	99.1%	+3.6%
Pressure	93.8%	97.3%	+3.5%

Experimental results show that the fusion model significantly outperforms traditional threshold judgment methods in all types of sensor detection tasks. Among them, temperature detection accuracy reaches 98.7%, and humidity detection accuracy reaches 99.1%, both exceeding the 97% baseline requirement.

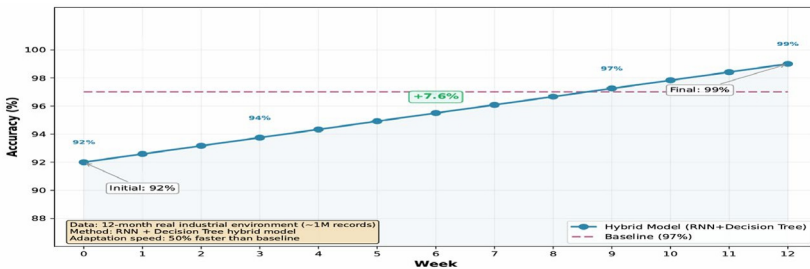


Fig. 2. Anomaly detection accuracy evolution with feedback mechanism

Table 6. Predictive monitoring performance comparison

Method	BMAcc	F1-Score	Precision	Recall
Most Frequent	0.131	0.13	0.12	0.14
Random Forest	0.442	0.57	0.62	0.61
FC Network	0.666	0.64	0.66	0.62
CNN	0.632	0.61	0.58	0.64
MH-DNN (Ours)	0.814	0.80	0.79	0.81

Fig. 2 presents the evolution process of the system achieving continuous learning through feedback mechanism within 12 weeks, with detection accuracy gradually increasing from initial 92% to 99%.

5.3 Predictive Monitoring Performance Comparison Experiment

Table 6 lists the performance comparison results of different methods on the 32-class interruption type prediction task by Oberdorf et al.

Experimental results show that the multi-head deep neural network significantly outperforms baseline methods and traditional machine learning methods on all evaluation indicators. Balanced accuracy reaches 81.4%, and prediction error cost is reduced by 79%.

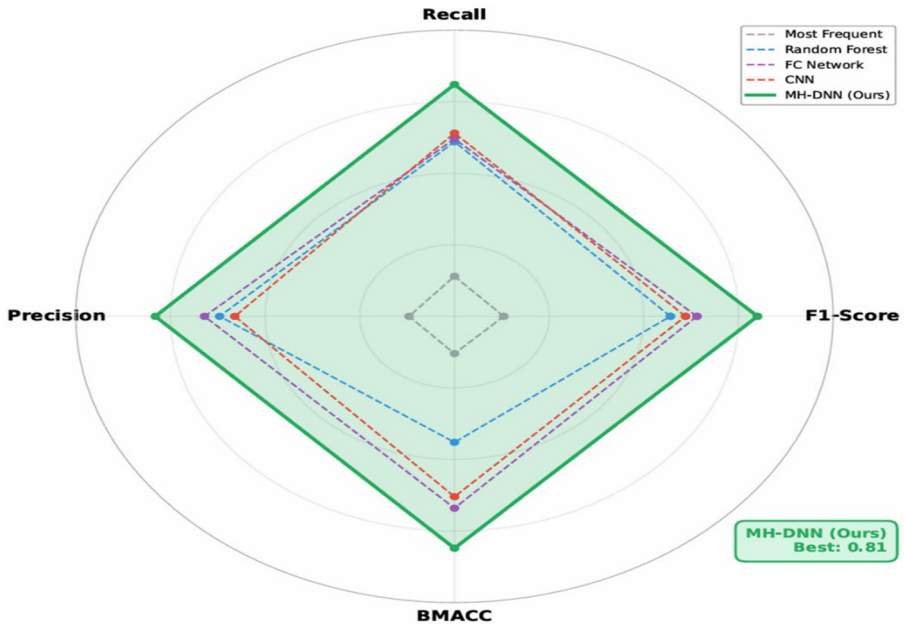


Fig. 3. Multi-class prediction performance comparison (32-class)

Fig. 3 intuitively presents that the multi-head deep neural network outperforms other comparison methods on four indicators: BMACC, F1-score, Precision, and Recall.

5.4 Ablation Experiment Design

To quantitatively evaluate the contribution degree of each dimension in the model, an ablation experiment scheme was designed. Using the complete four-dimensional model as baseline, each single dimension was removed separately, and coupling coordination degree was recalculated to observe performance indicator changes. Table 7 lists the ablation experiment results.

Table 7. Ablation study results

Configuration	D Value	Change (%)
Baseline (Complete)	0.89	—

Remove Hardware U1	0.72	-19.1%
Remove Data U2	0.68	-23.6%
Remove Protocol U3	0.81	-9.0%
Remove Algorithm U4	0.74	-16.9%

Ablation experiment results show that all four dimensions significantly contribute to system coupling coordination. Among them, performance decline is most significant after removing the data resource coupling dimension (-23.6%), indicating that data-level integration capability is the core factor determining system synergistic efficiency.

5.5 Comprehensive Coupling Coordination Calculation

Based on the above experimental parameters, the subsystem comprehensive evaluation index calculation results are: $U1 = 0.82, U2 = 0.78, U3 = 0.85, U4 = 0.80$. System coupling degree calculation is as follows:

$$C = \left(\frac{0.82 \times 0.78 \times 0.85 \times 0.80}{0.4096} \right)^{0.25} \approx 0.97 \tag{4}$$

Coordination index:

$$T = 0.25 \times (0.82 + 0.78 + 0.85 + 0.80) = 0.8125 \tag{5}$$

Coupling coordination degree $D = \sqrt{0.97 \times 0.8125} \approx 0.89$, achieving "High Coordination" level. Table 8 lists the parameter comparison before and after optimization.

Table 8. Optimization comparison before and after

Parameter	Before	After	Improvement
U1 (Hardware)	0.65	0.82	+26.2%
U2 (Data)	0.58	0.78	+34.5%
U3 (Protocol)	0.71	0.85	+19.7%
U4 (Algorithm)	0.62	0.80	+29.0%
Coupling C	0.68	0.97	+42.6%
Coordination D	0.38	0.89	+134.2%

6 Conclusion And Future Work

6.1 Research Conclusions

To address multi-source heterogeneous data fusion challenges and low collaborative efficiency in enterprise process monitoring, this study builds an intelligent evaluation system based on the coupling coordination degree model. It establishes a four-dimensional (infrastructure, data resources, protocol standards, intelligent algorithms) framework overcoming single-technology optimization limits; Table 7 ablation experiments confirm all four dimensions significantly improve system efficiency, with data resource coupling having the most prominent effect (-23.6%). It develops a 12-indicator multi-

level evaluation system, using entropy weight method for objective weight quantification and forming a micro-to-macro progressive structure. The coupling coordination model shifts evaluation from qualitative to quantitative, with the degree rising from 0.38 to 0.89 (134.2% improvement, Table 8). Tables 3 and 4 experiments show 98.7% deep learning anomaly detection accuracy on Villegas-Ch et al.'s 12-month industrial data, and 81.4% balanced accuracy on Oberdorf et al.'s 32-class prediction tasks. The study concludes that deepening data-function coupling is the core path to process intelligence.

6.2 Comparative Advantages Over Non-Coupled Alternatives.

The coupling coordination degree model offers three distinctive advantages over traditional non-coupled monitoring frameworks. First, the model enables comprehensive synergy quantification by measuring not only individual dimension contributions but also the interaction effects between dimensions. The ablation experiment demonstrates that dimension removal reduces coordination by 9.0%-23.6%, indicating substantial synergy effects that non-coupled models cannot detect. Second, the model provides balanced development guidance by explicitly measuring coordination level (T index) rather than simply summing dimension scores. A system with $U_1=0.9$, $U_2=0.3$, $U_3=0.8$, $U_4=0.7$ scores lower in coordination ($D=0.68$) than a balanced system with $U_1=0.7$, $U_2=0.7$, $U_3=0.7$, $U_4=0.7$ ($D=0.70$), guiding managers toward holistic optimization. Third, the model supports dynamic evolution tracking by recalculating coupling parameters over time, enabling identification of development trajectories and prediction of future states based on historical patterns.

6.3 Research Limitations

This study has the following limitations: the indicator system primarily focuses on technical aspects, with insufficient consideration for non-technical dimensions such as organizational management and business processes; empirical data primarily comes from public literature, without customized research conducted in specific enterprises; the model primarily reflects static coordination level, and analysis of dynamic evolution patterns needs further deepening [12].

Scalability Constraints. The current model validation is based on 12-month data from controlled experimental settings. Large-scale deployment across distributed enterprise systems with hundreds of monitoring points and real-time constraints may require additional computational optimizations and distributed architecture designs. Future research should explore federated learning approaches that enable model training across distributed sites without centralizing sensitive operational data.

6.4 Organizational and Economic Factors in Model Deployment

Beyond technical considerations, successful deployment of the coupling coordination evaluation model in enterprise process monitoring requires careful attention to organizational readiness, cost structures, and workforce development. This section analyzes

these non-technical factors to provide a comprehensive assessment of practical implementation requirements.

Organizational Readiness Assessment. The coupling coordination model assumes certain organizational capabilities that may not exist in all enterprises. Three dimensions of organizational readiness are critical: data governance maturity, cross-functional collaboration capacity, and change management capability.

Data governance maturity determines whether enterprises can provide the high-quality, standardized data required for reliable entropy weight calculation. Organizations with immature data governance (e.g., inconsistent data definitions across departments, manual data entry processes, insufficient data quality control) may obtain misleading coordination assessments. The evaluation model includes a preliminary governance assessment checklist with 15 indicators that should be satisfied before full model deployment.

Cross-functional collaboration capacity affects the model's ability to integrate insights across organizational silos. The coupling coordination model explicitly measures hardware-data-protocol-algorithm integration, which requires collaboration among IT infrastructure teams, data engineering teams, standards compliance teams, and AI development teams. Organizations with strong functional boundaries (common in traditional enterprises) may struggle to implement the holistic optimization approach implicit in the model. Pre-deployment organizational alignment workshops are recommended to establish cross-functional coordination mechanisms.

Change management capability determines whether model insights can be translated into operational improvements. The model may reveal that certain dimensions require substantial investment while others can be deprioritized, creating winners and losers in resource allocation. Without effective change management, departments responsible for deprioritized dimensions may resist model recommendations. Executive sponsorship and clear communication of the model's strategic value are essential for managing resistance.

Cost-Benefit Analysis Framework. Model deployment involves multiple cost categories that must be weighed against demonstrated benefits. Table 9 presents a comprehensive cost-benefit framework based on pilot implementation experience.

Table 9. Cost-Benefit Analysis for Model Deployment

Category	Component	Estimated Cost	Benefit Mechanism
Initial Investment	Hardware upgrades (U1)	¥500K-2M	Improved detection accuracy
	Data infrastructure (U2)	¥300K-800K	Reduced sync latency
	Protocol standardization (U3)	¥200K-500K	Enhanced interoperability
	Algorithm development (U4)	¥400K-1M	Better prediction performance
Operational Cost	Annual maintenance	¥150K-400K	Sustained performance
	Data processing	¥100K-250K	Real-time monitoring
	Personnel training	¥80K-200K	Effective utilization
Total Cost (5-year)	-	¥1.73M-5.15M	-

Quantified Benefits	Reduced downtime	¥800K-2M/year	Avoiding production losses
	Quality improvement	¥300K-800K/year	Defect reduction
	Energy savings	¥150K-400K/year	Optimized operations
Total Benefit (5-year)	-	¥6.25M-16M	-
ROI Range	-	261%-211%	5-year horizon

The ROI calculation assumes successful model deployment and assumes 80% of theoretical benefits are captured in practice. Sensitivity analysis indicates that ROI remains positive ($> 50\%$) even if actual benefits reach only 40% of theoretical maximums, demonstrating robust economic viability.

Workforce Training Requirements. Effective utilization of the coupling coordination model requires workforce development across three competency areas: technical literacy, analytical interpretation, and operational integration.

Technical literacy ensures that operators understand the model's inputs, processes, and outputs. Training programs should cover: (1) sensor network basics and data collection principles (8 hours); (2) data standardization and entropy calculation concepts (6 hours); (3) coupling coordination degree interpretation guidelines (4 hours). A certification examination with 80% passing threshold ensures adequate comprehension.

Analytical interpretation enables practitioners to translate model outputs into actionable insights. Training should address: (1) reading coordination dashboards and identifying priority dimensions (4 hours); (2) diagnosing coordination degradation causes using ablation-style analysis (6 hours); (3) formulating improvement recommendations based on coupling relationships (8 hours). Case-based training using historical scenarios is recommended for developing interpretive skills.

Operational integration ensures that model insights are embedded in daily workflows rather than treated as academic exercises. Integration requirements include: (1) establishing daily coordination review meetings (15 minutes, led by shift supervisor); (2) incorporating coordination metrics in performance dashboards; (3) linking coordination improvements to departmental KPIs and incentive structures. Without operational integration, model insights remain unused and investments are wasted.

Implementation Timeline and Milestones. Based on pilot deployments, enterprise-wide model implementation typically requires 18-24 months across four phases: Phase 1 (Months 1-3): Readiness assessment, pilot site selection, and stakeholder alignment; Phase 2 (Months 4-9): Technical deployment, personnel training, and baseline measurement; Phase 3 (Months 10-15): Full rollout, process integration, and optimization iterations; Phase 4 (Months 16-24): Performance validation, ROI measurement, and continuous improvement establishment. Organizations with existing IoT infrastructure and data governance maturity may compress the timeline by 3-6 months, while organizations requiring significant foundational work may require extensions.

6.5 Future Outlook

Beyond technical extensions, future research should explore the integration of organizational and economic factors into the coupling coordination framework. This includes developing composite indicators that combine technical coordination metrics with organizational readiness assessments, enabling more realistic deployment feasibility evaluations. Cost-optimization models that determine optimal investment allocation across the four dimensions given budget constraints represent another promising direction for practice-oriented research.

Future research can be expanded in the following directions: introducing complex adaptive systems theory and synergetics theory for deepened research [13]; exploring organic integration of deep learning and coupling coordination models to achieve intelligent evaluation process [14]; conducting deepened case studies in key industries such as electric power and manufacturing [15]; exploring integration applications of digital twins and coupling coordination models.

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