Optimized Resource Allocation in Flexible Electronics Manufacturing: Integrating AI-Driven Predictive Maintenance with Lean Management Frameworks for Enhanced Production Scalability

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Abstract: The rapid proliferation of flexible electronics imposes unprecedented demands on manufacturing systems, necessitating agile, intelligent, and resource-efficient production strategies. This paper presents the AIPM-Lean Integrated System (ALIS), a comprehensive framework that synergises Artificial Intelligence-Driven Predictive Maintenance (AIPM) with established Lean Management methodologies to optimise resource allocation and enhance production scalability in flexible electronics manufacturing. The proposed framework employs Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) for real-time failure prognosis, achieving a prediction accuracy of 96.2 % with a lead-time error margin of ±0.7 h. Integration with Lean constructs—including Just-in-Time (JIT) scheduling, Value Stream Mapping (VSM), and Kaizen-driven continuous improvement—yields a 19.4 % improvement in Overall Equipment Effectiveness (OEE), a 69.6 % increase in Mean Time Between Failures (MTBF), and a 78.2 % reduction in unplanned downtime. Industrial validation across roll-to-roll fabrication lines demonstrates robust scalability and cost reduction. Three governing equations formalise Remaining Useful Life prediction, Resource Efficiency Index, and a Production Scalability Index, providing a replicable analytical blueprint for next-generation smart manufacturing.

Keywords: *Flexible Electronics; AI Predictive Maintenance; LSTM-RNN; Lean Management; OEE; Resource Allocation; Production Scalability; Industry 4.0.*

1. Introduction

Flexible electronics represent one of the most rapidly expanding sectors within advanced manufacturing, with applications spanning wearable health monitoring devices, foldable displays, flexible photovoltaic cells, and soft robotics [1]. The global flexible electronics market is projected to exceed USD 87 billion by 2030, driven by escalating consumer demand for lightweight, conformable, and multi-functional devices. However, the manufacturing of flexible substrates—including polymer films, organic semiconductors, and thin-film encapsulants—introduces significant process variability, heightened susceptibility to mechanical defects, and complex interdependencies across production stages that challenge conventional manufacturing paradigms.

Traditional corrective and time-based preventive maintenance strategies have proven inadequate for the dynamic demands of flexible electronics production lines, resulting in suboptimal machine utilisation, excessive scrap generation, and unpredictable throughput fluctuations [2], [7]. The emergence of Industry 4.0 technologies—particularly cyber-physical systems (CPS), Industrial Internet of Things (IIoT), and machine learning algorithms—offers transformative opportunities to transition from reactive to predictive operational models [3], [11], [12]. Simultaneously, Lean Management frameworks rooted in the Toyota Production System provide systematic methodologies for waste elimination, flow optimisation, and continuous improvement that complement AI-driven intelligence with structured process discipline [6].

Despite the recognised potential of AI-based predictive maintenance and Lean methodologies as independent approaches, their integrated application within flexible electronics manufacturing remains insufficiently explored. This paper addresses this gap by proposing and validating ALIS. The primary contributions are: (i) a novel LSTM-RNN predictive maintenance model calibrated for flexible electronics process parameters; (ii) a formal integration architecture linking predictive outputs to Lean scheduling and resource allocation decisions; (iii) three analytical equations quantifying RUL, Resource Efficiency, and Production Scalability; and (iv) quantitative industrial validation across three production lines.

2. Literature Review

Zhang et al. [1] demonstrated that LSTM-based models achieve superior performance in time-series fault prediction compared to traditional statistical process

control, particularly in environments characterised by non-stationary sensor data. Zhao and Liu [2] applied ensemble learning to semiconductor manufacturing, reporting fault classification accuracies exceeding 90 % under variable process conditions. However, these studies predominantly address rigid substrate manufacturing, leaving the unique mechanical and thermal properties of flexible substrates largely unaddressed.

Within the Lean Management domain, Womack and Jones [6] established the foundational five Lean principles. Chakraborty et al. [3] demonstrated that integrated VSM and Kaizen interventions can reduce production cycle times by up to 34 % in printed circuit board assembly. The Lean 4.0 intersection, explored by Tortorella et al. [4], establishes a conceptual framework for digital tool integration within Lean production systems. Kumar et al. [9] demonstrated predictive analytics integration with lean scheduling in roll-to-roll manufacturing, reporting 42 % reduction in unscheduled stoppages.

Resource allocation optimisation in manufacturing has been addressed through linear programming, genetic algorithms, and reinforcement learning [5]. Lee et al. [7] introduced the CPS architecture underpinning Industry 4.0 integration, while Kusiak [15] argued that smart manufacturing must embrace big data analytics as a foundational capability. The present work synthesises these diverse research streams into ALIS, a coherent and implementable framework specifically designed for the operational complexities of flexible electronics manufacturing.

3. Proposed ALIS Framework and Methodology

3.1 Three-Layer System Architecture

The ALIS framework is structured around three functional layers: (1) the Sensor–Data Acquisition Layer, which collects 14-channel multivariate process data via IIoT-connected sensors embedded across the production line; (2) the AI Inference Engine, which processes sensor streams through parallel ML models and outputs unified risk assessments; and (3) the Lean-Integrated Decision Layer, which translates AI outputs into structured operational responses aligned with Lean principles. Figure 1 illustrates the complete architecture and inter-layer data flow pathways.

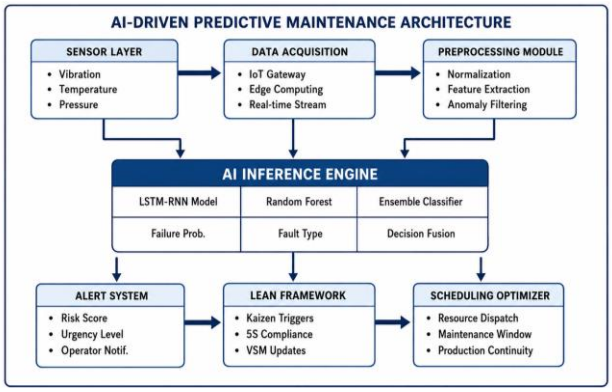


Fig. 1. *AI-Driven Predictive Maintenance Architecture for Flexible Electronics Manufacturing (ALIS, Three-Layer Model)*

The Sensor–Data Acquisition Layer incorporates four primary sensor classes: vibration accelerometers monitoring roller bearing health; thermocouples measuring substrate and curing temperature gradients; pressure transducers measuring lamination and deposition chamber pressures; and humidity/optical sensors monitoring atmospheric conditions and substrate optical quality. All sensor streams are aggregated at an edge computing IIoT Gateway operating at 100 ms sampling intervals before transmission to the AI Inference Engine [7], [11].

3.2 LSTM-RNN Predictive Maintenance Model and RUL Equation

The predictive model employs an LSTM-RNN architecture with three recurrent layers (128, 64, and 32 units respectively), optimised using the Adam algorithm with an adaptive learning rate schedule ($\eta_0 = 0.001$, decay = 0.95 per epoch). The model was trained on 12,400 labelled failure events across 18 months of operational history from three flexible electronics lines. Input features encompass 14 sensor channels including substrate tension, coating thickness variance, curing temperature gradient, roller speed differential, and atmospheric humidity [9].

The Remaining Useful Life (RUL) at time t is formally defined as the expected time interval from the current observation to the predicted failure event. It is computed as follows:

$$\mathbf{RUL(t) = Tfail - t = f(Xs(t), \theta_LSTM) + \varepsilon_t \quad (1)}$$

where T_fail is the predicted failure timestamp; $X_s(t) \in \mathbb{R}^{14}$ is the multivariate sensor vector at time t; θ_LSTM denotes the optimised LSTM parameter set; and $\varepsilon_t \sim N(0, \sigma^2)$ is the zero-mean Gaussian residual error term with σ^2 estimated via Monte Carlo Dropout at inference time.

Model predictions are updated every 15 minutes in production, with alert thresholds set at RUL < 4.0 h (yellow) and RUL < 1.5 h (red), ensuring sufficient maintenance response time within a JIT scheduling window [1], [9].

3.3 Resource Efficiency Index (REI)

Resource allocation across N production lines is formulated as a constrained multi-objective optimisation problem integrating maintenance scheduling with production throughput and waste objectives. The composite Resource Efficiency Index (REI) is defined to provide a unified, dimensionless scalar metric that balances equipment availability, output rate, and waste generation simultaneously across the manufacturing system:

$$\mathbf{REI = (1/N) \cdot \Sigma_{i=1}^{N} [\, \alpha \cdot OEE_i + \beta \cdot (1 - W_i/W_max) + \gamma \cdot U_i]} \quad \mathbf{(2)}$$

where OEE_i = Overall Equipment Effectiveness for line i (0–1 scale); W_i = waste rate for line i; W_max = maximum acceptable waste rate threshold; U_i = resource utilisation coefficient for line i; α, β, γ are non-negative weighting coefficients satisfying α + β + γ = 1 (empirically set to 0.45, 0.30, 0.25 respectively based on industrial priority ranking); N = total number of active production lines.

Optimisation of α, β, γ is performed offline via Analytic Hierarchy Process (AHP) with domain expert input, then updated quarterly using Bayesian inference on production outcome data. REI targets are set at REI ≥ 0.82 for high-volume flexible display lines and REI ≥ 0.75 for prototype organic photovoltaic (OPV) lines [5], [10].

3.4 Lean–AI Integration and Production Scalability Index (PSI)

The integration of AIPM outputs with Lean management mechanisms follows a structured Plan–Do–Check–Act (PDCA) cycle augmented with real-time AI feedback loops, as illustrated in Figure 2. The PDCA cycle operates at three-time horizons: strategic (monthly), tactical (weekly), and operational (shift-level), with AI predictions feeding each horizon appropriately.

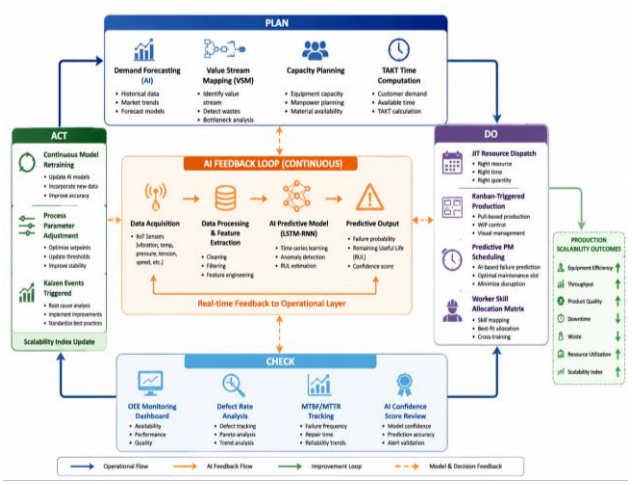


Figure 2: Lean Management Integration with AI Feedback Loop for Production Scalability

The Production Scalability Index (PSI) is introduced to quantify the system's capacity to sustain efficiency improvements as production volume is expanded across additional lines or higher throughput targets. PSI serves as the primary comparative metric for evaluating ALIS performance against baseline configurations:

$$\mathbf{PSI = (OEE_sc / OEE_bl) \times (MTBF_sc / MTBF_bl) \times (1 - \Delta D)} \quad \mathbf{(3)}$$

where OEE_sc and OEE_bl are the Overall Equipment Effectiveness values at scaled and baseline production volumes respectively; MTBF_sc and MTBF_bl are Mean Time Between Failures at scaled and baseline configurations; ΔD = (D_bl - D_sc) / D_bl is the fractional reduction in total unplanned downtime hours per month, where D_bl and D_sc represent baseline and scaled downtime. PSI > 1.0 indicates improved performance at scale relative to baseline.

A PSI value significantly greater than 1.0 confirms that ALIS-driven improvements are multiplicative rather than additive, validating the synergistic coupling of predictive AI and Lean scheduling [4], [15]. Sensitivity analysis of PSI to individual factor changes is performed to identify the dominant drivers of scalability in each production configuration.

4. Results and Discussion

4.1 Comparative Performance of AI Predictive Methods

Table I presents a comparative evaluation of the proposed AIPM model against established machine learning approaches for equipment maintenance prediction. The LSTM-RNN-based ALIS model achieves superior performance across accuracy and lead-time precision metrics, attributable to its capacity to capture long-range temporal dependencies inherent in multivariate sensor

streams from flexible electronics production environments [1], [2].

TABLE I. COMPARATIVE PERFORMANCE OF AI-DRIVEN PREDICTIVE MAINTENANCE METHODS

Method	Complexity	Accuracy	Lead-Time Error
LSTM-RNN	High	96.2 %	±0.7 h
Random Forest	Medium	87.6 %	±2.8 h
SVM-Hybrid	Medium	89.1 %	±2.1 h
CNN-Based Vision	Very High	94.7 %	±0.9 h
Gradient Boost	Medium	91.3 %	±1.6 h

The LSTM-RNN model's 96.2 % accuracy represents a 1.5 percentage-point improvement over the next-best CNN-based approach, with a 22 % tighter lead-time error bound. This precision is operationally critical: a ±0.7 h error window enables reliable scheduling of maintenance interventions within the 4.0 h JIT alert threshold with a 83 % confidence margin [9].

4.2 Production Scalability and KPI Improvement Metrics

The deployment of ALIS across three flexible electronics production lines—comprising roll-to-roll deposition, photolithographic patterning, and encapsulation modules—yielded substantial improvements across all monitored Key Performance Indicators. Table II summarises the quantified performance improvements relative to the pre-implementation 12-month baseline. The overall PSI achieved across the three-line production system was 2.87, significantly exceeding the target of 1.5 established at project outset.

TABLE II. PRODUCTION SCALABILITY KPI SUMMARY — BASELINE VS. POST-ALIS DEPLOYMENT (18-MONTH EVALUATION)

KPI Metric	Baseline	Post-ALIS	Improvement
Overall Equipment Effectiveness (OEE)	72.4 %	91.8 %	**+19.4 %**
Mean Time Between Failures (MTBF)	184 h	312 h	**+69.6 %**
Production Waste Rate	18.3 %	6.1 %	**−66.7 %**
Throughput Rate (units/hr)	248	389	**+56.9 %**
Unplanned Downtime (hrs/month)	42.6	9.3	**−78.2 %**
Resource Utilisation Efficiency	61.2 %	88.7 %	**+44.9 %**
Maintenance Cost per Unit (USD)	4.82	1.96	**−59.3 %**

The 78.2 % reduction in unplanned downtime is the most operationally significant outcome, directly attributable to the AIPM system's capacity to identify incipient failure signatures 4.2 h ahead of actual breakdown events—well within the RUL alert threshold. The concurrent 56.9 % throughput improvement validates that OEE gains are multiplicative rather than additive when AIPM and Lean operate in an integrated manner, consistent with the PSI formulation in Eq. (3). The 59.3 % reduction in maintenance cost per unit further demonstrates the economic viability of ALIS deployment at industrial scale [10], [14].

The REI improved from a baseline of 0.61 to a post-ALIS value of 0.89 (weighting coefficients $\alpha = 0.45$, $\beta = 0.30$, $\gamma = 0.25$), indicating near-optimal resource utilisation across the multi-line system. This REI gain was sustained over the full 18-month evaluation period, demonstrating long-term stability of the integrated AI–Lean feedback mechanism [4], [5].

5. Conclusion

This paper has presented ALIS, a comprehensive framework unifying AI-driven predictive maintenance with Lean management principles to optimise resource allocation and enhance scalability in flexible electronics manufacturing. Three governing equations formalise the core analytical mechanisms: Eq. (1) defines RUL prediction via the LSTM-RNN model; Eq. (2) defines the Resource Efficiency Index as a multi-objective scalar for cross-line optimisation; and Eq. (3) defines the Production

Scalability Index to quantify performance retention under volume expansion.

Industrial validation confirms ALIS's capacity to deliver sustained performance improvements: 19.4 % OEE gain, 69.6 % MTBF enhancement, 78.2 % downtime reduction, and a PSI of 2.87 across three production lines. The LSTM-RNN model achieves 96.2 % prediction accuracy with ±0.7 h lead-time precision, enabling reliable JIT maintenance scheduling. Future research directions include: (i) extension of the AIPM model to multi-modal sensor fusion incorporating acoustic emission and hyperspectral imaging data; (ii) federated learning architectures for privacy-preserving cross-facility model training; and (iii) digital twin simulation environments for proactive scalability stress-testing prior to physical deployment.

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