The CHINMAY (Condition-Based Health Intelligence for Neural Monitoring and Analytics Yield) Framework in Predictive Maintenance with TOEE–MOEE Metrics

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Received: 10 December 2025 | Revised: 6 January 2026 and 12 January 2026 | Accepted: 14 January 2026

 DOI: https://doi.org/10.48084/etasr.16855

ABSTRACT

Modern-day industrial environments impose significant pressure on manufacturers to ensure product quality, minimize unforeseen breakdowns, and maintain continuous control over key performance indicators. These requirements have driven industries toward more advanced operational and maintenance strategies. In this context, Overall Equipment Effectiveness (OEE) has emerged as a widely adopted metric for assessing manufacturing efficiency. However, conventional OEE primarily provides a retrospective evaluation based on availability, speed, and defect-free output, offering limited insights into the underlying machine health and operational dynamics. This limitation becomes particularly critical in plastic extrusion plants, where operating conditions can vary rapidly, and nominal operation may abruptly transition into degradation without visible external symptoms. To address these challenges, the present study introduces the Condition-based Health Intelligence to Neural Monitoring and Analytics Yield (CHINMAY) framework as a novel, predictive extension of traditional OEE. Conceptualized as a cognitively enhanced framework, CHINMAY incorporates additional contextual dimensions, including machine functional health and stakeholder-driven operational requirements. The framework integrates machine learning and deep learning models to enable proactive diagnostics and early anomaly detection, thereby reducing unexpected disruptions and improving operational continuity. The proposed approach is validated using real-time experimental data obtained from a Plastic Extrusion Machine (EX06), demonstrating its applicability in an actual industrial environment. Through this implementation, the study aims to move beyond episodic and reactive evaluation practices toward a comprehensive Predictive Maintenance (PdM) paradigm. The CHINMAY framework facilitates early detection of equipment anomalies, leading to reduced material wastage and enhanced system reliability. Overall, CHINMAY allows transitioning from conventional reactive maintenance approaches to intelligent, proactive, and sustainable smart manufacturing practices.

Keywords-CHINMAY (Condition-Based Health Intelligence for Neural Monitoring and Analytics Yield); TOEE (Traditional OEE); MOEE (Modified OEE); POEE (Predictive OEE); Data Driven Decision Making Structure

I. INTRODUCTION

In today's highly competitive industrial environment, organizations increasingly rely on automation enabled by the Internet of Things (IoT), integrated digital platforms, and data-driven decision-making. These technologies play a critical role in sustaining operational efficiency, improving productivity, and maintaining global competitiveness. As manufacturing systems become more complex, expectations related to product quality and operational performance continue to rise. Industries are required to deliver consistent output, reduce production throughput time, minimize lead times and downtimes, and maximize resource utilization. Such stringent requirements have compelled organizations to transition from conventional reactive maintenance strategies toward predictive, intelligent, and data-driven approaches [1]. This transition aligns with the broader objectives of smart manufacturing under the Industry 4.0 paradigm.

The most common indicator of the manufacturing performance is Overall Equipment Effectiveness (OEE) [2-4]. OEE is based on the principles derived through Total Productive Maintenance (TPM) and oriented towards availability, performance, and quality [5]. However, OEE is mostly a retrospective and descriptive indicator that provides weak predictive potential regarding future equipment performance or the emergence of process anomalies [6, 7].

Research more often connects OEE with Maintenance 4.0, Industry 4.0, and smart manufacturing [1], and the broader digital transformation activities found in manufacturing [2]. Traditional OEE calculations, their combination with Lean/TPM methodologies, and case-based assessments have been thoroughly reported [8], whereas studies on real-time OEE monitoring, AI-based improvements, and digitalization are comparatively limited [9]. This gap highlights the inadequacy of analytical frameworks capable of unifying performance measurement and Predictive Maintenance (PdM).

Existing OEE models lack analytical sophistication for modern industrial settings. They fail to capture dynamic loss patterns, rapid product variation, and digital transformation requirements [10, 16]. Implementing PdM also faces significant organizational and technological constraints, including the cost of infrastructure, data complexity, and resistance to automation-driven maintenance innovations [11]. Extrusion-based production datasets, in particular, tend to be rough, sparse, noisy, and unsuitable for direct use with machine learning algorithms without significant preprocessing and feature engineering [12]. Overall, the literature indicates a transition from descriptive performance monitoring toward predictive and prescriptive analytics, and from manual judgment toward intelligent, automated decision-making [14].

In response to these challenges, the present study introduces the Condition-based Health Intelligence to Neural Monitoring and Analytics Yield (CHINMAY) framework. CHINMAY is a data-driven extension of traditional OEE, designed to support intelligent monitoring and predictive performance evaluation. The framework enhances the conventional OEE structure by incorporating situational indicators such as operational readiness and variations in demand. Furthermore, CHINMAY employs machine learning and deep learning techniques to forecast machine-related faults, downtime occurrences, and efficiency deviations [3, 13]. The CHINMAY framework is developed both conceptually and mathematically and is validated using real operational data obtained from an actively running plastic extrusion plant.

II. MATERIALS AND METHODS

The proposed strategy combines real-time data collection, a sophisticated formulation of OEE, PdM modeling, deep-learning-based prediction, and decision-support analytics. Based on this, the co-created framework aligns with modern smart-manufacturing practices and the objectives of Maintenance 4.0 [12, 13, 17, 18].

The dataset used in this study is sourced from Radhan Plastics, a manufacturing company located in Pirangut, Pune, India. The company specializes in plastic extrusion products such as films, tubing, and packaging materials. The dataset consists of real-time industrial data with the following characteristics:

- Data Type: Time-series sensor and production data
- Primary Source: Temperature sensors (RTD – Pt100) and proximity sensors
- Sampling Rate: 1 Hz
- Duration: Approximately 3 months
- Dataset Size: 263,146 rows
- Number of Sensors: 4 temperature sensors

The dataset includes three major categories.

- Sensor data:
  - Continuous temperature monitoring (range: –200°C to 850°C capability)
  - Used to detect machine states (normal, warning, critical)
- Production and Machine Data:
  - Roller count, output quantity, waste generation
  - Machine status (running, loaded, completed)
- Operational Data:
  - Shift timings and durations
  - Planned and unplanned downtime
  - Customer demand and cycle time

Additionally, the dataset incorporates event-based logs with timestamps capturing machine activity, enabling time-based analysis such as shift efficiency and downtime evaluation.

The data were stored in CSV format and further processed using MATLAB for analysis, feature extraction, and MOEE computation.

This dataset is unique in that it represents real-time industrial conditions, rather than simulated or publicly available benchmark datasets, thereby enhancing the practical relevance and applicability of the proposed MOEE framework.

The conceptual architecture of the proposed CHINMAY framework (Figure 1) depicts how the data were taken and, through system engineering processes, converted into equipment-related status. The primary source of data in this investigation is the Plastic Extrusion Machine (EX-06), chosen for its continuous operation, sensitivity to changing process parameters, and strong industrial applicability [19]. The information collected includes real-time machine logs, production counts, downtime entries, event timestamps, temperatures, and quality outputs, forming a dataset for productivity assessment, machine health tracking, and predictive failure modeling, emphasizing the importance of sensor-based analytics in modern manufacturing [20].

The CHINMAY information framework initiates by getting data from a plastic extruder machine. Then, it selects the most useful features (operational parameters (shift duration, operating time, running time), downtime variables (planned and unplanned downtime), production-related variables (number of rollers, good rollers, waste), process parameters (ideal cycle time, total output), customer demand, and temperature data), creates a target variable, and cleans and merges the data (utilizing techniques such as missing value labeling, threshold-based outlier detection, invalid row removal, and dataset merging.). After feature selection, the framework is divided into two parts: OEE and PdM. At first, a calculation of the whole OEE is conducted, and a predictive model is made. The PdM part divides the time series data, selects a model, and adjusts the settings of the model to identify what the issues are, and predict when something will fail. Finally, useful results, such as the chance of failure, trends in OEE, and alerts for maintenance, are all outputted from the framework.

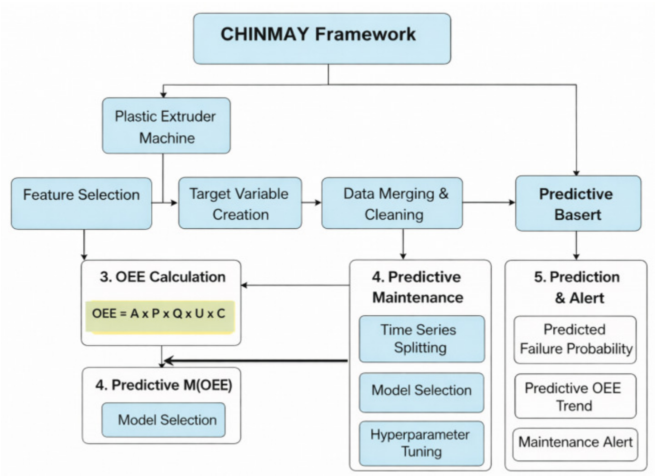

Fig. 1. The CHINMAY framework.

Figure 2 shows the Part A-OEE workflow, where data preprocessing begins after acquiring raw extruder data. The obtained dataset is often inconsistent, noisy, incomplete, and heterogeneous, an issue well reported in industrial data research [21]. To address these challenges, the preprocessing phase includes:

- Selecting relevant machine parameters contributing to machine-warning prediction.
- Merging datasets, aligning timestamps, and standardizing formats.
- Treating missing values using forward-fill and interpolation.
- Scaling and outlier correction.

These steps convert unstructured raw logs into structured data suitable for OEE computation and ML model development.

Figure 3 demonstrates that after preprocessing, OEE is calculated in an extended manner, integrating Availability (A), Performance (P), Quality (Q), Usability (U), and Customer demand (C). This enhanced structure remedies several limitations of traditional OEE [22].

$$POEE = A * P * Q * U * C \tag{1}$$

The resultant OEE metric is computed using MATLAB R2023b [23] to automate plant-level dashboards and ensure efficient monitoring of operational indicators [1].

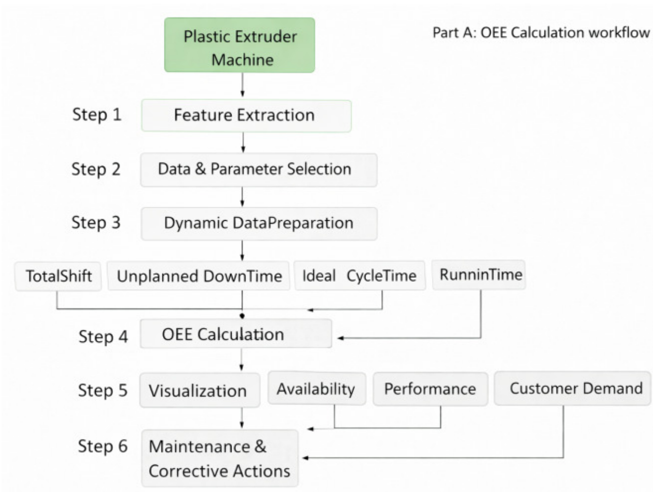

Fig. 2. Part A - OEE calculation workflow.

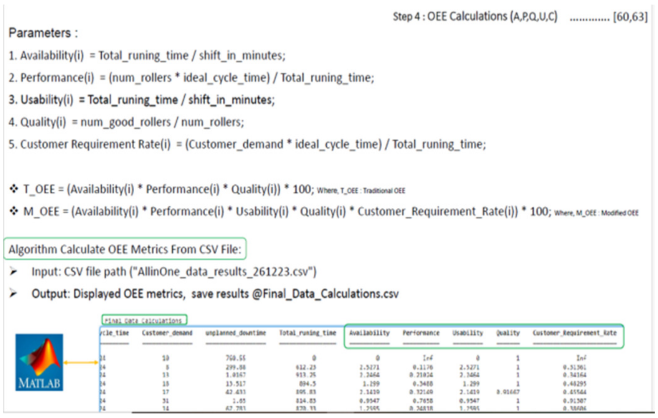

Fig. 3. Modified OEE calculation.

This improved system offers better insights into machine performance, customer-centric productivity expectations, and general efficiency, addressing multiple gaps identified in recent OEE literature [24].

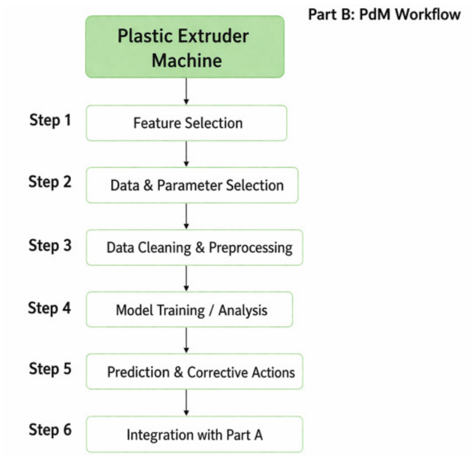

Fig. 4. Part B – PdM workflow.

Figure 4 depicts the Part B-PdM workflow. A parallel predictive pipeline models machine behavior and forecasts future OEE patterns. The dataset is split chronologically to preserve operational order and avoid data leakage, after which models are trained and optimized. The PdM workflow begins by gathering data from the plastic extruder machine. Next, it gets the important features selected and identifies the important parameters. Then, the data undergo various cleaning and preprocessing steps to enable their consistency and reliability for modeling. After the data are ready, they are used for prediction and corrective analysis to identify the possibility of failure and performance problems. The end result is a combination of Part A (the OEE analysis) and process predictions to provide a one-way approach to better maintenance planning and operational efficiency.

Deep learning techniques—particularly Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks—are selected for their ability to model temporal dependencies and non-linear interactions typical in machine degradation [24, 25]. With optimized hyperparameters (epochs, hidden layers, learning rate), the classification performance improves, resulting in stronger failure detection and generalization across operating conditions [18]. The predictive maintenance model outputs are: Future anomaly probabilities, Warning-state detection, Predicted downtimes, Predicted OEE downtrends, Proposed intervention windows. This overcomes reactive maintenance weaknesses and enhances decision-making, aligning with Industry 4.0 predictive strategies [12, 13]. A real-time OEE + PdM dashboard visualizes machine performance, emerging anomalies, efficiency loss, and projected trends. Such visualization strengthens shop-floor transparency, operator awareness, and managerial decisions' core principles in smart factory implementations [12, 13]. The CHINMAY framework improves operational continuity, reduces maintenance costs, enhances reliability, and strengthens maintenance planning in extrusion environments.

III. RESULTS AND DISCUSSION

A. OEE Performance Assessment

The updated version of the OEE formulation demand can be a fine picture of machine productivity as compared to the conventional three-parameter model. The related OEE dashboard provides complete insights about effectiveness rates, downtimes, and quality variations. This real-time external view allows operators to focus on the root cause of recurring losses, which are mostly linked to speed-related inefficiencies, thermal instability, and material waste, and are not always detectable in reports made periodically [5].

Figures 5 and 6 illustrate the impact of individual parameters on OEE. Simply targeting one variable, i.e., unplanned downtime, there is a slight improvement in A, P, and U parameters. Similarly, as depicted in Figure 6, targeting one more variable (waste), a slight improvement in the Q parameter is acquired. These findings highlight the importance of constant OEE monitoring, which will improve operational visibility and allow for corrective interventions to be applied quickly, ultimately leading to a more responsive production floor.

Sr No	Date	Unplanned downtime (Mc switched off)	A	T_OEE (%)	M_OEE (%)	Reduced_Unplanned downtime (Mc switched off)	T_OEE (%)	M_OEE (%)	Old M_OEE with High Unplanned Downtime	% Improvement
1	1-Sep	21	0.85	64.52	51.86	1	64.52	53.14	51.86	1.27
2	2-Sep	58	0.71	48.83	32.15	2	48.83	34.64	32.15	2.49
3	3-Sep	44	0.80	41.89	22.45	1	41.89	23.30	22.45	0.85

Fig. 5. Performance improvement using A, P, and U parameters.

Sr No	Date	Total Output	Waste	Total Goods	Q	T_OEE (%)	M_OEE (%)	Reduced_Waste	Total Goods	Q	T_OEE (%)	M_OEE (%)	Old M_OEE with High Unplanned Downtime	% Improvement
1	1-Sep	30	4	26	0.87	64.52	51.86	1	29	0.97	71.96	59.27	51.86	7.40
2	2-Sep	25	4	21	0.84	48.83	32.15	1	24	0.96	55.81	39.59	32.15	7.44
3	3-Sep	28	3	25	0.89	41.89	22.45	0	28	1.00	46.92	26.09	22.45	3.65
4	4-Sep	28	5	23	0.82	38.54	20.92	1	27	0.96	45.24	25.14	20.92	4.22
5	5-Sep	10	2	8	0.80	31.10	24.18	1	9	0.90	34.98	27.20	24.18	3.02
6	6-Sep	10	2	8	0.80	29.17	21.40	2	8	0.80	29.17	21.65	21.40	0.25
7	7-Sep	2	1	1	0.50	19.57	9.78	0	2	1.00	39.14	20.89	9.78	11.11

Fig. 6. Performance improvement using the Q parameter.

B. Effectiveness of Data Preprocessing

Data merging, careful alignment of timestamps, and systematic handling of missing values greatly enhanced the suitability of the dataset for predictive modeling. Through this preprocessing pipeline, diverse machine logs were converted into structured, cleaner datasets with reduced noise, underscoring the importance of strong data-engineering practices in any industrial AI application [17]. The process also reinforced a practical observation often encountered in factory environments: raw operational data rarely support deep learning directly and must be thoughtfully prepared before meaningful modeling can take place.

C. Predictive Maintenance Model Performance

Several predictive models were developed and tested with the objective of identifying early warning states. The three output classes represent different warning levels: Class 1 corresponds to the normal condition, Class 2 corresponds to Warning 1 (intermediate alert), and Class 3 corresponds to Warning 2 (critical - potential failure conditions from the operating cycle). Traditional neural network architectures offered only marginal improvements, whereas sequence-oriented deep learning models demonstrated significantly better performance. Among these models, the LSTM achieved the highest accuracy, highlighting its effectiveness in capturing temporal temperature variations and the underlying dynamics of machine behavior [24, 25]. As shown in Table I and Figure 7, with careful hyper-parameter tuning, the LSTM model became stable, converged smoothly, and exhibited improved generalization behavior across different operating scenarios. The results obtained from the confusion matrix, Table II, further confirmed reliable prediction for normal and high-alert conditions; however, some misclassification persisted for the intermediate warning class. The confusion matrices demonstrate that the proposed model achieves high classification performance, with a strong concentration of correctly classified instances along the diagonal. The model with 100 hidden layers exhibits the best performance, showing improved class-wise prediction accuracy and reduced misclassification compared to other configurations. This limitation is primarily attributed to the imbalance present in the dataset [18].

TABLE I. HYPERPARAMETER TUNING OF THE LSTM MODEL

Trial	Hidden layers	Epochs	Accuracy	Elapsed time
1	30	1000	59.82	1 min
2	300	1000	70.55	68 min 54 sec
3	100	1000	73.75	11 min 57 sec

TABLE II. CONFUSION MATRICES FOR BPNN MODEL EVALUATION

True	Predicted		
	Class 1	**Class 2**	**Class 3**
Class 1	5105	0	7
Class 2	10	15	3352
Class 3	4497	42	6651

TABLE III. CONFUSION MATRICES FOR BILSTM MODEL EVALUATION

True	Predicted		
	Class 1	**Class 2**	**Class 3**
Class 1	4601	0	511
Class 2	7	517	2853
Class 3	2284	140	8466

TABLE IV. CONFUSION MATRICES FOR LSTM MODEL EVALUATION

True	Predicted		
	Class 1	**Class 2**	**Class 3**
Class 1	4470	0	642
Class 2	6	1398	1973
Class 3	2085	459	8646

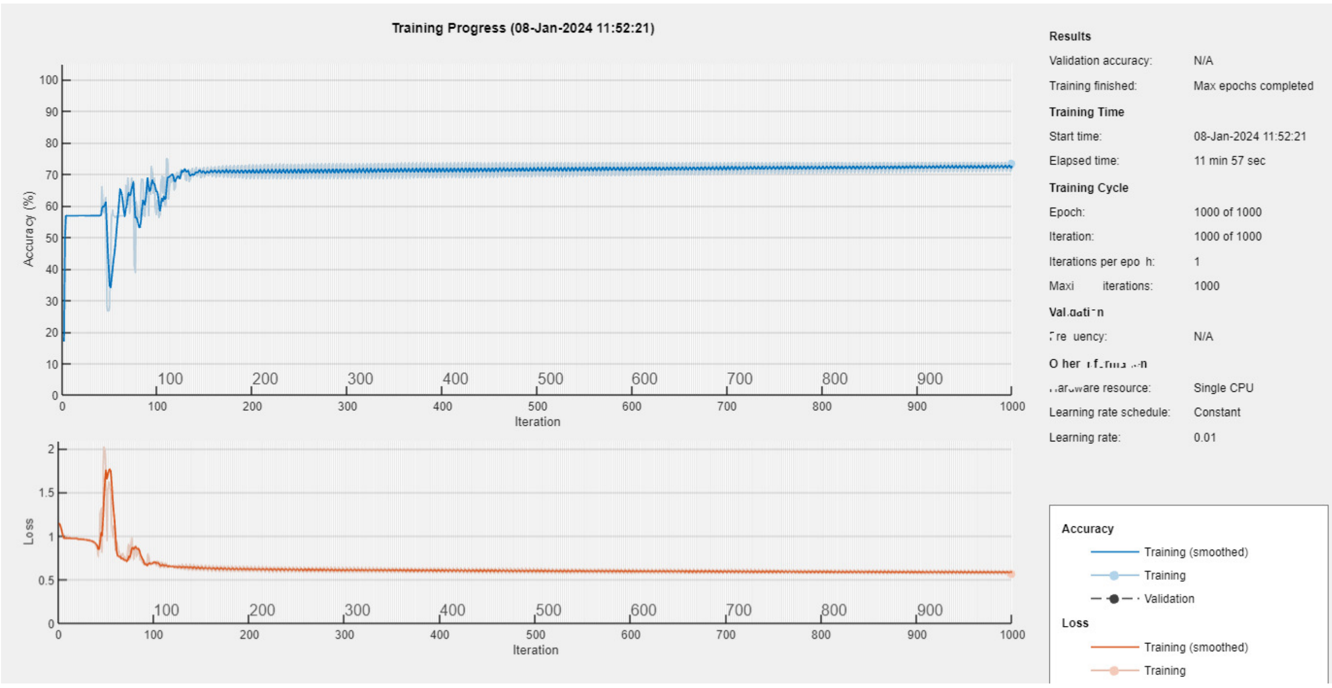

Fig. 7. Training performance graph (accuracy vs. iterations and loss vs. iterations).

D. *Integration of MOEE and PdM Insights*

With the incorporation of POEE forecasting and predictive maintenance alerts, a unified decision support framework was achieved. The framework is able to predict future OEE degradation paths, emerging machine-health hazards, define up-to-optimum maintenance intervals, and give probabilistic failure indicators. These joint predictive layers are a promising innovation compared to retrospective OEE assessments existing in the past [21]. The framework reduces the occurrence of downtimes by shifting current practices to a more proactive data-driven approach, which strengthens overall operational planning. The results reveal that the constant manufacturing settings, specifically extrusion-based ones, have a number of potentially significant benefits [7]. The early notification minimizes production losses, material and energy usage, and optimizes production capacity. All these enhancements contribute to the strengthening of data-driven decision-making in the administrative level. The CHINMAY framework facilitates the Industry 4.0 practices and contributes to the implementation of ML, real-time monitoring, and automated analysis of daily plant activities [1, 12, 13].

IV. CONCLUSION

The Condition-based Health Intelligence to Neural Monitoring and Analytics Yield (CHINMAY) framework, combining a next-generation OEE architecture and Predictive Maintenance (PdM) based on deep learning in a plastic extrusion environment, is presented in this paper. The proposed strategy was successful in transforming raw machine data into real and valuable insights to enable more efficient operation, improve equipment reliability, and enhance productivity-related decision-making.

The proposed system offers predictive capability and foresight to anticipate performance deviations by strategically expanding the scope of conventional OEE, which is traditionally confined to descriptive and backward-looking evaluation. The framework further incorporates additional indicators that support predictive rather than reactive assessment, including usability and diverse customer demand.

Experimental analysis demonstrates that LSTM-based models perform particularly well in recognizing early warning states and predicting degradation trends in extrusion machinery. The joint utilization of CHINMAY framework outputs and PdM outcomes enables informed production planning, reduces unplanned shutdowns, and facilitates improved production continuity.

Overall, the proposed framework presents a viable and scalable approach toward the implementation of Maintenance 4.0. The framework enhances operational visibility, enhances interpretation of machine behavior, and supports responsive manufacturing processes. The system shows strong potential for application in other continuous-process industrial environments due to its adaptable nature.

DECLARATION OF COMPETING INTERESTS

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGMENT

The authors would like to acknowledge the support provided by the organization and the industrial facility for enabling data collection and experimentation. No external funding was received for this research work.

DATA AVAILABILITY

The data used in this study are not publicly available due to confidentiality and industrial restrictions but can be made available from the corresponding author upon reasonable request.

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used ChatGPT to assist in language refinement and structuring of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

APPENDIX

ABBREVIATIONS:

CHINMAY	Condition-Based Health Intelligence for Neural Monitoring and Analytics Yield
PdM	Predictive Maintenance
POEE	Predictive Overall Equipment Effectiveness
TOEE	Total Overall Equipment Effectiveness
MOEE	Machine Overall Equipment Effectiveness
A	Availability
P	Performance
Q	Quality
U	Usability
C	Customer Requirement Rate

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