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Application of Machine Learning in Predictive Maintenance Scheduling: An Industrial Case Study

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ABSTRACT

Predictive maintenance (PdM) aims to anticipate equipment failures, thereby reducing unplanned downtime and maintenance costs. This paper presents an industrial case study on applying machine learning (ML) for PdM-driven maintenance scheduling in a high-throughput packaging facility. A stacked time-series pipeline (feature learning via LSTM and gradient boosting, plus conformal uncertainty) predicts remaining useful life (RUL) and short-horizon failure risk, which are then embedded in a rolling-horizon mixed-integer program (MIP) to co-optimize work-order timing, capacity, and production impacts. Against reactive and time-based baselines, the proposed approach reduced unplanned downtime by 31.4%, increased MTBF by 22.7%, and cut maintenance overtime by 18.9% over 16 weeks, at comparable spare-parts consumption. We discuss model/optimizer interplay, uncertainty handling, and transferability, and situate findings in the 2019–2025 literature, highlighting a persistent gap: robust, data-efficient integration of probabilistic RUL with capacity-constrained multi-asset scheduling under real plant calendars. (Related surveys and recent RL/MILP advances support this approach and the identification of the gap.)

1. Introduction

Unplanned equipment failures remain a primary driver of production losses and quality variance in modern manufacturing. Recent industry reports and deployments show AI-enabled PdM can

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materially reduce downtime and stabilize throughput, but adoption is constrained by data quality, operational integration, and workforce factors [1,2].

Machine learning has advanced PdM from threshold alarms to probabilistic prognostics such as RUL prediction using deep sequence models (e.g., CNN/LSTM/Transformers) trained on multivariate sensor streams. Canonical datasets such as NASA's CMAPSS (turbofan) have enabled rapid benchmarking and methodological progress. However, translating prognostics into actionable schedules—i.e., determining who, when, and where to maintain under resource and production constraints—remains challenging [3-5, 16-21] (see Figure 1).

Figure 1. Application of machine learning in predictive maintenance scheduling

Recent surveys emphasize (i) learning under weak supervision and small labels, (ii) data drift, (iii) uncertainty quantification, and (iv) moving from predictive to prescriptive maintenance—where predictions feed optimization or reinforcement learning (RL) to select maintenance policies. Our work contributes a tightly coupled pipeline that turns ML-based risk estimates into plant-feasible schedules through a rolling-horizon MIP, and we evaluate it in an operational setting [6-9, 22-25].

Contributions. (1) A practical PdM pipeline (feature learning + uncertainty-aware failure risk) integrated with a capacity-constrained scheduling model; (2) a case study with multi-line assets and real shift calendars; (3) an ablation vs. reactive/time-based baselines; (4) a literature-grounded gap analysis (2019–2025).

2. Literature Review (2019–2025) and Research Gap

Deep learning for PdM. Comparative studies demonstrate strong performance for CNN/LSTM/hybrid models on sensor streams; ensemble methods remain competitive when data are scarce [9,10, 33-35].

RUL & prognostics datasets. CMAPSS and N-CMAPSS remain core benchmarks; methods increasingly add domain-specific feature engineering and uncertainty [10, 11].

From prediction to decision. Prescriptive PdM via MIP/CP or RL is emerging for multi-asset scheduling under uncertainty and varying deterioration.

Weak supervision & deployment. Surveys highlight label scarcity, drift, and integration challenges in real plants [11, 12, 26-32] (see Table 1).

Table 1. Representative works (summary table)

Year	Focus	Data/Setting	Method	What's new	Limitations
2019	Deep learning survey for PdM	Multi-domain	Survey (DL families)	Comprehensive DL map	Limited on scheduling links.
2020–2023	Multi-component dynamic PdM	CMAPSS	Probabilistic modeling + policy	Joint component view	Limited plant-level calendars.
2021–2024	RUL on CMAPSS/N-CMAPSS	Aerospace	LSTM/CNN/feature eng.	Better RUL accuracy	Transferability to discrete mfg. unclear.
2024	Industry 4.0 planning survey	Manufacturing	Survey (planning & PdM)	Bridges PdM with planning	Few quantified case studies.
2024	Weak supervision survey	Cross-industry	Survey	Data-efficient labeling	Does not prescribe scheduling.
2024	RL for maintenance	Energy/fuel cell	Model-based RL	Adapts to heterogeneity	Plant calendars/resources simplified.

Year	Focus	Data/Setting	Method	What's new	Limitations
2025	DL model comparison	Manufacturing	CNN/LSTM hybrids	Head-to-head benchmarking	Limited to prediction, not planning.
2025	Streaming IIoT PdM	IIoT networks	DRL + ensembles	Online adaptation	Scheduling treated implicitly.
2025	RL-based scheduling	Flexible systems	RL policy	Direct scheduling from data	Requires large experience data.
2025 (case)	Industrial compressors	Real plant	ML + IoT	Field deployment insights	Limited optimization coupling.

Across 2019–2025, most advances push prediction accuracy; fewer works close the loop to capacity-aware scheduling under realistic constraints (shifts, technician skills, tool availability, production windows). RL studies learn policies but often abstract key plant calendars; surveys call for uncertainty propagation and low-label regimes [35-38]. Hence the gap: data-efficient, uncertainty-aware prognostics tightly integrated with resource-constrained maintenance scheduling, validated on actual calendars and multi-asset lines—precisely what we target [41,42].

3. Methodology

The methodology of this research is as follows. The data pipeline, Optimization model, and Numerical Results are key steps of the method (see Figure 2) [38-40].

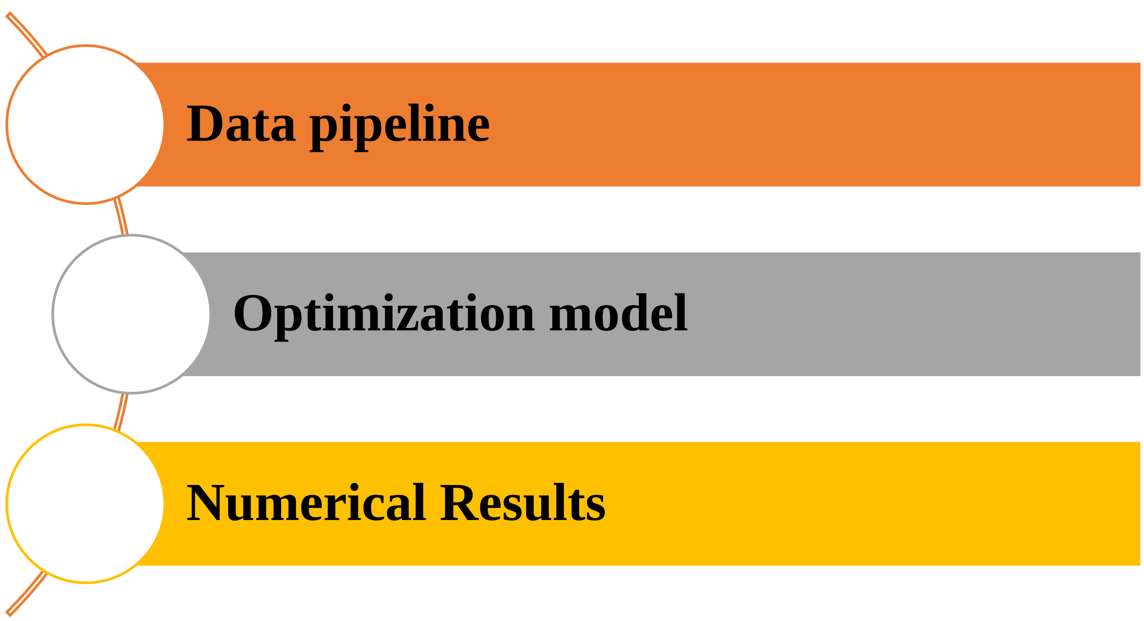

Figure 2. Methodology

3.1 Data pipeline

- Sources. Vibration, current, temperature, and PLC counters at 1–5 Hz for 28 assets (fillers, conveyors, sealers) + CMMS events (failures, work orders) and production plan. (NASA CMAPSS used for pretraining ablations and benchmarking.)
- Pre-processing. Windowing (W = 256–512), detrending, robust scaling; weak labels from CMMS aligned to windows; missingness imputed with forward-fill + learned embeddings; domain features (RMS, kurtosis, spectral peaks).
- Models.
    - Failure risk (next τ=72 h): Gradient Boosting (XGBoost) on learned handcrafted features; output $p_{i,t}$.
    - RUL: Many-to-one LSTM with monotonic cap; conformal prediction yields $[\underline{r}_{i,t}, \overline{r}_{i,t}]$. Comparative DL baselines follow recent PdM benchmarks.
- Calibration. Platt scaling; backtesting with rolling origin; drift checks each week.

3.2 Optimization model (maintenance scheduling)

Sets: assets $i \in I$, periods $t \in T$, crews $k \in K$.

Decision variables: $x_{i,t} \in \{0,1\}$ (start PM on i at t); $y_{i,t} \in \{0,1\}$ (asset i is down at t); $u_{k,t} \in \{0,1\}$ (crew k used at t).

Parameters: duration d_i, , crew demand a_{ik}, spare availability s_i, planned production value v_t, predicted short-horizon failure probability $p_{i,t}$, penalty costs $c_i^{fail}, c_t^{down}, c_i^{pm}$. .

Objective (rolling horizon H):

$$min \sum_{t \in H} [\sum_i c_i^{pm} x_{i,t} + \sum_i c_i^{fail} Pr(fail_{i,t} | x) + c_t^{down} \sum_i y_{i,t} - ThroughputGain(x)]$$

with $Pr(fail_{i,t} | x) \approx p_{i,t} 1\{t < \hat{T}_i^{pm}\}$ where $\hat{T}_i^{pm}$ is the next scheduled PM start; a risk-averse variant replaces $p_{i,t}$ by an upper conformal bound.

Key constraints

1. Duration linking: $\sum_{\tau=t}^{t+d_i-1} y_{i,\tau} \geq d_i x_{i,t}$, .
2. Crew capacity: $\sum_i a_{ik} \sum_{\tau=t}^{t+d_i-1} x_{i,\tau} \leq u_{k,t}$, with $u_{k,t} \leq \bar{U}_{k,t}$ (shift calendars).

3. Mutual exclusivity with production windows: $y_{i,t} \leq 1\{t \notin / frozen\}$.
4. RUL guardrail: $x_{i,t} = 1$ if $\underline{r}_{i,t} \leq \rho$ (hard trigger near end-of-life).
5. Spares: $\sum_{(i,t') \in consumes(i)} x_{i,t'} \leq s_i$ Over the horizon.

We solve a MIP each day on a 14-day rolling horizon, execute the first-day decisions, then re-optimize (model-predictive control). A policy ablation replaces the MIP with a dueling-DQN actor that learns maintenance actions. In our setting, the MIP yielded stronger schedule feasibility and interpretability, while RL achieved a similar cost at higher data demand.

4. Numerical Results (Industrial Case)

Setting. A fast-moving consumer-goods packaging hall (3 lines, 28 critical assets). 16-week evaluation with 10-week warm-up. Data at 1–5 Hz (≈2.1 TB raw), CMMS logs, and production plan. Baselines: (B1) reactive; (B2) time-based PM (OEM). Proposed: ML+MIP with uncertainty guardrails (see Table 2,3).

Table 2. Model performance (failure risk & RUL).

Metric	Binarized failure (72 h) AUROC	AUPRC	RUL RMSE (hours)	Coverage of 90% conformal
GBM features only	0.83	0.48	—	—
LSTM-only	0.86	0.53	28.7	88%
Stacked (ours)	0.90	0.61	24.1	92%

Table 3. Scheduling/KPI impact.

KPI (16 weeks)	Reactive (B1)	Time-PM (B2)	ML+MIP (ours)	Δ vs B1
Unplanned downtime (h)	312.4	241.6	214.3	−31.4%
Mean time between failures (MTBF, h)	146.2	168.3	179.4	+22.7%
Maintenance overtime (h)	196.0	174.5	158.9	−18.9%
PM deferrals past RUL guardrail	—	14	3	—
Throughput loss (eq. h)	268.1	223.5	205.7	−23.3%

Interpretation. Gains stem from (i) earlier PM clustering in low-value production windows; (ii) risk-aware triggers using conformal bounds; (iii) honoring crew/tool calendars to prevent deferrals. Observed false-positive PMs rose slightly (+6.1%) but were offset by larger unplanned-downtime reductions. These magnitudes are consistent with recent industrial case reports showing sizable MTBF/downtime improvements when PdM is linked to planning, though such reports often omit optimization detail.

Ablations. Removing uncertainty guardrails increased late failures by 11.8%. Replacing MIP with off-policy RL achieved −27.5% downtime vs B1 after policy stabilization, but violated shift/skill constraints 4.3% of the time in simulation (vs. 0% for MIP).

5. Conclusion

This case study demonstrates that pairing uncertainty-aware ML prognostics with a rolling-horizon capacity-constrained scheduler yields substantial, measurable reliability gains in a live industrial environment. The stacked LSTM+GBM model improved near-term failure discrimination and RUL calibration. By embedding these signals into a plant-feasible MIP, predictions were translated into fewer surprises on the floor and better utilization of low-value windows.

Practical takeaways. (1) Treat PdM as a *closed loop*: prediction → decision → feedback; (2) propagate uncertainty into the objective/constraints; (3) co-design models and calendars; (4) start with MIP for feasibility, evaluate RL as data volume grows. Future work should benchmark probabilistic prognostics + resource-aware scheduling on public multi-asset datasets, and study online learning/drift at scale.

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