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IMPROVING THE EFFICIENCY OF MAINTENANCE PROCESS IN MANUFACTURING SYSTEMS USING INDUSTRY 4.0 TOOLS

PH.D. THESES

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Miskolc
2026

Use of Artificial Intelligence Tools

Artificial intelligence tools (specifically large language models) were used during the preparation of this dissertation to support language refinement, structural organization, and the clarification of explanations.

In addition, AI-assisted coding practices—sometimes referred to as “vibe coding”—were employed during the development of selected software components and data processing pipelines. In this context, AI tools were used to accelerate prototyping, suggest implementation patterns, and improve code readability. All generated code was critically reviewed, validated, and, where necessary, adapted by the author to ensure correctness, consistency, and alignment with the research objectives.

All scientific content, including the development of concepts, models, and conclusions, is the original work of the author. AI tools were used solely as assistive instruments and did not replace independent scientific reasoning, analysis, or interpretation.

The author takes full responsibility for the content, implementation, and integrity of this dissertation.

Miskolc, April 8, 2026

Hermans Marc Philip

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1 Introduction and Motivation

1.1 Context and Industrial Relevance

1.1.1 Economic Drivers: Energy, Waste, and Stability

In recent years, global disruptions—including the energy crisis triggered by geopolitical conflicts, supply chain volatility, and the increasing urgency of climate change—have intensified the pressure on manufacturing companies to improve operational efficiency. Modern production systems must maximize stability while simultaneously reducing energy consumption and material waste.

In this context, maintenance logistics plays a pivotal and integrative role within production planning and control. Minimizing unplanned downtime not only safeguards productivity but also directly contributes to energy efficiency and the reduction of industrial waste.

The economic impact of maintenance optimization on energy usage, scrap, and throughput is substantial. For example, in a high-volume p roduction line consisting of ten machines, reducing unplanned downtime from 300 to 210 hours per year avoids approximately 7,200 kWh of wasted energy. Furthermore, improved production stability can reduce scrap rates from 5% to 3%, which translates to a 40% reduction in total scrap volume.

Consequently, advanced maintenance strategies have evolved from a secondary support function into a critical factor for achieving stable, sustainable, and economically viable manufacturing systems, particularly in serial production environments.

1.1.2 The Industrial Problem: Limitations of Preventive and Predictive Maintenance

Despite its recognized importance, the strategic potential of maintenance remains underutilized in many industrial settings. Historically, maintenance activities have been predominantly reactive—performed only after failures occur—or strictly preventive, relying on predefined time intervals rather than the actual condition of the equipment.

Although preventive maintenance reduces unexpected breakdowns, fixed-interval scheduling is inherently flawed: it inevitably leads either to premature interventions that waste resources or to insufficient protection against sudden failures.

To reconcile this dilemma, the industry frequently proposes predictive maintenance as the ultimate solution. However, its real-world implementation is far from trivial. True predictive maintenance depends heavily on extensive sensor infrastructures, complex data acquisition networks, and advanced analytical methods such as machine learning and high-frequency signal processing.

Beyond the steep initial hardware investments, these systems require domain expertise and the continuous retraining of maintenance personnel. These barriers make predictive maintenance economically and organizationally unfeasible for many small and medium-sized enterprises, and exceedingly difficult to deploy at scale on legacy manufacturing equipment.

Furthermore, even when successfully implemented, predictive maintenance often fails to provide sufficient advanc e planning time for logistical preparation in serial production environments characterized by very short cycle times.

1.2 Scientific Positioning

1.2.1 The Scientific Gap

Addressing these industrial limitations requires the integration of production performance measurement, reliability engineering, and digital-twin-based simulation. However, an analysis of the existing literature reveals that these domains have evolved largely independently.

Overall Equipment Effectiveness (OEE) research focuses primarily on retrospective performance measurement and process optimization, but rarely interprets OEE dynamically as a probabilistic indicator of system deterioration.

Total Productive Maintenance (TPM) literature emphasizes maintenance organization and operational improvement, yet it provides limited mechanisms for directly linking production performance indicators to optimal maintenance timing.

Digital Twin research is heavily concentrated on sensor-based monitoring and predictive analytics, but it rarely incorporates standard production indicators like OEE into integrated maintenance decision frameworks.

As a consequence, existing research does not provide a framework that explicitly links probabilistic performance indicators, degradation modelling, and risk-aware maintenance decision-making into a unified probabilistic system.

1.2.2 Core Idea: Maintenance as a Probabilistic Decision Under Uncertainty

To bridge the gap between rigid preventive scheduling and overly complex predictive approaches, this dissertation explores an alternative paradigm: leveraging discrete-event simulation and probabilistic modeling—particularly Bayesian Neural Networks (BNNs)—to enable predictive decision-making without relying on extensive sensor infrastructures.

This framework utilizes timestamp-based production logs to reconstruct OEE as a dynamic, probabilistic signal. Instead of attempting to predict an exact time-to-failure, the system evaluates the degree of synchronization between system degradation and maintenance actions.

By interpreting performance deviations as a loss of operational confidence, the proposed model estimates the explicit probability that production performance will fall below a critical threshold if maintenance is postponed.

This necessitates a fundamental conceptual shift in how industrial reliability is governed:

"Maintenance is not scheduling; it is risk management under uncertainty."

Rather than treating maintenance as a deterministic scheduling task, this research reframes it as a Bayesian confidence-based decision process. By mathematically quantifying the epistemic uncertainty of degradation, maintenance interventions are triggered by a probabilistic confidence threshold.

This shifts the operational focus from attempting to predict unavoidable failures to accurately quantifying the safety and risk of postponement, facilitating broader applicability across partially observable and legacy production lines.

2 Research Objectives and Questions

2.1 General Research Objective

The overarching objective of this dissertation is the formulation and investigation of a probabilistic, timestamp-driven framework for maintenance decision-making in serial production environments. The research aims to move beyond rigid, time-based preventive maintenance policies by integrating production performance measurement, reliability theory, simulation-based modeling, and probabilistic machine learning into a unified analytical framework.

This requires bridging the historical gap between the deterministic measurement of equipment efficiency and the stochastic nature of system degradation.

2.2 Central Research Question

Guided by the need to support decision-making under uncertainty, this research is driven by the following fundamental scientific question:

> **How can Overall Equipment Effectiveness (OEE), degradation modelling based on reliability theory, and Bayesian probabilistic inference be integrated into a coherent framework that supports maintenance decision-making in serial production systems?**

2.3 Specific Research Sub-Questions

To systematically address the central research question, the problem is decomposed into three core sub-questions spanning measurement, degradation modeling, and probabilistic inference:

- **Reconstruction of Performance Indicators (Measurement):** How can OEE be redefined and calculated objectively from timestamped production logs in a way that is consistent, independent of predefined ideal cycle times, and highly relevant for dynamic maintenance decision-making?

- **Representation of Degradation Dynamics (Modelling):** What are the limitations of traditional, constant-hazard failure models (such as the Negative Exponential distribution), and how can alternative approaches—specifically Weibull-based saw-tooth hazard models—provide a more realistic representation of age-dependent degradation in periodically maintained systems?
- **Uncertainty Quantification and Decision Support (Inference):** How can Bayesian Neural Networks (BNNs) incorporate both the reconstructed OEE signals and epistemic uncertainty to estimate the explicit probability that a scheduled maintenance intervention can be safely postponed without violating critical production performance thresholds?

Methodological Note To investigate these sub-questions systematically, Discrete Event Simulation (DES) is utilized as an experimental laboratory to generate reproducible synthetic production data and evaluate varying maintenance strategies under statistically controlled operating conditions.

2.4 Research Hypothesis

The foundational premise of this work challenges the traditional view of maintenance as a rigid, time-based scheduling task. Instead, the central hypothesis of this dissertation is formally defined as follows:

Maintenance decisions can be reformulated as probabilistic confidence decisions based on OEE-derived evidence.

More precisely, the hypothesis posits that interval-based preventive maintenance policies can be effectively transformed into probabilistic, confidence-based threshold decisions. This is achievable when Overall Equipment Effectiveness is not treated as a static, deterministic ratio, but rather reconstructed from raw, timestamp-based production data and reinterpreted within a rigorous Bayesian inference framework.

By mathematically quantifying the uncertainty of degradation, this approach shifts the objective from predicting exact times-to-failure to confidently managing the operational risk associated with postponing maintenance actions.

3 Scientific Positioning and Research Gap

3.1 State of the Art

A systematic evaluation of the existing literature reveals that the core domains relevant to manufacturing performance and maintenance optimization have evolved largely independently. While each area contributes significantly to production efficiency, their traditional applications remain isolated. [1]

- **Overall Equipment Effectiveness (OEE) as a retrospective KPI:** Historically, OEE research has focused primarily on performance measurement, process optimization, and operational evaluation. In the current state of the art, OEE is utilized as a static, retrospective Key Performance Indicator (KPI) to summarize past production losses, but it is rarely interpreted as a dynamic, probabilistic indicator of ongoing system deterioration.
- **Total Productive Maintenance (TPM) as an organizational concept:** TPM literature strongly emphasizes maintenance organization, cultural shifts, and operational implementation strategies. While it is highly effective at standardizing maintenance tasks, TPM is treated predominantly as an organizational concept. It currently provides limited quantitative mechanisms for explicitly linking dynamic production performance indicators to optimal maintenance timing.
- **Digital Twin for monitoring and prediction:** Research into Digital Twin technologies focuses heavily on real-time condition monitoring, discrete-event simulation, and sensor-driven predictive analytics. However, these advanced predictive maintenance applications rarely incorporate standardized production performance indicators, such as OEE, into their maintenance decision frameworks.

3.2 Identified Research Gap

Although these domains share obvious conceptual connections, the literature demonstrates a distinct void at their intersection. The most significant identified gap is the absence of an integrated analytical framework that simultaneously incorporates the following three elements:

- **Performance:** The dynamic measurement of production efficiency through OEE.
- **Degradation:** The mathematical representation of age-dependent system deterioration through hazard-based models.
- **Decision Logic:** The formulation of maintenance execution based on uncertainty-aware, probabilistic rules.

While prior studies have explored combinations of OEE, TPM, and digital twin technologies, none provide an explicit connection between performance degradation and risk-aware maintenance decision-making within a unified framework. Existing approaches fail to translate operational performance measurements into explicit probabilities of future system failure.

3.3 Research Positioning

To address this gap, this dissertation introduces a methodological paradigm shift. The primary novelty of this research lies not in the creation of isolated tools, but in their integration into a unified, probabilistic maintenance decision-support framework.

To clearly distinguish the contribution of this research from existing approaches, the positioning of this thesis is summarized as follows:

- **Deterministic → Probabilistic:** Moving away from deterministic preventive maintenance schedules, rigid condition-based thresholds, or exact Remaining Useful Life (RUL) predictions, this research adopts probabilistic decision-making based on explicit confidence thresholds.
- **Point Estimate → Distribution:** Instead of relying on conventional machine learning methods that output single point estimates, this framework utilizes Bayesian Neural Networks to generate full predictive probability distributions, explicitly modelling and propagating uncertainty.
- **Sensor-Heavy → Minimal Data:** Bypassing the need for complex, sensor-intensive data collection networks, this work advocates a minimal-data approach. It relies on a time-based probabilistic interpretation of production data and is supported by synthetic data generated via Discrete Event Simulation.

- **Heuristic → Bayesian Decision Rule:** Replacing heuristic or simple threshold-based decision logic with a rigorous Bayesian decision rule founded on the calculated probability of performance degradation.

The identified lack of integration necessitates a unified framework in which performance measurement, degradation behaviour, and maintenance decisions are treated as a single probabilistic system.

4 Conceptual Framework

The methodological architecture of this research is built upon a layered structure that integrates measurement theory, reliability modelling, discrete-event simulation, and probabilistic machine learning. By moving away from deterministic approaches, this framework provides an analytically grounded basis for managing maintenance logistics under uncertainty.

4.1 Core Concepts

The technical implementation of the research artifact consists of four interrelated analytical components, which together transform time-based maintenance scheduling into a dynamic, uncertainty-aware decision process.

4.1.1 Probabilistic OEE (Prior vs. Posterior)

Overall Equipment Effectiveness (OEE) is traditionally defined as a retrospective, deterministic performance indicator. In this framework, OEE is reinterpreted as a time-based stochastic signal derived directly from production timestamps. This formulation eliminates the need for predefined ideal cycle times and supports a timestamp-based reconstruction of OEE from event data.

To operationalize this probabilistic interpretation, two distinct forms are defined:

- **Prior OEE:** The expected performance before the machine, assuming ideal manufacturing conditions.
- **Posterior OEE:** The observed performance after the machine, reflecting actual system behaviour and disturbances.

The deviation between prior and posterior OEE serves as a quantifiable indicator of performance degradation and forms a primary input to the Bayesian maintenance decision framework.

4.1.2 Hazard-Based Degradation

To represent realistic failure behaviour beyond constant hazard assumptions, this research utilizes a Weibull-based hazard model with an increasing hazard rate:

$$\beta > 1 \tag{4.1}$$

where:

- β is the Weibull shape parameter governing the evolution of the hazard rate

In periodically maintained systems, this results in a sawtooth-shaped hazard structure. The hazard rate increases steadily due to wear-out processes between maintenance events and is partially or fully reset following planned interventions.

This provides a mathematically consistent representation of maintenance-induced reliability dynamics.

4.1.3 Bayesian Decision Logic

Maintenance decision-making is reframed from a fixed-interval scheduling task into a probabilistic confidence problem.

The decision is expressed as:

$$P\left(OEE_{t+1} < OEE_{\text{planned}} \,\middle|\, \text{evidence}, \neg M_t\right) \tag{4.2}$$

where:

- OEE_{t+1} is the predicted future production performance
- OEE_{planned} is the planned or acceptable performance level
- evidence represents observed production data and inferred system state
- $\neg M_t$ denotes postponement of maintenance at time t

A Bayesian Neural Network estimates this probability together with its associated uncertainty.

A maintenance intervention is triggered only if:

$$P\left(OEE_{t+1} < OEE_{\text{planned}} \,\middle|\, \text{evidence}, \neg M_t\right) > \tau \tag{4.3}$$

where:

- τ is the predefined risk tolerance threshold

This formulation enables maintenance decisions to be governed by quantified risk rather than fixed schedules.

4.1.4 Digital Twin as Generative Simulation Model

To evaluate the proposed framework, the discrete-event simulation model acts as a generative digital twin.

The focus is not on real-time cyber-physical integration, but on controlled data generation and scenario exploration. The simulation environment functions as an experimental laboratory, producing synthetic timestamp data that reflects system behaviour under controlled degradation scenarios and varying maintenance regimes.

4.2 System Interpretation

A fundamental conceptual shift introduced in this dissertation concerns the interpretation of the predictive model.

In contrast to traditional condition monitoring approaches, the Bayesian Neural Network does not directly estimate the physical state of the system. Instead, it evaluates the degree of synchronization between system degradation and maintenance actions.

This distinction is critical. The model does not attempt to predict the physical condition of individual components. Rather, it interprets deviations in performance as a loss of operational confidence.

In doing so, it assesses whether the current maintenance strategy remains aligned with the underlying stochastic degradation dynamics.

This shifts the operational focus:

- from diagnosing physical wear
- to quantifying the logistical risk of misaligned maintenance timing

4.3 Integrated Perspective

The methodological contribution of this research lies in the integration of individual analytical elements into a coherent probabilistic decision-support framework.

The framework follows a structured analytical chain:

$$\text{OEE} \rightarrow \text{Degradation} \rightarrow \text{Probabilistic Inference} \rightarrow \text{Maintenance Decision}$$

OEE (Measurement) A timestamp-based formulation reconstructs production performance, capturing the deviation between expected (prior) and observed (posterior) efficiency.

Degradation (Modelling) This deviation is mapped onto the system timeline using a sawtooth degradation model, representing both wear accumulation and maintenance-induced resets.

Probabilistic Inference (Uncertainty Quantification) The derived features are processed using Bayesian inference to estimate the probability of critical performance degradation together with prediction uncertainty.

Maintenance Decision (Execution) The quantified risk is translated into a decision rule, enabling maintenance actions to be executed or postponed based on a predefined confidence threshold.

This integrated framework demonstrates that maintenance can be treated as a probabilistic control problem, where performance measurement, degradation dynamics, and decision-making are unified into a single analytical system.

5 Methodological Framework

The technical realization of the proposed research artifact follows a layered methodological structure that integrates measurement theory, reliability modelling, simulation experimentation, and probabilistic machine learning into a coherent decision-support framework.

5.1 OEE Reconstruction

The first component of the framework involves the objective measurement of production performance. Overall Equipment Effectiveness (OEE) is reconstructed exclusively from raw, timestamped production data, forming an empirical and distribution-free foundation.

Cycle times are calculated directly from part timestamps:

$$CT_i = t_i - t_{i-1} \tag{5.1}$$

where:

- CT_i is the cycle time of part i
- t_i is the timestamp of part i
- t_{i-1} is the timestamp of the preceding part

Performance and availability losses are detected using robust statistical measures, such as median-based cycle time estimation and interquartile range (IQR) analysis.

Crucially, this timestamp-based formulation eliminates the need for predefined ideal cycle times. By deriving the theoretical cycle time directly from the statistical mode or median of the observed data, the metric remains objective and adaptable across different manufacturing environments, avoiding biases associated with externally defined design specifications.

5.2 Degradation Modelling

To mathematically represent system wear and deterioration, the framework moves beyond traditional constant-hazard failure assumptions by incorporating a Weibull-based hazard model.

An increasing hazard rate is modeled using a Weibull distribution with shape parameter:

$$\beta > 1 \tag{5.2}$$

where:

- β is the Weibull shape parameter

In the experimental validation, a representative case of $\beta = 2$ is applied, resulting in a linearly increasing hazard rate over time.

In periodically maintained manufacturing systems, this produces a characteristic sawtooth structure: the hazard rate accumulates continuously due to wear-out processes and is subsequently reset to a baseline level following maintenance interventions.

5.3 Data Generation

To validate the models and analyze system behavior, the research relies exclusively on synthetic datasets generated through Discrete Event Simulation (DES), implemented in Siemens Plant Simulation.

The DES environment functions as a controlled experimental laboratory in which failure distributions, maintenance strategies, and degradation intensities can be systematically varied.

The use of synthetic data is methodologically motivated. A simulated environment ensures statistical consistency and enables the isolation of causal relationships between degradation processes, OEE evolution, and maintenance decision outcomes. This approach avoids issues such as missing data, unobserved disturbances, and confidentiality constraints typically associated with real-world industrial datasets.

5.4 Bayesian Decision Model

The final component integrates reconstructed OEE signals and degradation models using Bayesian inference, transforming maintenance from a deterministic scheduling task into a probabilistic decision problem.

A Bayesian Neural Network is employed to estimate both:

- the probability of performance degradation
- the associated epistemic uncertainty

The core maintenance execution is governed by the following decision rule:

$$P\left(OEE_{t+1} < OEE_{\text{threshold}} \mid \text{Evidence}, \neg M_t\right) > \tau \tag{5.3}$$

where:

- OEE_{t+1} is the predicted production performance in the next decision interval
- $OEE_{\text{threshold}}$ is the minimum acceptable performance level
- τ is the risk tolerance threshold
- Evidence represents observed production data and inferred system state
- $\neg M_t$ denotes the decision to postpone maintenance at time t

The parameter τ reflects the organization's risk appetite. Maintenance is triggered only if the probability of falling below the critical performance threshold exceeds this predefined limit.

By continuously evaluating this probabilistic condition, maintenance decisions are no longer based on fixed schedules but on quantified risk, enabling dynamic and context-aware intervention strategies.

6 Main Scientific Results

6.1 OEE as a Probability Measure for Production Performance (Thesis 1)

Traditionally, Overall Equipment Effectiveness (OEE) is treated as a deterministic, retrospective ratio used to summarize past production losses. The first major scientific result of this research is the conceptual and mathematical reinterpretation of OEE as a probability measure. [2]

In this formulation, OEE quantifies the likelihood of a discrete manufacturing system achieving ideal operating conditions:

$$\text{OEE} = P(\text{ideal manufacturing conditions}) \tag{6.1}$$

Each component of the classical OEE formulation—Availability, Performance, and Quality—is consequently interpreted as a conditional probability.

This provides a rigorous foundation for performance-based reasoning. By reconstructing OEE exclusively from empirical, timestamped production logs, the calculation becomes entirely distribution-free. The theoretical cycle time is derived from statistical properties of observed data, such as the median or mode, thereby eliminating dependence on predefined or externally specified values.

Within a Bayesian context, the deviation between expected and observed OEE can be interpreted as an evidence signal. This deviation reflects the degree of departure from ideal system behaviour and forms the basis for adaptive, data-driven maintenance strategies.

6.2 Degradation Representation via Sawtooth Hazard and Maintenance Profiles (Thesis 2)

The second core result addresses the mathematical representation of system degradation under repeated maintenance interventions. [3]

Classical reliability models often assume a constant hazard rate during stable operation. However, such assumptions fail to capture the dynamics of periodically maintained systems.

This research introduces a degradation model based on a Weibull distribution with an increasing hazard rate:

$$\beta > 1 \tag{6.2}$$

where:

- β is the Weibull shape parameter controlling the evolution of the hazard rate

In the applied case, $\beta = 2$ results in a linearly increasing hazard rate over time.

Link to Maintenance Cycles The resulting degradation behaviour follows a sawtooth pattern. The hazard rate increases continuously during operation due to wear-out processes and is periodically reduced to a baseline level following maintenance interventions.

System-Level Implications This representation enables a quantitative evaluation of maintenance strategies. By comparing the cumulative hazard over a maintenance interval with a constant baseline, the model provides an explicit measure of maintenance effectiveness.

An approximately balanced system corresponds to an equilibrium between accumulated degradation and maintenance intervention. Deviations from this balance indicate either excessive maintenance (resource inefficiency) or insufficient maintenance (increased failure risk).

6.3 Probabilistic Decision Framework with Bayesian Neural Networks (Thesis 3)

Building upon the probabilistic interpretation of OEE and the sawtooth degradation model, this research formulates a confidence-based maintenance decision framework using Bayesian inference. [4]

Instead of predicting a deterministic time-to-failure, the framework addresses the following question:

How confident are we that maintenance can be safely postponed?

The decision process is formalized through the following probabilistic expression:

$$p_t = P(Y_{t+1} = 1 \mid \mathbf{x}_t, \neg M_t) \tag{6.3}$$

where:

- p_t is the probability of performance degradation in the next interval
- Y_{t+1} is a binary indicator of whether performance falls below a critical threshold
- $\mathbf{x}_t$ represents the observed system state and derived features
- $\neg M_t$ denotes the decision to postpone maintenance at time t

Uncertainty is treated as a first-class output. By employing Bayesian Neural Networks, model parameters are represented as probability distributions, enabling the propagation of epistemic uncertainty into predictions.

To ensure conceptual clarity, the decision architecture is decomposed into three distinct functional components:

- **Survival-BNN:** Estimates the probability that the system will continue operating without failure until the next planned maintenance intervention.
- **Policy-BNN:** Transforms probabilistic risk estimates into actionable maintenance categories, such as under-maintained, balanced, or over-maintained regimes.
- **Phase-BNN:** Characterizes the current degradation state of the system, capturing transitional dynamics that may not yet be reflected in observable performance metrics.

6.4 Integration Result

The central scientific contribution of this dissertation lies in the integration of measurement, degradation modelling, and decision-making into a unified probabilistic framework.

$$\text{Measurement} \rightarrow \text{Degradation} \rightarrow \text{Decision}$$

Within this architecture, empirical production data is continuously transformed into a probabilistic performance signal. This signal is evaluated against a mathematically consistent degradation trajectory that reflects both wear accumulation and maintenance effects.

The resulting features are processed through Bayesian Neural Networks to produce explicit probability estimates of performance degradation, along with associated uncertainty measures. These outputs are then compared against predefined risk thresholds to determine whether maintenance should be executed or postponed.

This integrated approach demonstrates that maintenance can be formulated as a probabilistic confidence evaluation. It enables decision-making based on quantified risk, using minimal data derived from timestamped production logs, and avoids reliance on complex sensor infrastructures.

7 Validation and Evaluation

To evaluate the proposed framework and its ability to support maintenance decisions under uncertainty, validation was conducted in a controlled experimental environment.

Because real-world industrial event logs contain unmeasured disturbances and are subject to strict confidentiality constraints, validation was performed using synthetic datasets generated via Discrete Event Simulation (DES), implemented in Siemens Plant Simulation.

The simulation model was intentionally minimal in structure—not as a simplification of reality, but to isolate causality between stochastic disturbances, maintenance interventions, and production flow.

7.1 Validation of OEE Formulation (Thesis 1)

The first stage of validation confirmed the feasibility of the distribution-free, timestamp-based OEE reconstruction.

Within the DES environment, no predefined availability or quality rates were imposed; these emerged endogenously from simulated failures and maintenance interventions.

The simulation generated only raw event data, including:

- arrival timestamps
- completion timestamps
- failure events
- maintenance interventions

Using a rolling window aggregation scheme (window size of 120 observations with a step size of 10), OEE components were successfully reconstructed entirely from these raw increments.

This reconstruction did not rely on predefined or theoretical ideal cycle times. The results demonstrate that empirical timestamp data is sufficient to derive OEE as a dynamic and probabilistic signal, capable of capturing early degradation effects before structural failure occurs.

7.2 Validation of Degradation Model (Thesis 2)

The second validation phase evaluated the necessity and accuracy of the sawtooth degradation representation by comparing system behaviour under different failure assumptions.

Memoryless vs. Age-Dependent Behaviour Systems modeled with exponential failure distributions (constant hazard) exhibited high throughput variability and weak sensitivity to maintenance adjustments.

In contrast, systems with Weibull-distributed failures ($\beta = 2$) showed:

- reduced throughput variance
- increased mean production rate (Jobs Per Hour)

This demonstrates that system performance is not governed solely by average availability, but strongly influenced by the shape of the failure-time distribution. The results validate the necessity of modelling age-dependent degradation through a sawtooth hazard structure.

System-Level Implications of Maintenance Timing Further experiments evaluated different maintenance regimes:

- **Over-maintained systems (C1):** Excessive maintenance interventions significantly reduced throughput due to unnecessary interruptions.
- **Under-maintained systems (C2):** Delayed maintenance increased throughput variability and reduced system stability.
- **Balanced regime (B):** Optimal performance was achieved when maintenance interventions aligned with the underlying degradation process, resulting in both high and stable throughput.

These results confirm that maintenance timing must be synchronized with system degradation dynamics rather than applied as a fixed schedule.

7.3 Validation of the Probabilistic Decision Framework (Thesis 3) using Simulation Data and BNN Calibration Metrics

To evaluate the decision framework, reconstructed OEE signals and degradation features were processed using three layered Bayesian Neural Networks:

- Survival-BNN
- Policy-BNN
- Phase-BNN

The evaluation demonstrates that probabilistic inference can be effectively translated into actionable maintenance decisions.

Survival-BNN The Survival-BNN estimates the probability of critical performance degradation. It achieved approximately 75% classification accuracy on unseen degradation trajectories.

A key observation is that predictive uncertainty increases as the remaining time to maintenance approaches zero:

$$\Delta t_{\text{maint}} \to 0 \tag{7.1}$$

This behaviour is physically consistent, as uncertainty in system condition naturally increases near critical decision boundaries.

Policy-BNN The Policy-BNN successfully separates operational regimes into:

- over-maintained
- balanced
- under-maintained

This enables direct translation of probabilistic outputs into interpretable maintenance strategies.

Phase-BNN The Phase-BNN captures the internal degradation state of the system. The results show that an increase in predictive variance precedes observable performance deterioration.

This confirms that the model detects transitional degradation phases before they manifest in classical performance indicators.

7.4 Decision Reliability over Point Forecast Accuracy: Model Calibration

The most critical finding of the validation phase is that predictive accuracy alone is insufficient for maintenance decision support.

For operational applicability, the framework must ensure decision reliability. This requires that predicted probabilities correspond to observed event frequencies.

Calibration was evaluated using reliability diagrams and Expected Calibration Error (ECE).

Risk Estimation The Survival-BNN achieved a very low ECE, indicating that predicted probabilities closely match observed failure frequencies.

Regime Stability The Policy-BNN maintained strong probabilistic consistency across maintenance regimes, demonstrating stable and reliable classification behaviour.

Transitional Coherence The Phase-BNN exhibited slightly higher calibration error, reflecting the intrinsic uncertainty of transitional degradation states. However, predictions remained statistically coherent and physically interpretable.

Absence of Overconfidence Across all models, no systematic overconfidence was observed. Uncertainty increased naturally in unstable operating regions, leading to conservative and reliable predictions.

These results confirm the central objective of this research: the outputs of the Bayesian Neural Networks can be interpreted as explicit and reliable operational risk measures.

This enables maintenance decisions to transition from deterministic schedules to probabilistic, confidence-based control.

8 Scientific Theses

This chapter summarizes the principal scientific contributions of the dissertation. The findings are structured into three formal scientific theses. The first two theses stand independently as foundational developments in performance measurement and degradation modelling, respectively. The third thesis synthesizes these foundations into a unified probabilistic decision-making framework.

8.1 Thesis 1 — Performance Foundation

8.1.1 Statement

It can be demonstrated that Overall Equipment Effectiveness (OEE) can be reconstructed objectively and in a parameter-independent manner using exclusively timestamped production cycle data. This reconstruction eliminates the need for predefined ideal cycle times and subjective loss parameters traditionally used in OEE calculations.

Furthermore, the reconstructed OEE can be interpreted as a probabilistic state variable representing the conditional likelihood of ideal production behaviour. Through this reinterpretation, OEE is transformed from a descriptive performance indicator into a stochastic system state suitable for reliability-based analysis and decision-making in production systems. [2]

8.1.2 Interpretation

Historically, OEE has been treated as a deterministic, retrospective ratio designed to summarize past production losses and measure capacity utilization. This thesis reformulates OEE as a forward-looking probability measure, quantifying the likelihood that a discrete manufacturing system achieves ideal conditions.

By abandoning predefined or externally specified ideal cycle times, the calculation becomes distribution-free. Theoretical and actual cycle times are derived empirically from the statistical properties of timestamp data, such as the mode and median.

Consequently, OEE becomes an objective, real-time probabilistic signal. Within a Bayesian context, the deviation between expected (prior) and observed (posterior) OEE serves as evidence of system deterioration and forms the basis for adaptive maintenance reasoning.

8.1.3 Proof

The proof of this thesis is established through the deductive derivation of the data-driven reconstruction method, grounded in finite difference calculus and production flow principles. It is verified through statistical analysis of cycle-time distributions generated in controlled simulation environments.

8.2 Thesis 2 — Degradation Modelling

8.2.1 Statement

It can be demonstrated that degradation processes in periodically maintained serial production systems can be represented by a sawtooth-shaped hazard rate derived from a Weibull failure distribution with shape parameter:

$$\beta > 1 \tag{8.1}$$

Between maintenance interventions, the hazard rate increases as a function of system age, while maintenance actions reset the degradation state. This produces a periodic hazard structure that reflects the interaction between wear-out processes and maintenance interventions. [3]

8.2.2 Interpretation

Classical reliability models frequently assume a constant, memoryless hazard rate. However, this assumption does not capture the behaviour of systems subject to wear and periodic maintenance.

By using a Weibull distribution with an increasing hazard rate, this thesis captures age-dependent degradation dynamics. The periodic reset introduced by maintenance results in a sawtooth hazard trajectory.

This representation enables a quantitative evaluation of maintenance strategies. By comparing cumulative degradation over time, the model provides a criterion for assessing whether a system is over-maintained or under-maintained.

8.2.3 Proof

The proof is based on the analytical derivation of the sawtooth hazard structure and its behaviour under periodic resets. It is further validated through simulation experiments demonstrating that system performance and stability are strongly influenced by the shape of the failure-time distribution.

8.3 Thesis 3 — Probabilistic Decision Framework

8.3.1 Statement

Preventive maintenance planning in serial production systems can be reformulated as a probabilistic decision problem when system performance is represented by a stochastic state variable derived from production data.

Within this framework, maintenance interventions are triggered based on the probability that system performance will fall below a predefined threshold within a future decision interval, rather than at fixed time intervals.

It can be demonstrated that Bayesian Neural Networks can estimate both the probability and uncertainty of such performance degradation events when trained on production-derived degradation sequences. [4]

Furthermore, discrete-event simulation experiments confirm that maintenance strategies based on probabilistic confidence thresholds produce distinguishable and consistent operational regimes.

8.3.2 Interpretation

This thesis represents the integrative contribution of the dissertation. It combines performance measurement, degradation modelling, and probabilistic inference into a unified analytical chain:

$$\text{Measurement} \rightarrow \text{Degradation} \rightarrow \text{Inference} \rightarrow \text{Decision}$$

Timestamp-based production data is transformed into a probabilistic performance signal. This signal is mapped onto a degradation trajectory that reflects both wear accumulation and maintenance resets. These features are then processed through a Bayesian inference mechanism to estimate risk and uncertainty.

The focus of maintenance shifts fundamentally. Instead of predicting an exact time-to-failure, the system evaluates the confidence with which maintenance can be safely postponed. Maintenance becomes a probabilistic risk management problem governed by confidence thresholds.

8.3.3 Internal Structure

To ensure conceptual clarity, the framework is decomposed into three distinct analytical components:

Phase / State Synchronization The Phase-BNN characterizes the degradation state independently of the maintenance schedule. It identifies whether the system operates in a balanced, over-maintained, or under-maintained regime. An important finding is that uncertainty increases before observable performance degradation, indicating early detection of transitional states.

Survival / Risk Estimation The Survival-BNN estimates the probability that the system will reach the next maintenance interval without critical performance loss. The model outputs full probability distributions, allowing uncertainty to be explicitly quantified. This uncertainty increases as the system approaches critical decision boundaries:

$$\Delta t_{\mathrm{maint}} \to 0 \tag{8.2}$$

Policy / Maintenance Regime Classification The Policy-BNN translates probabilistic risk estimates into actionable maintenance strategies. It distinguishes between over-maintained, balanced, and under-maintained regimes, enabling direct decision support.

8.3.4 Proof

The proof of this integrative thesis is established through two complementary approaches:

Simulation-Based Validation Discrete-event simulation experiments demonstrate that different maintenance strategies produce structurally distinct system behaviours in terms of throughput and variability.

Calibration Analysis The probabilistic outputs of the Bayesian models are evaluated for reliability. The results show that predicted probabilities align with observed outcomes, confirming that the model provides calibrated and trustworthy risk estimates.

This framework demonstrates that maintenance decisions can be derived directly from production data as uncertainty-aware, probabilistic control actions. It establishes a complete transformation from timestamp-based observations to risk-informed maintenance execution.

9 Practical Implications

The framework developed in this dissertation establishes a closed-loop architecture that fundamentally alters how maintenance is executed and integrated within a manufacturing environment.

By utilizing Overall Equipment Effectiveness (OEE) as a probabilistic signal, updating degradation states via Bayesian inference, and applying a confidence-based decision rule, maintenance is no longer treated as an isolated technical function. Instead, it becomes a risk-governed control variable embedded within production economics and l ogistics coordination.

The practical implications of this shift are most evident across four key operational domains.

9.1 Maintenance Planning

Maintenance planning in this framework is driven by probabilistic OEE signals, hazard-based degradation models, and BNN outputs, rather than fixed time intervals.

The proposed probabilistic framework transforms maintenance planning into a dynamic, uncertainty-aware process.

The Bayesian Neural Network approach demonstrates that optimal intervention timing is not a fixed parameter, but shifts dynamically in response to the actual degradation rate. By continuously quantifying the probability of a performance drop, the framework allows maintenance to be postponed when operational confidence remains sufficiently high.

This leads to:

- reduction of unnecessary preventive interventions
- lower maintenance costs
- preservation of acceptable failure risk boundaries

Furthermore, maintenance windows can be aligned more effectively with natural production breaks and technician availability, avoiding disruptions during critical production periods.

9.2 Spare Parts Logistics

The integration of probabilistic failure estimation extends beyond maintenance execution and directly impacts supply chain and inventory management.

Traditional spare parts provisioning is based on deterministic failure rates or worst-case assumptions, which often leads to excessive inventory levels.

The probabilistic decision framework enables risk-based spare part provisioning. By continuously estimating the likelihood of equipment failure relative to lead times, inventory policies can be dynamically adjusted.

This enables:

- systematic reduction of safety stock levels
- maintenance of predefined service levels
- reduction of capital tied up in inventory

This approach is particularly effective in environments with stable supplier lead times, where probabilistic forecasts can be reliably translated into logistical decisions.

9.3 Production Stability

A central concern when postponing maintenance is the potential impact on production throughput.

However, the validation results demonstrate that probabilistic postponement does not lead to a linear degradation in system performance.

Because the framework accounts for the buffering effects of intermediate storage and material flow interactions, the relationship between maintenance timing and throughput becomes nonlinear.

Under controlled risk thresholds:

- throughput remains within a statistically stable operating range
- variability is constrained
- effective capacity utilization increases

This ensures that reduced maintenance frequency does not result in unstable or erratic system behaviour.

9.4 Applicability Without Sensors

The framework remains applicable in environments with limited or no condition-monitoring sensors, because it relies primarily on production timestamps, aggregated performance data, and simulation.

These requirements create significant economic and organizational barriers, particularly for small and medium-sized enterprises and legacy production systems.

The framework proposed in this dissertation follows a minimal-data approach. All required signals are derived from timestamped production logs, which are already available in standard Manufacturing Execution Systems (MES) and shop-floor reporting tools.

This enables:

- immediate deployability without additional hardware investment
- applicability to legacy systems
- scalability across diverse production environments

By extracting predictive information from timestamp distributions, the framework enables a transition from traditional maintenance practices toward predictive, risk-aware decision-making without reliance on sensor-heavy infrastructures.

Overall, the practical contribution of this research lies in demonstrating that advanced maintenance strategies can be implemented using existing production data, transforming maintenance into an integrated, probabilistic control mechanism within modern manufacturing systems.

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