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A Simulation-Driven Framework for Risk-Based Maintenance Using Digital Twin

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The increasing complexity of industrial systems requires maintenance strategies that strike a balance between reliability, cost-effectiveness, and uninterrupted production. This paper proposes a simulation-driven framework for risk-based maintenance (RBM) that integrates digital twins (DTs), process mining (PM), Discrete Event Simulation (DES) and real-time, sensor-based diagnostics. The framework is intended for maintenance planners who decide when to intervene and how to schedule maintenance activities while accounting for system-level impacts on production. It is particularly applicable in settings where assets provide diagnostic signals and operational and maintenance event logs are available from Manufacturing Execution Systems (MES) / Computerized Maintenance Management Systems (CMMS). Within the proposed architecture, DTs replicate the behavior of machines and processes using sensor data, while PM extracts operational patterns and activity dependencies from event logs to continuously calibrate model structure and parameters. These representations are then linked to a DES module that simulates various maintenance and fault scenarios and assesses their impact on production KPIs such as availability, cost, and downtime. The framework allows maintenance and production strategies to be evaluated dynamically through 'what if' scenario simulations, providing a quantitative basis for decision-making in uncertain and evolving operational contexts. Simulations outcomes are then integrated into a CMMS, closing the loop between data-driven prediction, risk evaluation and operational execution. This approach supports both predictive and prescriptive maintenance, enhancing system resilience by combining continuous monitoring with model-based simulation. By facilitating scenario-based risk assessment and optimization, the framework serves as a valuable asset in transitioning industrial maintenance from reactive and preventive strategies to intelligent, simulation-assisted decision-making within the context of Industry 5.0.

Keywords: Risk-based maintenance, Discrete Event Simulation, Digital Twin, CMMS

1. Introduction

In this paper, we present a simulation-driven framework for RBM that is enhanced by DT technologies. This framework integrates multiple information sources and decision-support components into a unified architecture. This framework incorporates: (I) a DT enabling real-time, bidirectional data exchange between the physical system and its virtual representation; (II) the capabilities of an industrial CMMS for maintenance planning and execution; (III) real-time, sensor-based fault diagnostics providing continuously updated health indicators and failure probability estimates; and (IV) PM methods applied to operational and maintenance event data. This process knowledge is then used to capture not only machine-level behaviour, but also changes in production workflows. This enables the framework to adapt to evolving system conditions. The central contribution of the proposed approach is the integration of a DES module into the core of the DT. This enables the systematic evaluation of different maintenance strategies and scheduling policies (through the ”What if” scenarios), including their impact on production KPIs such as availability, throughput and downtime.

The reliability, availability, and safe operation of industrial systems are closely linked to the quality and organisation of maintenance (Introna and Santolamazza (2024)). Maintenance is a strategic activity spanning the entire asset life cycle, significantly influencing operational risks, productivity, and cost-effectiveness (Ahmed et al. (2023); Introna and Santolamazza (2024)). The poorly planned or executed maintenance increases the likelihood of unexpected downtime, reduces equipment reliability, and may lead to significant long-term economic and safety consequences (Salawu et al. (2023); Siyad and Khayal (2025)).

Traditional time-based or reactive maintenance strategies are increasingly insufficient to meet the demands of modern industrial environments, particularly in the case of complex, multi-component systems (Ahmed et al. (2023)). Growing system complexity, variable loading conditions, and ageing equipment introduce additional uncertainties, highlighting the need for more accurate condition information and structured decision support for effective maintenance management (Introna and Santolamazza (2024); Salawu et al. (2023)). As a result, maintenance practices are shifting from isolated interventions towards data-driven, predictive, and risk-oriented approaches aimed at reducing operational uncertainty (Ahmed et al. (2023); Siyad and Khayal (2025)).

In this context, digitalised maintenance has emerged as a response to the evolving challenges of industrial operations (Ahmed et al. (2023)). The digitisation of maintenance processes enables continuous monitoring of asset condition, systematic analysis of faults and failure patterns, and informed decision-making based on objective and timely data (Ahmed et al. (2023); Introna and Santolamazza (2024)).

Equipment events, work orders, faults, and interventions can only support robust analysis and decision-making if they are consistently recorded within a unified system (Stazić et al. (2023); Ahmed et al. (2023)). CMMSs play a central role in this process by ensuring data integrity, traceability, and organisation-wide accessibility (Stazić et al. (2023)). Traditionally, CMMS solutions have primarily provided administrative support for operational maintenance activities, particularly in work order management and asset history documentation (Stazić et al. (2023)). In a digitalised maintenance environment, however, their role expands significantly, as CMMS platforms increasingly serve as central hubs for the collection and integration of maintenance data (Ahmed et al. (2023)). By linking asset history, maintenance activities, and operational feedback, CMMSs establish the foundation for advanced data-driven and risk-based maintenance strategies (Stazić et al. (2023); Introna and Santolamazza (2024)). Consequently, CMMS can be regarded not only as execution tools but also as critical infrastructure for digital maintenance. Without such systems, higher-level maintenance decision support and risk-informed optimisation cannot be reliably implemented (Ahmed et al. (2023); Stazić et al. (2023)).

As we described, the landscape of industrial maintenance has witnessed a paradigm shift over the last few decades, transitioning from purely reactive interventions to sophisticated strategies, including preventive, condition-based, predictive, and prescriptive maintenance (van Dinter et al. (2022)). Central to this evolution is the utilization of DTs, which facilitate this move from time-based or reactive strategies to condition-based and predictive maintenance, and then towards prescriptive and optimized maintenance planning. The DT contains three parts, the physical entities in the Physical space, the corresponding virtual entities in the Virtual space and the connections between them, that connects physical and the virtual entities (Grieves (2014)). A DT acts as a virtual reflection of a physical entity, facilitating behavioral simulation, performance prediction, and operational optimization.

When maintenance decisions are made in a production environment, the interdependencies between maintenance activities and production operations must be explicitly considered, since interventions directly influence throughput, scheduling, and resource availability. Therefore, process-level knowledge is required, and DES - which is a modeling technique that enables the detailed analysis of complex systems - provides an effective mechanism to model these dependencies and evaluate their consequences through scenario-based analysis. In maintenance, simulation-based techniques facilitate the simultaneous analysis of component survivability and maintainability, providing frameworks for the implementation and optimization of maintenance strategies (Azadeh and Abdolhossein Zadeh (2016)). In this regard, scenario simulation methods in maintenance provide the ability of assessment and evaluation of future conditions for decision-makers by analysing various potential scenarios (Liu et al. (2025)). This process involves presenting scenarios that integrate normal operations with various maintenance activities, thereby simulation offers a clear illustration of how different strategies, actions, and variables impact system performance. These dynamic modelling capabilities capture equipment behaviour under a range of conditions and support optimization by identifying the most effective strategies and support the evaluation of maintenance outcomes and process optimization by identifying the most effective strategies (Liu et al. (2025).

Simulation involves using a model to reconstruct and analyze a system's dynamic behavior. By presenting an abstract and simplified representation, simulation facilitates a deeper understanding of the system through its execution over time. DES uses a time-ordered Event Queue to process state changes sequentially and ensures consistency despite the irregular timing of events (Soykan et al. (2025)). The event-oriented framework of DES makes it particularly effective for modeling complex dynamic systems where activities take place at sporadic intervals. DES is highly appropriate for modeling systems with discrete state changes particularly in production and logistics. It captures real-world issues like queues, resource constraints, and failures (Lozano-Cruz et al. (2025)). Traditional manual modeling for DES relies heavily on qualitative inputs like interviews, assumptions and documentation. This process is time-consuming and error-prone, as it depends on subjective human perception rather than the objective reality of the system, leading to a gap between the model and reality (Rozinat et al. (2009)).

PM is at the center of data mining and process model-driven approaches, bridging the gap between data science and process science, offering tools to extract process knowledge from event data (Van der Aalst (2016)). PM provides a solution for adequately representing the underlying true nature of processes (Aalst (2010)). PM is more than just process discovery - building a model without using a-priori information - it also brings conformance checking, deviations detecting, delay prediction, decision making support, process enhancement, and process redesign recommendation possibilities.

DT and PM technologies share the objective of exploiting real-time and historical data to construct accurate, continuously updated representations of manufacturing systems (Grobis et al. (2025)). DTs primarily rely on sensor data and cyber–physical system signals to replicate the dynamic states and behavior of machines and production systems, while PM extracts operational patterns, activity dependencies, and performance characteristics from event logs generated by information systems such as MES, and CMMS. Their integration enables the convergence of system-level state information and process-level behavioral knowledge, leading to the Digital Process

Twin (DPT) (Grobis et al. (2025)). DTs are frequently realized through DES models that mirror the physical system's dynamics (Lugaresi (2024)).

The integration of PM using event logs generate simulation models and extract critical simulation parameters, such as probability distributions for activity durations, arrival rates of new cases, and routing probabilities at decision points. PM contributes to simulation modeling in different modeling tasks, such as assign attributes to entities, identify entity types, define activities, determine activity duration, define control-flow and routing logic, and identify resource roles (Jadrić et al. (2020)). Coupling PM with simulation bridges the gap between data and action, enabling the creation of dynamic models that drive continuous business process improvement (Jadrić et al. (2020)).

The three techniques, PM, simulation and DT are integrated as a whole system in our proposed framework to create a solution for RBM. In this framework, maintenance risk is represented as the expected impact of failure events on production and cost outcomes under a given policy. Reliability models provide probabilistic failure behavior, while DES converts that probabilistic behavior into system-level consequences (more downtime, throughput loss). This enables maintenance policies to be compared using expected cost/risk metrics rather than only asset-level health indicators. The framework supports maintenance planners responsible for maintenance activities prioritization and long-term maintenance plans, reliability engineers tasked with failure risk estimation, and production planners who must keep high throughput and delivery performance. The framework is suitable for discrete manufacturing lines and multi-stage production systems where maintenance actions can also cause non-local effects. Practical deployment assumes availability of sensor streams for asset health indicators and event logs from MES/CMMS (work orders, failure events, interventions, and production execution events). The framework provides the strongest benefit when short-term availability gains from postponing maintenance increase failure risk and long-term downtime costs.

2. Developed Framework

The architecture of the framework (see Figure 1) represents a DT with an integrated PM module and standardized data exchange interfaces designed to connect to physical manufacturing systems through sensor data, to CMMS, MES and to DES assuring analytical and decision-support layers necessary for predictive and prescriptive maintenance, enhancing system resilience by combining continuous monitoring with model-based simulation. The architecture is organized into several interconnected subsystems that work together to achieve data-driven RBM.

At the first level of the system lies the physical layer, consisting of machines and sensors operating on the production floor. Each machine is equipped with one or more sensors that continuously capture operational parameters such as temperature, or vibration. The sensor data form the essential input for the DT. These data streams in the integration layer are managed and preprocessed by data collectors, which send them to DT API endpoints and then to the timeseries database (TDB) through the communication layer. This intermediary step ensures that raw measurements are properly structured, timestamped, and validated before they enter the DT.

Above these layers sits the DT itself, integrating information from multiple data sources. Sensor data are received through dedicated API endpoints, while contextual information such as operational metrics, asset hierarchies, and event logs are obtained through API connections of the MES, and CMMS respectively. These external systems contribute master data, historian and current state data to the digital model.

The MES API endpoint provides access to production-related information of the MES database, such as throughput, process times, costs and operation related event logs. These production data and production cost parameters are given to the DT, assuring an accurate digital representation of the physical environment. The CMMS API endpoint exposes the maintenance-related information of the CMMS database, including definitions of assets, failure types, recorded failures,

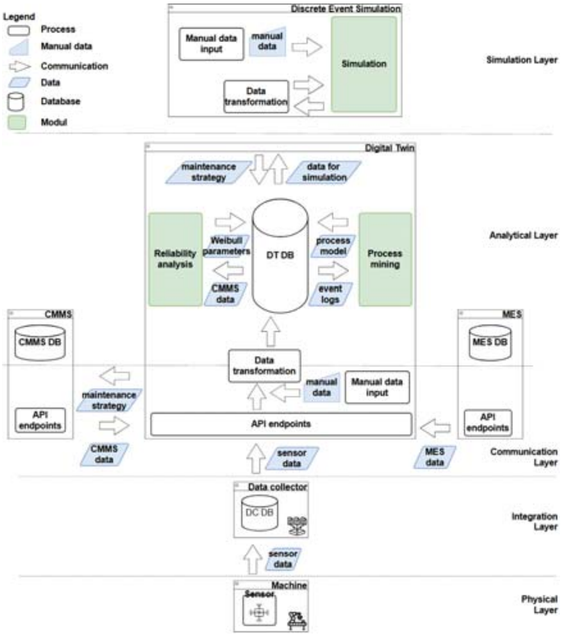

Fig. 1. The proposed system architecture

maintenance lists, and maintenance event logs as well as historical maintenance records. The DT consumes these inputs to maintain a synchronized and more accurate digital representation of the physical environment.

Within the DT system a PostgreSQL database with a TimescaleDB extension acts as the unified repository for all synchronized data and supports subsequent analytical operations, such as PM. Additionally, a user interface for manual data input allows human operators or engineers to enter supplementary or corrective data.

The analytical layer of the architecture is built around PM and reliability analysis (RA). RA characterizes asset-level stochastic failure behavior (e.g., Weibull distributions) from condition and failure evidence, providing probabilistic models of when and how assets degrade. PM characterizes the process-level operational reality (e.g., control-flow, routing, resources, and time distributions) extracted from MES/CMMS event logs. In combination, RA determines what failure processes may occur, while PM determines how the production and maintenance processes actually behave, how failures and interventions affect the system. The DES layer then integrates both to quantify risk–performance trade-offs for alternative policies. Using both historical data and live sensor readings, the RA module applies statistical and machine-learning-based methods to determine the shape and scale parameters of the Weibull probability density function. The output of this process is then communicated to the internal DT database and then later to the simulation layer to use by the DES. The PM module identifies the process flows and deviations, generates process models and their parameters. The results of this process are fed back into the DT database, enriching the model with a better understanding of real-world operations. The PM module outputs used by DES include the discovered or updated control-flow models of production and maintenance execution, routing, resources, and time distributions, and conformance/deviation indicators that trigger simulation model updates.

The DES represents the simulation layer of the architecture, pulls calculated data from the DT API endpoints to perform virtual experiments and run simulations based on realistic factory conditions to answer the ”What if” scenarios. The simulation models include representations of the routing table, layout, and other plant configuration data, which define how resources and workflows are organized. Once simulations are executed, the simulation results — such as bottleneck analysis, capacity utilization, process efficiency metrics and the optimal maintenance strategy — are then fed back to the DT for validation and further decision support (e.g. send the optimal maintenance strategy to the CMMS).

Overall, the system operates as an interconnected ecosystem where data flow continuously between the physical, digital, and analytical domains. The physical machines provide real-world measurements; the DT centralizes, interprets, and analyzes this data; the MES enriches it with production context; the CMMS enriches it with maintenance context; the PM and the RA modules extract the relevant data needed for simulation; and the DES produces information that can be transformed into actionable insights. The outcomes of the simulations are integrated into a CMMS, closing the loop between data-driven prediction, risk evaluation and operational execution. This approach supports both predictive and prescriptive maintenance, enhancing system resilience by combining continuous monitoring with model-based simulation. By facilitating scenario-based risk assessment and optimization, the framework serves as a valuable asset in transitioning industrial maintenance from reactive and preventive strategies to intelligent, simulation-assisted decision-making.

3. The data flows and descriptions

The simulation environment is supported by a relational database schema (see Figure 2), which is part of the whole DT database schema. The core of the simulation-related part of the database schema comprises the scenario, simulation run and event log tables. Together, these tables capture the structure, execution and outcomes of the DES runs. Surrounding these there are definition tables describing assets, product types, and process flows.

The database schema forms a logically connected structure based on entity types necessary for the simulation: (1) The scenario is defined for the simulation run in order to create an event log that represents the chronological execution and tracking chain of the simulation. (2) Asset type, exit control type, asset, process step, routing define the physical and logical structure of the system being simulated. (3) Failure type, asset, asset failure type, weibull define the parameters of the Weibull probability density function for simulating the reliability of assets based on the historical data stored in the database. (4) Product type and product describe the entities that traverse the simulated process network. (5) Performance metrics and simulation performance store quantitative evaluations derived from simulation outcomes. (6) Relationships are maintained using UUID-based foreign keys, enabling scalable integration with external systems and APIs.

To connect the analytical layer with the simulation layer of the system we defined an API endpoint for standardized data exchange interface and use JSON files for standardized data transfer format. The JSON format provides a tool-agnostic, human-readable, and machine-interpretable representation, thereby supporting reproducibility, portability, and automated model generation from DT database. The simulation model is configured using a declarative JSON schema that integrates resource definitions, spatial layout, process steps, routing logic, and stochastic failure behavior. The JSON represents a single executable model instance, whose execution in the simulation layer generates event logs and performance data. The resulting simulation outputs are subsequently persisted in the database as performance metrics and simulation performance records, thereby closing the analytical loop between configuration, execution, and evaluation.

4. Discussions and further research

In this paper, we present a framework based on DT that places DES at the core of decision support for maintenance strategies, with a specific focus on RBM. The proposed approach integrates DES with PM algorithms, enabling maintenance deci-

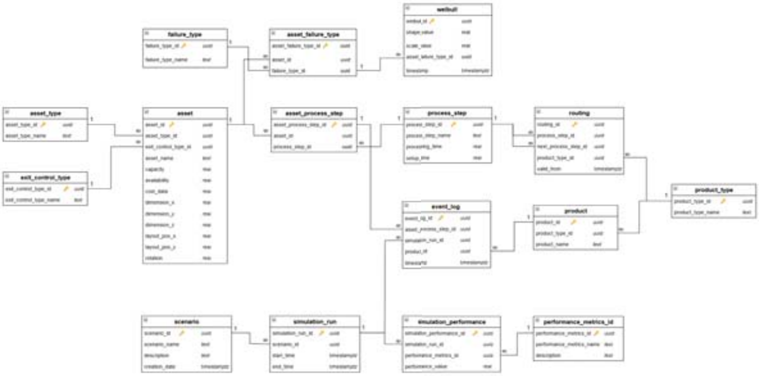

Fig. 2. The DT database schema - simulation-related tables

sions to be informed by machine-level condition data and knowledge extracted from production and maintenance processes. Embedding the simulation model into the DT enables the framework to perform systematic ’what if’ analyses, evaluating alternative maintenance strategies with respect to their impact on production performance, risk and system availability. The paper explained the conceptual foundations and architecture of the framework. We provided a detailed overview of the system’s overall structure, the interaction between the DT, PM and DES components, and the role of the CMMS in execution and data management. Particular attention was given to the data model and database structure, including the definition of data tables and the data flow that supports PM and simulation-based analysis.

At the present stage, the contributions of this paper are conceptual and architectural, and can be summarized as follows: (1) Simulation-driven risk-based maintenance: DES is embedded as a decision-support layer, enabling systematic comparison of maintenance policies under uncertainty. (2) Integrated reliability–production modeling: probabilistic asset failure behavior (reliability) is evaluated together with operational dependencies and constraints (production) to quantify risk–performance trade-offs. (3) Process mining as a mechanism for continuous model updates: PM supports ongoing adaptation of the simulation model by discovering process control-flow and by deriving parameters from event logs. (4) Closed-loop integration with maintenance execution: results are translated into executable maintenance actions (priorities/schedules) for the CMMS, enabling continuous improvement. (5) Interoperable data exchange: standardized JSON/API-based interfaces are proposed to improve reproducibility and portability of the framework.

Large-scale quantitative validation using real industrial data is still part of ongoing and future research. The framework is designed to be extensible and reusable. The present study focuses on integrating DTs, PM and maintenance systems within a simulation-centred framework, rather than optimising a specific industrial use case. This scope enables the framework to be adapted to different production environments and maintenance contexts. The next step is to develop the DES component using real-life industrial data. This will enable the quantitative evaluation of maintenance strategies in operational environments. To this end, a plant-level simulation model will be developed and integrated into the proposed framework. The system’s modular architecture already supports this integration, and preliminary tests have confirmed that simulation models can be embedded seamlessly into the DT environment. This builds directly on our previous research into simulation-based DTs (Ruppert and Abonyi (2020)), in which real-time sensor data were fused with adaptive simulation models to analyse production performance and human resource effectiveness. This study showed how continuously synchronised simulation-driven DTs can predict production states and support performance monitoring through dynamic, data-informed simulation.

From a practical perspective, the proposed framework allows maintenance planners and production engineers to virtually evaluate alternative maintenance strategies before implementation, thereby reducing operational risk and supporting more informed, risk-aware decision-making. Combining real-time data, process knowledge and simulation-based 'what if' analysis provides a realistic pathway towards Simulation 4.0-enabled risk-based maintenance, where maintenance and production decisions are optimised dynamically and interpretably.

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