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HYBRID DIGITAL TWIN AND MONTE CARLO SIMULATION FOR RELIABILITY OF ELECTRIFIED MANUFACTURING LINES WITH HIGH POWER ELECTRONICS

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Abstract

Reliability assessment of electrified manufacturing lines with high power electronics had remained difficult because disruption behavior had been driven by electro-thermal stress, operating-regime variability, restoration logistics, and line-level propagation effects that had produced heavy-tailed downtime and throughput-loss distributions. This study had developed and evaluated a hybrid digital twin integrated with Monte Carlo simulation and discrete-event line modeling to estimate distribution-based reliability and production-impact outcomes for a converter-driven manufacturing line. The merged operational timeline had covered 12 months, had included 18 converter-driven stations, and had captured 86,400 scheduled production minutes. A total of 3,462 disruption events had been reconciled, comprising 2,691 protection trips, 412 hard stops, and 359 reduced-capacity events. Line-level cumulative downtime had totaled 8,964 minutes, corresponding to an operational availability of 89.6%, and downtime per event had been right-skewed with a mean of 2.59 minutes and a median of 1.10 minutes. Downtime concentration had been evident, as the top three stations had contributed 41.2% of total downtime. Correlation analysis had shown that the thermal stress proxy had been strongly associated with downtime totals ($r = 0.68$) and throughput loss ($r = 0.57$), while utilization intensity had been most aligned with stop counts ($r = 0.62$). Regression modeling based on 6,480 station-days had indicated that thermal stress increased stop incidence (IRR = 1.24, 95% CI 1.16–1.33, $p < 0.001$), and high-load regimes increased stop rates (IRR = 1.19, 95% CI 1.10–1.28, $p < 0.001$). Repair-duration modeling using 412 repairs had shown that maintenance delays inflated restoration time by 18% ($p < 0.001$) and hard-stop class produced longer repairs (ratio = 1.74, $p < 0.001$). Monte Carlo–discrete-event simulation had matched weekly downtime distributions with a Kolmogorov–Smirnov distance of 0.09 and improved tail accuracy, reducing ninety-fifth-percentile downtime absolute error from 210 minutes (independence) to 172 minutes (dependency), an 18.1% reduction.

Keywords

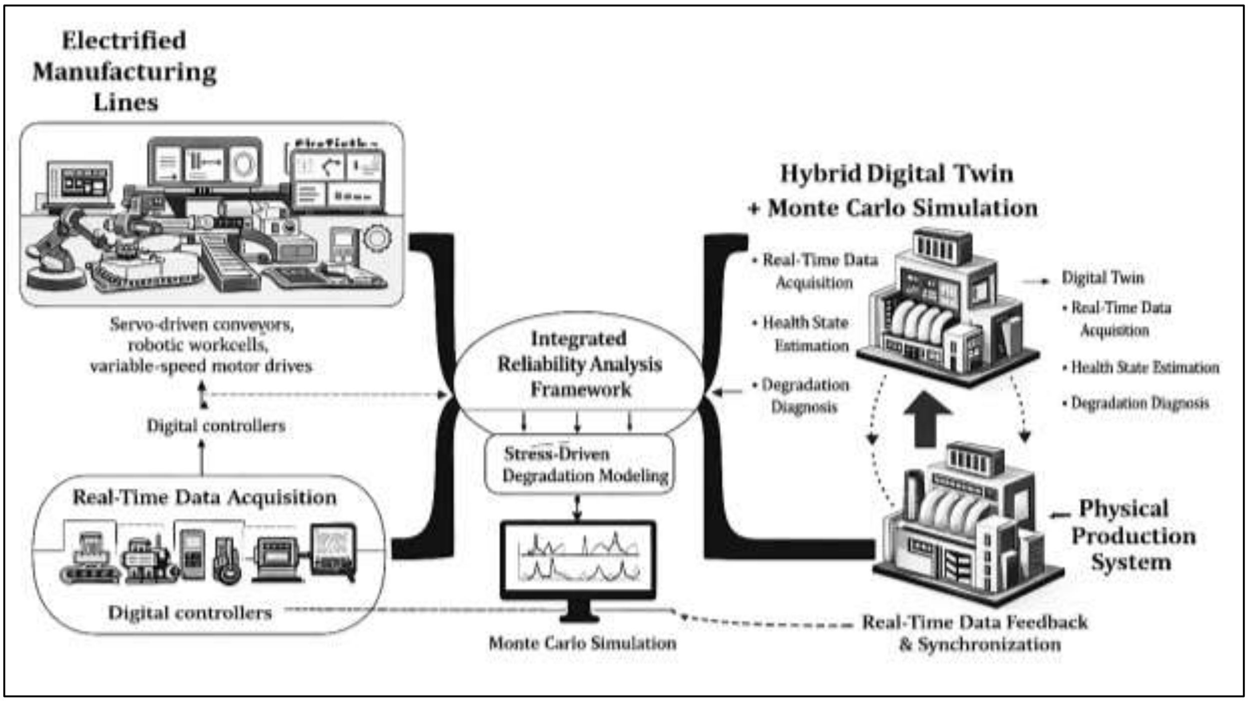
Hybrid digital twin, Monte Carlo simulation, manufacturing reliability, high power electronics, downtime distributions.

INTRODUCTION

Digital transformation in manufacturing refers to the structured use of data, computation, and automation to improve how production systems are designed, operated, and maintained across globally distributed plants. Within this transformation, electrified manufacturing lines can be defined as production systems in which the main sources of motion, actuation, and process energy are delivered through electrical power conversion, electrical drives, and digitally controlled actuators rather than primarily hydraulic or purely mechanical means (Borangiu et al., 2019). These lines typically include servo-driven conveyors, robotic workcells, variable-speed motor drives, precision motion controllers, industrial networks, and supervisory control layers that coordinate material flow and machine states. A second key definition is high power electronics, which in industrial manufacturing commonly refers to power conversion and switching subsystems that regulate and deliver electrical energy at high current and/or high voltage to loads such as motors, heaters, welders, and power supplies. These subsystems include converters and inverters, semiconductor switches, gate drivers, DC-link capacitors, magnetics, sensors, thermal interfaces, and protection circuitry. The third definition is reliability, meaning the probability that a system performs its intended function without failure for a specified time under stated conditions. In electrified lines, reliability is not merely a component property; it is an operational property that determines whether production targets can be met under variability in loads, environments, and maintenance conditions (Butt, 2020; Mohiul, 2020). Internationally, electrified manufacturing lines are central to industries such as automotive, electronics, appliances, and process manufacturing, where the same product families are produced in different countries under different climates, grid qualities, operator practices, and supply constraints. Because of this global dispersion, reliability must be quantified in a way that remains comparable across sites yet sensitive to local operating conditions. Electrification also increases the number of tightly coupled cyber–physical interactions: switching behavior influences temperature, temperature influences aging, aging influences fault likelihood, and faults propagate quickly into line stoppages. As a result, quantitative reliability assessment needs methods that can capture both physical degradation mechanisms in power electronics and system-level consequences in complex production networks (Savastano et al., 2019). This requirement motivates the use of digital representations that remain linked to real operational data and simulation approaches that propagate uncertainty rather than assuming single deterministic conditions.

A digital twin can be defined as a dynamic digital representation of a physical asset or system that is continuously updated using operational data to reflect the asset's evolving condition and context. Unlike a static model used for offline analysis, a digital twin is designed to remain synchronized with the physical system through data streams such as sensor measurements, event logs, control signals, and maintenance records (Jinnat & Kamrul, 2021; Mourtzis & Panopoulos, 2022). In manufacturing, digital twins may represent machines, process modules, robotic cells, conveyor systems, or entire lines, depending on the scope and the decision questions. A hybrid digital twin can be defined as a twin that integrates physics-based modeling with data-driven modeling. Physics-based modeling captures known relationships such as electrical losses, thermal dynamics, stress–strength behavior, and degradation accumulation, while data-driven modeling captures patterns that are difficult to express analytically, such as latent operating modes, anomalous signatures, and non-obvious combinations of variables that precede failure. Hybridization is especially relevant for electrified manufacturing lines with high power electronics because failures are often driven by electro-thermal interactions that are mechanistic in nature, yet real factory variability introduces complexities like variable duty cycles, product mix changes, ambient shifts, control tuning changes, and maintenance interventions (Albukhitan, 2020). A hybrid twin can therefore maintain a mechanistic "core" for interpretability and extrapolation while using data-driven elements for calibration, state estimation, and detection of deviations from normal behavior. Another definitional element is the notion of synchronization, which in twin design refers to the process by which the digital representation updates its internal states and parameters based on real-time or near-real-time data. Synchronization makes it possible to track the health of power-electronic components, the operational state of stations, and the material-flow conditions of the line. At an international scale, synchronization also supports standardization: the same twin template can be deployed across sites while ingesting different data streams and reflecting different operating conditions. This approach aligns with the need for reliability quantification that can travel across borders without losing sensitivity to local realities (Cohen et al., 2019; Hasan & Shaikat, 2021).

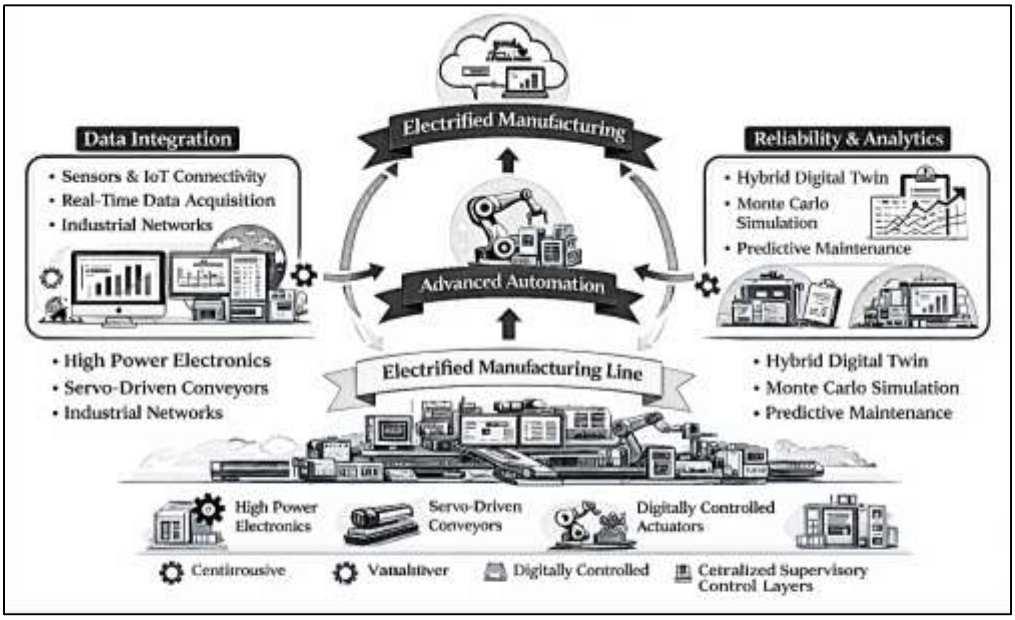
Figure 1: Hybrid Digital Twin Reliability Framework



Reliability modeling for electrified manufacturing lines with high power electronics begins with recognizing that dominant failures are frequently stress-driven, time-varying, and mission-profile dependent (Dall'Ora et al., 2021; Rabiul & Samia, 2021). In high power electronics, reliability is strongly influenced by temperature cycles, current ripple, voltage transients, switching frequency, load steps, vibration, humidity, and contamination. Components such as semiconductor power modules, capacitors, gate drivers, and thermal interfaces can degrade through mechanisms that accumulate damage over time (Mohiul & Rahman, 2021; Rahman & Abdul, 2021). For instance, repeated temperature swings can drive fatigue processes in interconnects and solder layers, while sustained high temperature can accelerate aging in dielectric materials and polymer structures. Reliability can be modeled at the component level by mapping stress histories to degradation states and then mapping degradation states to failure probabilities. However, in manufacturing lines, system-level reliability is not a simple sum of component reliabilities. A power-electronic failure can stop a station, a station stop can starve downstream processes, buffers can mask or amplify downtime, and line control logic can change operating conditions in response to reduced capacity. Therefore, a quantitative reliability framework must represent both continuous degradation dynamics and discrete operational consequences (Chen et al., 2020; Haider & Shahrin, 2021; Zulqarnain & Subrato, 2021). This is where line-level modeling becomes essential: a line can be represented as a network of stations, buffers, and transport links with rules for blocking, starving, batching, and rework, and these operational rules determine how a failure translates into production loss. In electrified lines, the coupling between energy conversion and operational performance is especially strong because control actions—such as derating, speed reduction, or load redistribution—may change thermal stress profiles and thus influence subsequent reliability. The reliability problem is therefore inherently dynamic and coupled: reliability affects operation, and operation affects reliability (Habibullah & Farabe, 2022; Arman & Kamrul, 2022; Moghaddam et al., 2018). A hybrid digital twin provides the structure to represent these couplings by maintaining a unified representation of physical health, operational state, and control behavior.

Monte Carlo simulation can be defined as a computational method that estimates probabilities, expectations, and distributions by repeatedly sampling random variables and running a model many times. In reliability analysis, Monte Carlo simulation is used to propagate uncertainty in failure times, repair times, operating conditions, and model parameters through complex systems where analytic solutions are not feasible (Qi & Tao, 2018). For electrified manufacturing lines, Monte Carlo simulation is particularly suitable because the system includes both discrete events (failures, repairs, production routing, buffer transitions) and continuous phenomena (electro-thermal dynamics, degradation accumulation). Each Monte Carlo run can represent one possible "life history" of the line over a time horizon, where component failure occurrences and repair durations are generated according to probabilistic models, operating loads vary according to production schedules, and environmental conditions fluctuate. By repeating these runs, the analyst can estimate distributions of time-to-failure, availability, downtime, throughput loss, and the probability of meeting production targets (Cheng et al., 2020). A key advantage is that Monte Carlo simulation can incorporate dependencies and conditional behavior: the failure likelihood of a converter can depend on its temperature trajectory, temperature can depend on load and switching behavior, load can depend on line state and product mix, and line state can depend on prior failures and buffer levels. Monte Carlo simulation also enables layered uncertainty treatment. Some uncertainties are aleatory, reflecting natural variability in loads or environmental fluctuations, while others are epistemic, reflecting imperfect knowledge of model parameters or incomplete data. By sampling both types in a structured manner, the simulation yields not only point estimates but uncertainty ranges for reliability metrics. Internationally, this matters because plants differ in data quality and operational patterns; Monte Carlo simulation can explicitly represent those differences as inputs rather than forcing all sites into a single deterministic assumption set (Szalavetz, 2020). When paired with a digital twin, Monte Carlo simulation becomes even more relevant because the twin can supply updated parameter estimates and current state values, so simulations can reflect what is actually happening in the plant rather than relying on historical averages alone.

Figure 2: Electrified Manufacturing Digital Transformation Framework



A quantitative foundation for integrating a hybrid digital twin with Monte Carlo simulation requires careful definition of states, variables, and measurable outcomes. In a hybrid twin for an electrified manufacturing line, state variables may include component health indices for power modules and capacitors, cumulative thermal cycle counts, estimated junction temperature statistics, insulation-aging indicators, and operational states such as station up/down status, buffer levels, and production routing (Rashid & Praveen, 2022; Kamrul & Omar, 2022; Savastano et al., 2018). Inputs may include production schedules, control setpoints, ambient temperature, humidity, grid quality indicators, and maintenance actions. Outputs may include reliability metrics such as survival probability over a horizon, expected number of failures, expected downtime, availability, and distributions of production loss. The hybrid twin must also define how data enters the model: sensor data may update temperatures and currents, event logs may update failure and repair events, and maintenance records may reset or partially restore health states after replacements (Rahman, 2022; Rony & Samia, 2022). The data-driven portion of the twin may be responsible for inferring hidden operating modes, detecting abnormal signatures, or calibrating uncertain parameters based on observed behavior. The physics-based portion may be responsible for converting electrical and thermal loads into stress measures and damage accumulation (Abdul & Rahman, 2023; Aditya & Rony, 2023; Fatima et al., 2022). Monte Carlo simulation then operates as the uncertainty propagation layer by sampling uncertain variables and running the twin forward in time under many possible trajectories. Importantly, the simulation must represent how failures occur. This can be done by sampling stochastic failure times from lifetime distributions conditioned on stress, or by updating hazard rates dynamically based on stress and degradation state, which is particularly relevant for components whose failure propensity increases as damage accumulates (Arfan & Rony, 2023; Ara & Shaikh, 2023). Repairs can be modeled as random durations with distributions that reflect maintenance logistics, and repair actions can change the system state by replacing components and restoring performance. At the line level, each failure triggers discrete-event consequences: downstream starving, upstream blocking, rerouting if available, and shifts in operational load for remaining stations (Habibullah & Mohiul, 2023; Hasan & Waladur, 2023). The combined hybrid twin and Monte Carlo structure allows reliability to be quantified as an emergent property of interacting physical degradation, operational dynamics, and maintenance behavior (Liu et al., 2021; Arman & Nahid, 2023; Mesbaul, 2023).

Another essential element in this topic is the interpretation of "reliability of manufacturing lines" as a system property that interacts with productivity, quality, and operational constraints. In practice, a line may continue producing under degraded conditions, such as reduced speed, increased cycle times, or intermittent faults that trigger short stops (Milon & Mominul, 2023; Mohaiminul & Muzahidul, 2023; Panetto et al., 2019). These behaviors are common in electrified systems where protective controls may trip and auto-reset, or where control strategies may derate a drive to avoid overheating. Reliability analysis must therefore distinguish among failure modes that cause total stoppage, partial capacity reduction, and quality degradation (Musfiqur & Kamrul, 2023; Rezaul & Kamrul, 2023). High power electronics can contribute to all three: hard failures in power modules can stop a station, drifting sensor calibration or thermal interface degradation can raise temperatures and increase nuisance trips, and unstable power conditioning can cause process variability affecting quality. A robust quantitative model must categorize these failure modes and represent their operational impacts. The hybrid digital twin is well-suited to this categorization because it can represent both continuous degradation leading to increased fault frequency and discrete threshold events that cause stoppage (Lu, Xu, et al., 2020; Amin & Praveen, 2023; Rabiul & Mushfequr, 2023). Monte Carlo simulation can then quantify not only expected downtime but the full distribution of outcomes, including tail risks such as rare but severe cascades where multiple failures occur close together or where repairs are delayed by spare-part unavailability. In globally distributed manufacturing, tail risks matter because supply-chain commitments often depend on worst-case scenarios rather than average conditions (Shahrin & Samia, 2023; Roy, 2023). Moreover, international operations may face different constraints in maintenance staffing, spare inventory, and grid stability, which can be represented as probabilistic inputs to the simulation. The modeling approach also supports comparability across plants by using a consistent structure while allowing site-specific parameters, enabling quantitative benchmarking of reliability under consistent definitions and metrics (Rakibul & Majumder, 2023; Rifat & Rebeka, 2023; Rocha et al., 2021). Throughout, the focus remains on explicit definitions, measurable variables, and probabilistic estimation of reliability outcomes rather than narrative claims, ensuring the introduction aligns with a quantitative research framing (Kumar, 2023; Saikat & Aditya, 2023).

At the core of the paper's title, the integration of a hybrid digital twin and Monte Carlo simulation can be framed as a unified method for estimating reliability in complex electrified manufacturing lines where high power electronics are reliability-critical and uncertainty is unavoidable (Nagy et al., 2018; Zaki & Masud, 2023; Zaki &Hossain, 2023). A hybrid digital twin provides an evolving digital representation of the line that can track operational context and health states, combining mechanistic models of electrical and thermal stress with data-driven updates from real measurements. Monte Carlo simulation provides a systematic way to propagate uncertainty through that representation to estimate reliability metrics as distributions rather than single values (Rashid, 2024; Zulqarnain & Subrato, 2023). This combination directly addresses the complexity of modern electrified lines: power-electronic components age according to stress histories, stress histories are shaped by production schedules and control strategies, control strategies respond to operational disturbances, and disturbances propagate through the line structure governed by buffers and routing. A quantitative approach must therefore represent coupling, uncertainty, and time evolution (Md & Praveen, 2024; Mohaiminul & Majumder, 2024; Pal, 2020). The hybrid twin supplies coupling and time evolution through states and synchronized updates; Monte Carlo supplies uncertainty propagation through repeated sampling of operating conditions, failure processes, and repair dynamics (Foysal & Abdulla, 2024; Md. Ibne & Aditya, 2024). Together, they enable reliability to be expressed in terms that are measurable and decision-relevant within quantitative research: probability of failure-free operation over a horizon, expected downtime with uncertainty bounds, expected production loss distribution, and availability distributions under defined operating conditions. Because the same electrified manufacturing paradigms are deployed internationally across diverse environments, a probabilistic and adaptable framework is essential for achieving reliability quantification that is both generalizable and grounded in real operational data. This framing establishes the definitional and methodological basis for a quantitative investigation of reliability in electrified manufacturing lines dominated by high power electronics, using hybrid digital twin modeling as the representational backbone and Monte Carlo simulation as the computational engine for uncertainty-aware reliability estimation (Illa & Padhi, 2018; Milon & Mominul, 2024; Mosheur & Arman, 2024).

The objective of this quantitative study is to develop and apply an integrated, measurement-driven framework that combines a hybrid digital twin with Monte Carlo simulation to estimate the reliability of electrified manufacturing lines in which high power electronics are reliability-critical elements, and to express reliability outcomes as probabilistic distributions that reflect real operational uncertainty rather than single deterministic values. Specifically, the study aims to (1) construct a hybrid digital twin that unifies physics-based representations of electro-thermal stress and degradation in power-electronic subsystems with data-driven state estimation using operational signals such as current, voltage, temperature, switching behavior, line events, and maintenance logs; (2) define and quantify component- and system-level reliability variables, including failure probability over a stated horizon, time-to-failure distributions, mean time between failures, mean time to repair, availability, downtime frequency, and production-loss distributions derived from station stoppages and line interactions; (3) encode the manufacturing line's operational structure through a system model that captures station dependencies, buffer dynamics, blocking and starving effects, and repair/restoration logic so that component failures in power electronics can be translated into system-level reliability and throughput impacts; (4) implement Monte Carlo simulation as the uncertainty-propagation engine by sampling variability in operating conditions (product mix, duty cycles, ambient conditions, grid disturbance indicators), parameter uncertainty in degradation and failure models, and stochastic repair durations to generate many plausible operating histories of the line; and (5) statistically evaluate the framework's performance by comparing simulated reliability outputs against observed line behavior over a defined data window, using quantitative goodness-of-fit indicators and error measures for event counts, downtime duration distributions, and availability metrics. The study further aims to determine the sensitivity of line reliability to dominant stressors and configuration factors by quantifying how changes in electro-thermal loading profiles, component health states, and repair logistics shift the resulting reliability distributions, thereby identifying which measured variables contribute most to uncertainty in reliability estimates. By meeting these objectives, the study positions the hybrid digital twin as the evolving digital representation that maintains state fidelity and parameter relevance, while Monte Carlo simulation operationalizes uncertainty handling to produce robust quantitative reliability metrics for electrified manufacturing lines dominated by high power electronics.

LITERATURE REVIEW

The literature review for this quantitative study establishes the conceptual and empirical foundation for integrating hybrid digital twins with Monte Carlo simulation to estimate the reliability of electrified manufacturing lines where high power electronics act as reliability-critical subsystems (Münch et al., 2019). Because electrified lines combine tightly coupled electrical conversion, motion control, automation logic, and discrete material-flow behavior, the reliability problem spans multiple modeling layers: component degradation and failure physics in power electronics; stochastic failure and repair processes; line-level dependence created by buffers, bottlenecks, and control logic; and uncertainty arising from variable duty cycles, environmental conditions, and maintenance actions (Zaoui & Souissi, 2020). The literature review therefore organizes prior work around (a) definitions and reliability metrics at component and system levels, (b) failure mechanisms and stress–life relationships specific to high power electronics, (c) manufacturing line modeling approaches that translate component events into throughput and downtime distributions, (d) digital twin and hybrid modeling strategies that unify mechanistic and data-driven representations, and (e) Monte Carlo methods for uncertainty propagation, rare-event estimation, and distribution-based reliability reporting (Münch et al., 2020). The purpose of this section is to identify what is already established, what assumptions dominate existing approaches, which quantitative gaps persist when these methods are applied to electrified lines, and how a combined hybrid-twin plus Monte Carlo framework can be positioned as a measurable, testable approach for reliability estimation under real operating variability.

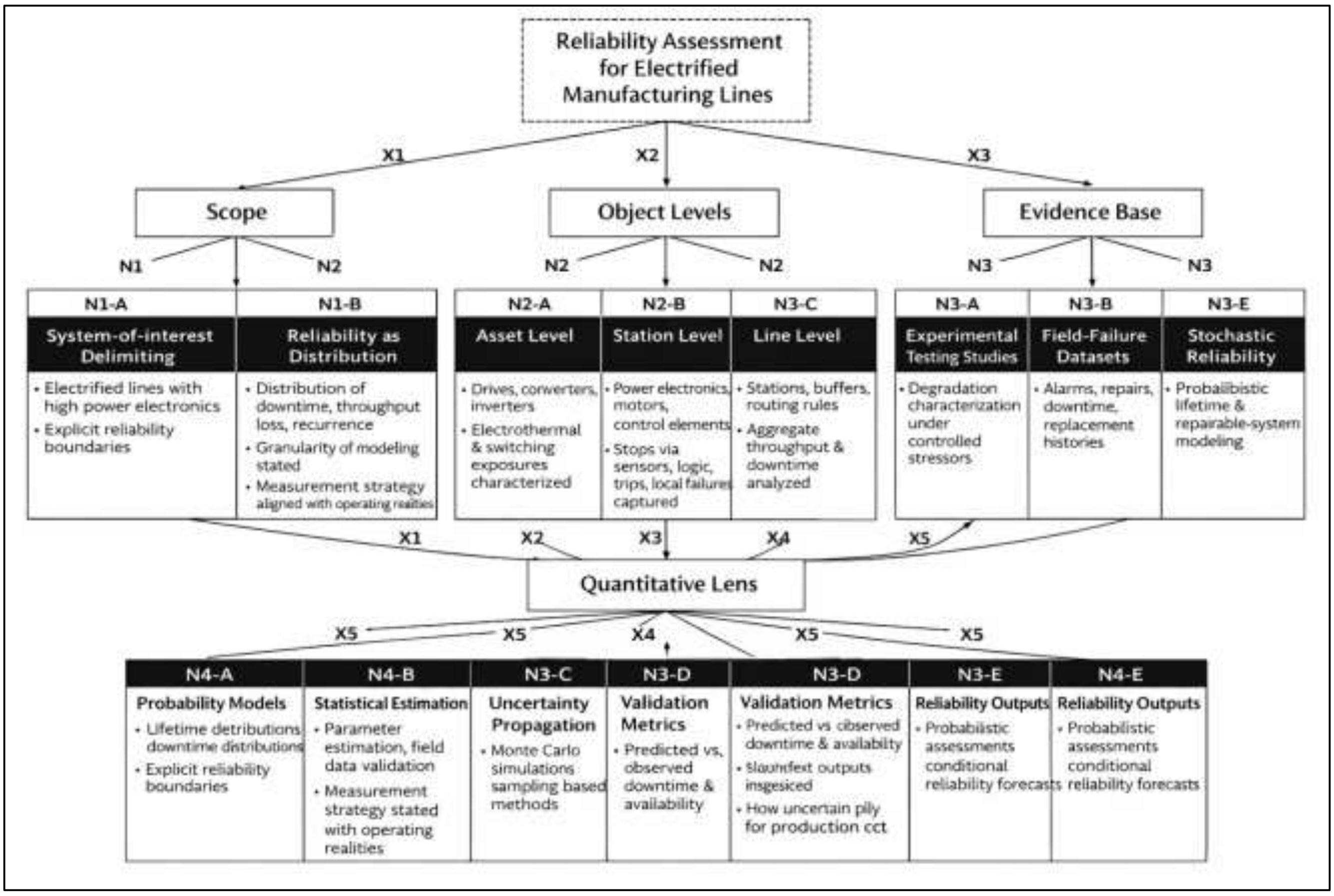
Literature Review (Section Roadmap)

The literature on reliability assessment for electrified manufacturing lines has increasingly emphasized the need to define clear scope boundaries because these systems combine electrical power conversion, motion control, automation logic, and discrete material flow in ways that make reliability outcomes nontrivial to interpret (Alcantara & Martens, 2019). Within this scope, “electrified manufacturing lines” are treated as production lines whose principal actuation and process energy rely on electrical drives and digitally controlled equipment, while “high power electronics” are treated as converter- and inverter-based subsystems that condition and control power for motors, robots, welding, heating, and other industrial loads. Studies across manufacturing systems engineering and industrial reliability show that failures in power-electronic subsystems often propagate beyond a single component, creating line-level downtime patterns that are shaped by buffers, inter-station dependency, and control reactions rather than only by the intrinsic weakness of a device. For that reason, a major boundary in recent scholarship is the shift from reliability as a single point estimate to reliability as a distribution of possible outcomes, where downtime, throughput loss, and failure recurrence vary under changes in operating load, ambient conditions, grid disturbances, and repair logistics. This distribution-based framing is consistent with reliability engineering research that distinguishes between component survival behavior, repairable-system availability behavior, and system performance behavior in production contexts (Kerr & Phaal, 2021; Rahman & Aditya, 2024; Saba & Hasan, 2024). It is also consistent with modern simulation-driven manufacturing research that reports not only mean downtime but also variability, quantiles, and tail outcomes that matter for production commitments. Another boundary addressed by the literature concerns the granularity of modeling: some studies focus narrowly on converter hardware aging, while others focus on line-level production flow (Kumar, 2024; Sai Praveen, 2024); however, electrified lines require an explicit boundary statement on what phenomena are included (electro-thermal stress, nuisance trips, protective shutdowns, maintenance restoration) and what is excluded (for example, purely human-factor stoppages or upstream supply shortages) to avoid conflating reliability with broader operational risk. Across the reviewed work, the rationale for these boundaries is primarily quantitative: without bounded definitions and measurable outcomes, model calibration becomes ambiguous, validation targets become inconsistent, and comparisons across plants or product mixes become unreliable (Li et al., 2022; Saikat, 2024; Shaikat & Aditya, 2024). Consequently, the literature review roadmap in this topic area begins by delimiting the system-of-interest, defining reliability outputs as probabilistic distributions, and aligning the measurement strategy with the operating realities of electrified manufacturing lines dominated by high power electronics.

A second theme in the literature concerns the definition of core research objects at multiple levels—asset-level, station-level, and line-level—because each level implies different data requirements, different failure semantics, and different reliability metrics. At the asset level, the dominant research object is typically a power conversion unit such as a drive, converter, inverter, or power module assembly (Arfan, 2025; Ara, 2025; Kovacs & Moshtari, 2019). Research at this level frequently characterizes degradation through observed thermal loading, ripple currents, switching behavior, and cooling conditions, linking these exposures to the likelihood of faults or protective trips and to the time distribution of functional failure (Jinnat, 2025; Rashid, 2025b). At the station level, the object expands to include the interaction between power electronics, motor or actuator, embedded control, sensors, and local safety logic. Station-level work demonstrates that many stoppages are not strictly catastrophic component failures but are triggered events resulting from threshold violations, control instabilities, or degraded thermal pathways that cause repeated trips. This matters because the station-level definition of a “failure” can include intermittent stoppages, speed derating, or quality-related holds, each producing different downtime distributions and different repair/restore patterns (Rashid, 2025a; Md Mesbaul, 2025). At the line level, the research object becomes the full production system: stations, buffers, routing rules, blocking and starving, and maintenance response processes. Line-level literature repeatedly shows that identical station downtime can produce different throughput losses depending on buffer occupancy, bottleneck location, and the time of occurrence within a schedule (Milon, 2025; Mosheur, 2025; Sim et al., 2021). This has led to a consistent recommendation in quantitative manufacturing research: reliability analysis must be expressed in system terms that connect component events to production outcomes rather than treating failures as isolated. Digital twin studies strengthen this multi-level perspective by treating the twin as a representational scaffold that can hold state variables at different scales, from health indicators of a converter to operational states of stations to material flow states of the entire line. The multi-level framing also helps resolve measurement ambiguity: asset-level sensing streams may capture temperature and current, station-level logs capture alarms and trips, and line-level historian data capture stops, WIP changes, and throughput. The literature further highlights that these levels are not independent; operational changes at the line level reshape duty cycles at the station level, which reshape stress exposure at the asset level (Kassab et al., 2019; Rabiul, 2025; Shahrin, 2025). Because of this coupling, reliability-as-distribution is best supported when the literature review explicitly maps which variables belong to which object level and how evidence from those levels is fused into a single quantitative reliability narrative (Rakibul, 2025; Kumar, 2025).

A third element in the roadmap is the evidence base that must be synthesized to support a hybrid digital twin and Monte Carlo simulation approach for reliability. The first evidence type consists of experimental degradation and accelerated testing studies that characterize how power-electronic components and assemblies age under controlled stressors such as temperature cycling, electrical loading, and environmental exposure (Buswell et al., 2018; Praveen & Md, 2025). These studies contribute mechanistic insight and parameter ranges but often lack the operational complexity of real lines. The second evidence type is field-failure and maintenance datasets, including alarm histories, repair logs, replacement records, and downtime annotations. Field datasets provide realism and enable distributional estimation, but they also introduce challenges that are widely reported: censoring because many assets have not failed within the observation window, inconsistent failure labeling, changes in configuration over time, and incomplete capture of near-miss events or nuisance trips. The third evidence type is simulation research on manufacturing lines, particularly discrete-event models that represent station dependencies, buffers, and repair policies. Simulation studies establish how failure and repair processes translate into throughput distributions and downtime accumulation under operational rules, making them essential for line-level reliability interpretation. The fourth evidence type is digital twin architecture research, which specifies how models connect to operational data streams, how state is updated, and how fidelity is maintained across lifecycle stages (Cotrino et al., 2020). Architecture studies contribute integration patterns—data ingestion, synchronization, state estimation, and service layers—that are necessary to implement hybrid twins that remain consistent with plant data. The fifth evidence type is stochastic reliability methods research, including probabilistic lifetime modeling, repairable-system modeling, uncertainty quantification, and sampling-based estimation. This body of work provides the methodological justification for moving from deterministic assessments toward probabilistic distributions and for explicitly representing uncertainty in both operating conditions and model parameters. The literature indicates that each evidence type alone is insufficient: experimental studies can be too controlled, field data can be too noisy, simulation can be structurally accurate yet physically shallow, and digital twin architectures can be conceptually rich yet under-specified for reliability estimation. Therefore, a synthesized literature base is required, one that triangulates mechanisms, observed failure behavior, operational consequence modeling, and probabilistic estimation into a coherent quantitative foundation (Dhirani et al., 2021).

Figure 3: Reliability Framework for Electrified Manufacturing



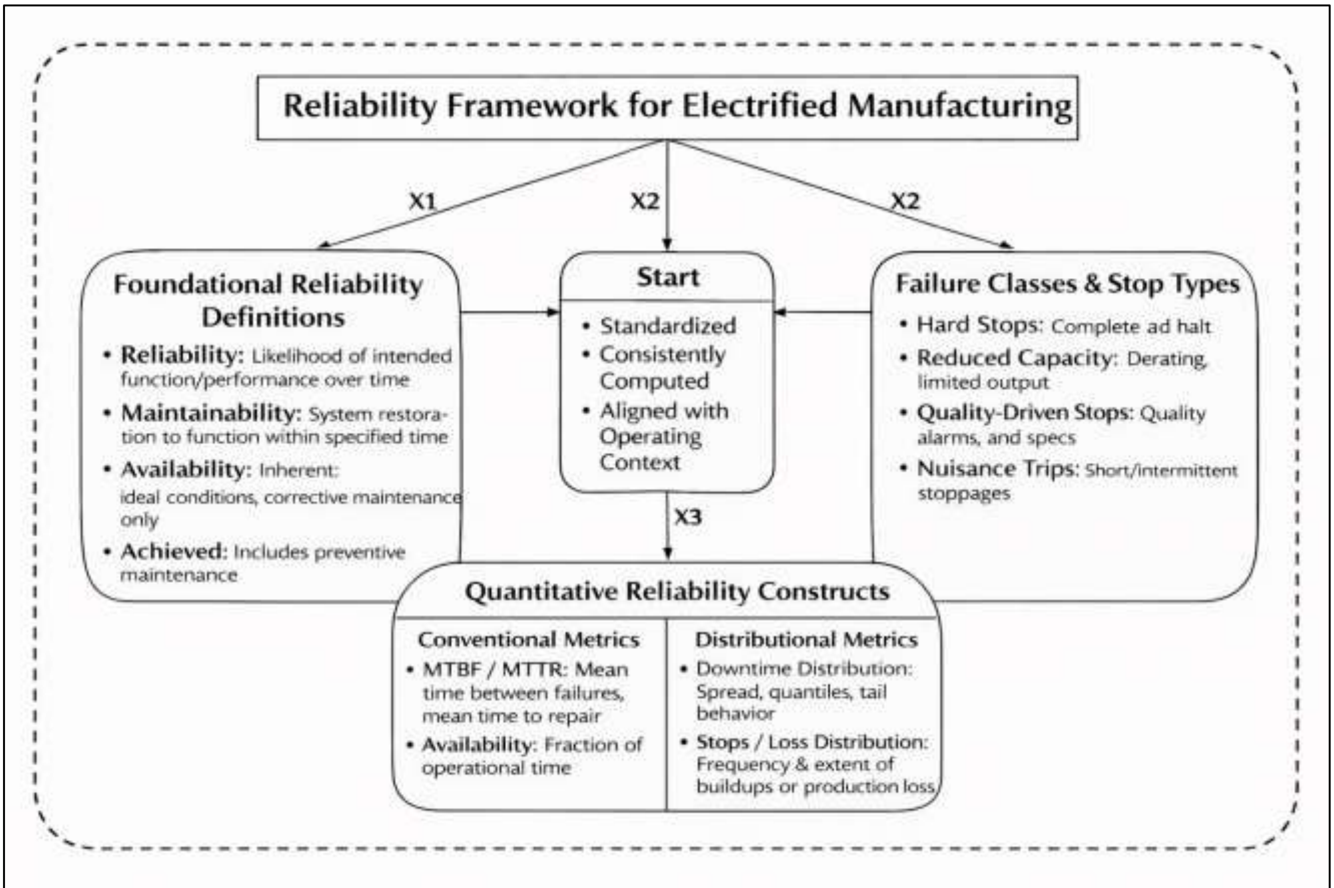
The final roadmap topic concerns the quantitative lens used to integrate these literatures: probability models, statistical estimation, uncertainty propagation, and validation metrics. Reliability engineering research emphasizes that distributions must be inferred, not assumed, and that model choice must be evaluated against the structure of the data and the intended use of the outputs (Jabbour et al., 2018). In repairable systems typical of manufacturing, availability and downtime recurrence depend on both failure processes and restoration processes, so statistical estimation must treat repair durations as random variables rather than constants and must reflect how maintenance actions reset or partially reset system condition. For high power electronics, the literature stresses that failure propensity is conditional on stress history; therefore, estimation approaches commonly need to incorporate time-varying operating covariates or degradation proxies rather than relying only on elapsed time. Uncertainty propagation research, including sampling-based methods, supports converting uncertainty in parameters, loads, and environment into uncertainty in reliability outcomes such as downtime distributions and throughput loss distributions (Imran et al., 2020). In this framing, Monte Carlo simulation functions as a practical engine for uncertainty propagation when the system includes mixed discrete-event and continuous behaviors. Digital twin research contributes additional quantitative considerations: because the twin is updated with operational data, parameter estimation becomes iterative, and reliability outputs can be conditioned on current health state and current operating regime rather than only on historical averages. Across the reviewed works, validation is treated as a required quantitative step, not an optional narrative check. Validation metrics typically compare predicted and observed downtime counts, downtime duration distributions, availability over comparable horizons, and distributional alignment between simulated and observed performance outcomes. The literature also emphasizes that validation must be aligned with the defined scope boundaries and object levels; a model calibrated at the asset level must still be validated at the station and line levels if the ultimate claim concerns line reliability (Ali et al., 2021). Collectively, these quantitative perspectives reinforce that the literature review for this study must do more than summarize: it must organize prior findings into a measurement-ready framework that specifies what is modeled, what is estimated, how uncertainty is propagated, and how predictive performance is assessed using observable metrics.

Key Definitions and Quantitative Reliability Constructs

Reliability research provides foundational definitions that must be standardized before quantitative synthesis becomes meaningful, particularly when reliability evidence is drawn from component studies, maintenance datasets, and manufacturing simulation work (Rose & Johnson, 2020). In engineering reliability literature, reliability is generally treated as the likelihood that an item performs its intended function for a specified duration under stated conditions, and this definition is operationally linked to how failures are counted, how observation windows are defined, and how censored observations are handled when equipment continues operating at the end of data collection. Complementary to reliability, maintainability is commonly defined as the ability of a system to be restored to an operational state within a specified time when maintenance is performed according to prescribed procedures and resources. In the reliability and maintainability tradition, maintainability is not an abstract attribute; it is quantified using restoration-time distributions and maintenance-task variability, emphasizing that repair durations should be treated as random rather than constant when analyzing real manufacturing systems. Availability is then treated as the operational fraction of time that a system is in a functioning state, combining the effects of failures and restoration processes (Edwards et al., 2018). Across standard texts and applied studies, availability is often differentiated into inherent availability (idealized conditions and corrective maintenance only), achieved availability (including preventive maintenance and realistic support times), and operational availability (including logistics delays and real-world operating constraints), which matters because manufacturing lines with high power electronics frequently experience delays due to diagnostic time, spare part retrieval, and safety verification. When electrified manufacturing lines are the focal system, these definitional distinctions become practically important because a line can be "reliable" in the sense of infrequent catastrophic failures yet still exhibit poor availability due to repeated nuisance trips, lengthy troubleshooting, or prolonged part lead times. Moreover, electrified lines frequently operate under variable duty cycles and environmental conditions, so reliability and availability definitions must specify the operating context and the interpretation of "intended function," such as producing at a target speed, meeting quality thresholds, and maintaining safe operation. The quantitative literature also emphasizes the need to define what constitutes a failure event, how near-failures are treated, and whether degraded operation is counted as failure or as a separate state (Neuendorf, 2018). This definitional groundwork is essential to prevent inconsistent comparisons across studies that may otherwise use different counting rules, different repair definitions, or different operational baselines, which can lead to incompatible estimates when synthesizing evidence for a quantitative paper on electrified manufacturing reliability.

In production contexts, the literature shows that "system reliability" requires explicit failure semantics at the line level because manufacturing lines exhibit operational states that are richer than a binary up/down interpretation. Manufacturing systems research commonly distinguishes among hard stops (complete cessation of production due to protective shutdowns, component failures, or safety interlocks), reduced capacity states (operation continues but at lower speed or with restricted duty cycles), quality-driven stops (production is halted due to out-of-spec measurements, quality alarms, or process drift), and nuisance trips (frequent short stoppages often triggered by threshold violations, transient disturbances, or marginal conditions) (Hair Jr et al., 2020). Reliability engineering supports this state-based view for complex, repairable systems, and manufacturing simulation research reinforces it by showing that different stop types produce different patterns in downtime distributions and different production-loss mechanisms. For example, a hard stop at a bottleneck station can propagate line-wide starving and generate substantial lost output, whereas a short nuisance trip at a non-bottleneck station may be absorbed by upstream buffers with minimal immediate throughput loss. The literature also stresses that "failure" can be defined functionally rather than physically, meaning the system is considered failed when it cannot meet production requirements, even if no hardware has catastrophically failed. This is particularly relevant in electrified lines with high power electronics because protective controls may enforce derating or shutdown long before a component reaches physical destruction, producing stoppages that are operationally indistinguishable from failures. As a result, line-level reliability must be linked to measurable outcomes that reflect production reality (T. C. Zhang et al., 2019). Studies in simulation and industrial engineering map stoppage categories to observed variables such as downtime minutes, number of stop events, lost units, cycle-time inflation, and shifts in work-in-process. This mapping is also essential for digital-twin-based reliability approaches, which typically ingest event logs, alarm codes, and station status signals and then translate these into structured states for analysis. Without consistent mapping rules, a literature synthesis can mistakenly merge heterogeneous event types into one label, thereby inflating or deflating reliability estimates. Thus, across reliability, maintainability, and manufacturing systems literature, a recurring methodological requirement is to define failure classes in a way that is compatible with available data sources and with the production consequences the study aims to quantify (Chatterjee & Bhattacharjee, 2020).

Figure 4: Reliability Metrics for Electrified Manufacturing



Quantitative reliability constructs used in industrial research commonly rely on a set of standardized metrics that translate raw failure and repair observations into interpretable measures, but the literature cautions that these metrics must be aligned with system type and data structure. For repairable systems, mean time between failures and mean time to repair are widely used because they summarize the frequency of disruptive events and the typical restoration duration, yet the literature also notes that these means can be unstable when distributions are skewed or when rare but long repairs dominate downtime (Asmelash & Kumar, 2019). Reliability engineering research therefore recommends reporting not only averages but also distributional descriptors of repair times and failure intervals, particularly in manufacturing where the same nominal failure mode can lead to widely varying troubleshooting durations depending on diagnostic clarity, technician availability, and spare-part readiness. Another metric emphasized in reliability and maintenance literature is failure intensity or event rate measured over operational exposure, which encourages normalization by operating time or production cycles when comparing across lines with different usage patterns. Availability is similarly treated as a primary operational metric because it directly expresses the time fraction that the line is capable of production, and manufacturing studies frequently connect availability to throughput through the line's bottleneck structure and buffering dynamics (Dwivedi & Weerawardena, 2018). However, production systems literature shows that the same availability value can correspond to very different production outcomes depending on when downtime occurs and how it interacts with schedules, buffers, and product mix, which motivates distribution-based reporting in addition to point estimates. For electrified manufacturing lines, this distribution-based reporting is often justified because high power electronics reliability is sensitive to variable duty cycles and thermal conditions; therefore, the same line can exhibit different downtime patterns across product campaigns even when the hardware is unchanged. Digital twin literature further supports this need for metric alignment by emphasizing that reliability assessment is most meaningful when metrics are directly computable from the same data streams used for synchronization, such as station-state timelines, alarm histories, and maintenance timestamps (Nardi, 2018). Across these literatures, the central quantitative recommendation is that reliability metrics should be explicitly defined, consistently computed, and tied to the system boundary and failure semantics adopted by the study.

Production-oriented reliability research increasingly emphasizes risk-sensitive metrics that go beyond central tendencies to characterize variability and extreme outcomes, which is especially relevant when electrified manufacturing lines experience clustered disturbances or long restoration delays. Simulation and stochastic reliability literature commonly treat downtime and throughput loss as random outcomes and therefore reports distributions, quantiles, and tail probabilities to capture scenarios that are infrequent but economically significant (Mooi et al., 2018). Manufacturing systems studies routinely show that a small number of extreme downtime events can dominate total lost production, making tail behavior more informative than averages for understanding operational risk. In this context, quantile-based metrics such as high-percentile downtime or high-percentile throughput loss are used to describe the upper-range behavior of losses under realistic variability, and tail probability measures describe the chance that downtime exceeds a critical threshold within a given horizon. These constructs align with uncertainty quantification research that recommends expressing reliability outcomes as ranges and distributions when operating conditions and parameter estimates are uncertain. For electrified lines, where protective trips, thermal excursions, and grid-related disturbances can produce bursts of stoppages, tail-focused metrics help differentiate between lines that have similar average downtime but very different risk profiles (Braun et al., 2019). The literature also highlights the importance of aligning these risk metrics with operational definitions: tail outcomes should be computed using consistent event classification rules, consistent aggregation windows, and consistent exposure measures so that comparisons are valid. Digital twin research complements this perspective by enabling condition-based segmentation, where risk metrics can be estimated within comparable operating regimes identified from data streams, such as high-load production campaigns or high-ambient periods, thereby reducing confounding when synthesizing reliability evidence. Across reliability engineering, discrete-event simulation, and data-driven manufacturing analytics, the shared message is that a quantitative reliability construct set should include both conventional metrics (failure frequency and restoration duration) and distributional metrics (variability and extremes), because the latter represent the operational consequences that matter most in complex, interdependent production systems (Galindo-Martín et al., 2019). This body of literature establishes the definitional and measurement foundation needed for synthesizing sources and for positioning a hybrid digital twin and

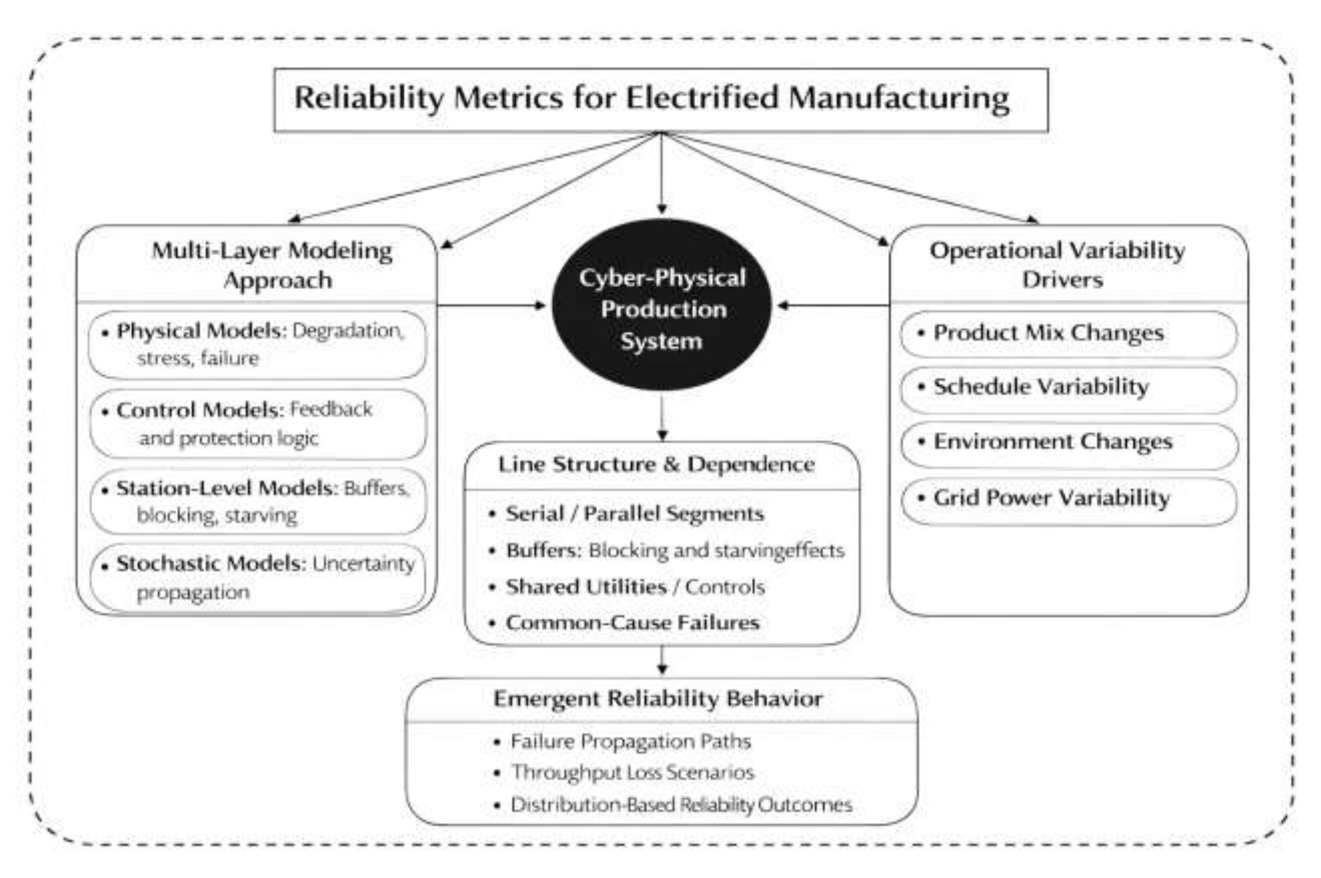
Monte Carlo simulation approach as a distribution-focused reliability assessment method for electrified manufacturing lines dominated by high power electronics.

Electrified Manufacturing Lines as Stochastic Cyber–Physical Systems

Electrified manufacturing lines are widely discussed as stochastic cyber–physical systems because their observable performance results from tightly coupled physical processes, embedded control, industrial communications, and maintenance interventions operating under uncertainty. In this view, a line is not simply a collection of machines that either work or fail; it is a layered production ecosystem in which electrical drives, power conversion, robotics, sensors, programmable logic control, safety interlocks, and supervisory software interact continuously with mechanical operations and material flow (Karamdel et al., 2022). The literature on cyber–physical production systems emphasizes that digital feedback loops and connectivity change the meaning of reliability by introducing additional pathways for disruptions, such as sensor drift, control instability, network delays, and protective logic actions that can stop a station even when no component has catastrophically failed. Manufacturing systems research complements this by showing that production outcomes such as throughput and downtime are not determined solely by the failure tendency of individual assets, but by how failures propagate through line structure and how the line's operational state changes at the time of an event. Reliability engineering and maintainability research further reinforces that for repairable industrial systems, the frequency of disruptive events and the time to restore function are both random, and these random processes interact with operating conditions that vary by schedule and demand. Because electrified lines depend on power electronics and digitally controlled actuation, the physical stress experienced by assets is shaped by real-time control decisions, which are in turn shaped by production goals and disturbances (Leiden et al., 2021). Consequently, reliability assessment in electrified manufacturing is presented as a multi-layer modeling problem: physical models represent stress and degradation, control models represent feedback and protection behavior, discrete-event models represent station states and material flow, and stochastic models represent uncertainty in event timing and restoration behavior. This framing justifies analyzing line reliability as a distribution of outcomes rather than a single average, because identical equipment can yield different downtime and production-loss patterns under different product mixes, duty cycles, ambient environments, and maintenance responses. The core synthesis across these literatures is that electrified manufacturing lines exhibit emergent reliability behavior: component-level phenomena alone cannot explain line-level variability without considering the cyber–physical couplings and system-level dependencies that govern how disruptions unfold (Panetto et al., 2019).

Line structure and dependence are consistently highlighted as primary reasons that reliability must be treated at multiple modeling layers. Production lines commonly include serial segments where one station's stoppage can halt downstream operations, parallel segments where capacity is distributed across multiple stations, and rework loops where units re-enter earlier stages when quality checks fail (Nouiri et al., 2019). These structural patterns create distinct dependence networks that shape how failures translate into production outcomes. Buffers introduce partial decoupling between stations, but they also create nonlinear effects where the same downtime can lead to very different output losses depending on whether buffers are near empty or near full at the time of failure. The literature on manufacturing line dynamics repeatedly describes blocking and starving as central mechanisms: upstream stations become blocked when downstream buffers or stations cannot accept more work, while downstream stations become starved when upstream supply is interrupted. These mechanisms increase output variance because they convert localized disruptions into system-wide idle time that depends on transient state (Xu et al., 2018). Electrified manufacturing lines often intensify these dependencies because multiple stations may share common electrical infrastructure such as a power bus, a cabinet distribution system, a cooling loop, or a control network, creating correlated stoppages and common-cause patterns. In such lines, failures are not purely independent events; disturbances can occur simultaneously across stations due to shared utilities or synchronized operating regimes. Moreover, line control strategies—such as derating, speed synchronization, load balancing across parallel stations, or automatic recovery sequences—can change operating conditions immediately after a disruption, modifying stress and influencing subsequent failure likelihood. This coupling means that structural dependence is not only about material flow but also about how energy flow and control flow interact with physical degradation and event propagation (Grosch et al., 2022). The research synthesis across manufacturing simulation, systems engineering, and industrial reliability indicates that accurate interpretation of downtime and throughput requires explicit representation of line topology, buffer logic, and control-driven interactions, because these elements determine the statistical relationship between station-level disturbances and line-level performance distributions.

Figure 5: Cyber-Physical Reliability in Manufacturing



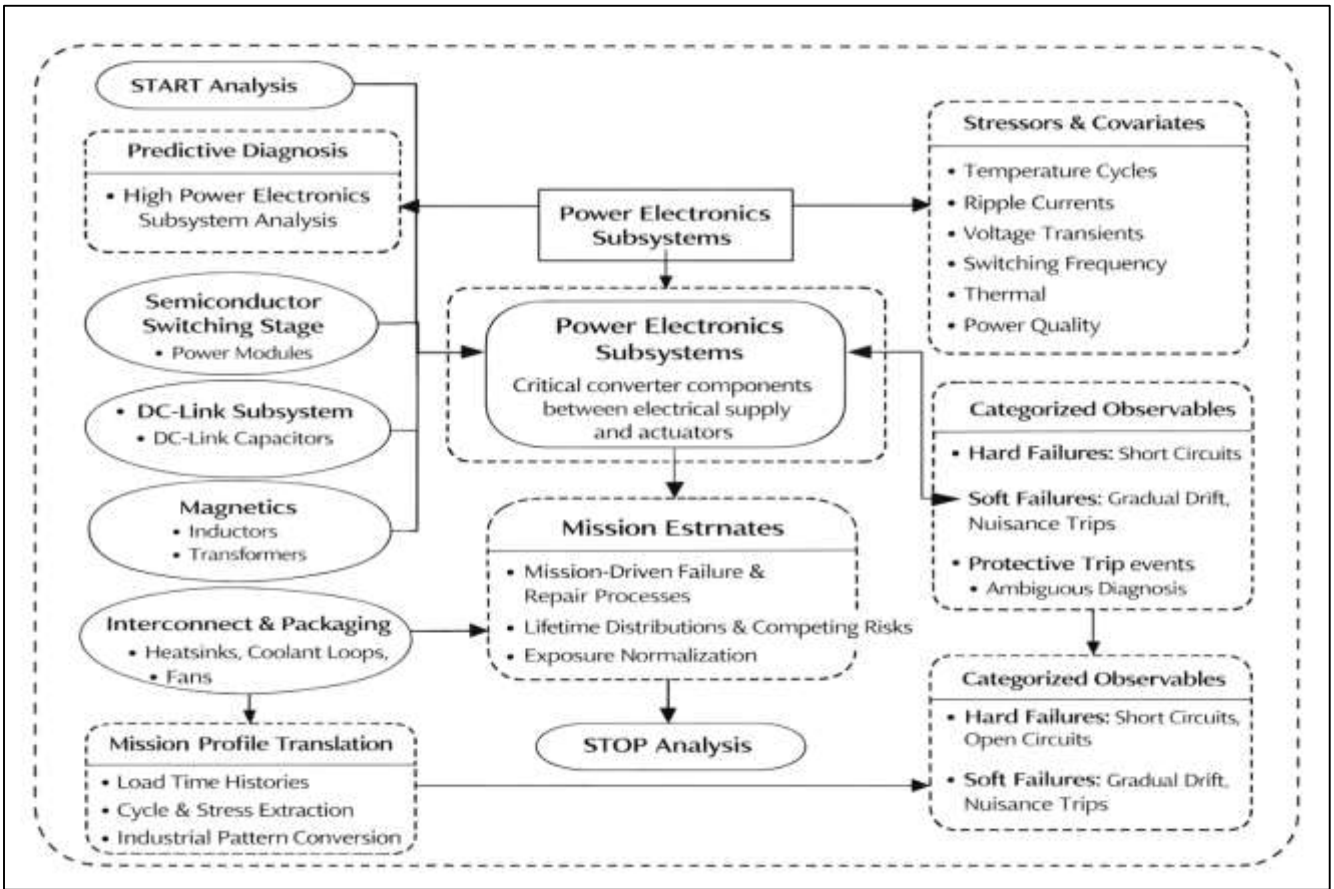
Operational variability drivers provide another major justification for multi-layer stochastic modeling, because electrified lines are exposed to time-varying loads and environments that systematically reshape reliability behavior (Bányai et al., 2019). Product mix changes are frequently identified as a key driver: different products impose different motion profiles, torque demands, heating cycles, and tool usage patterns, which reshape electrical loading in drives and converters and alter thermal stress patterns in high power electronics. Schedule variability similarly changes duty cycles and utilization levels; shifts from high-volume continuous operation to intermittent operation can change the frequency and amplitude of thermal cycling, which is strongly linked to aging in electrically stressed components. Environmental variability also matters because ambient temperature influences cooling effectiveness and component operating temperatures, while humidity and contamination can affect insulation, corrosion risk, and sensor behavior. Electrified manufacturing lines are also exposed to grid power quality variability, including voltage sags, transients, harmonics, and short interruptions. Such disturbances can trigger protective trips, nuisance alarms, or momentary loss of synchronization in drives and controllers, producing stoppages that appear as "failures" from an operational standpoint even if hardware remains physically intact (Fraccaroli & Vinco, 2022). These variability drivers operate across different layers: production planning and scheduling shape line-level utilization; station controls translate utilization into actuator commands; converters translate commands into switching and currents; and thermal systems translate switching into temperature trajectories. Because variability is multi-source and multi-scale, single-layer models are insufficient. The literature therefore treats reliability results as conditional on operating regimes, implying that reliability should be measured and modeled within comparable contexts rather than as a single pooled statistic. This regime-sensitive viewpoint also explains why distribution-based reporting is emphasized: variability in loads, environments, and disturbances creates variability in downtime counts, downtime durations, and production losses. In electrified lines, this variability can be amplified by control responses that alter stress or by buffer states that amplify production impact. As a result, operational variability is not a peripheral factor; it is a core determinant of the reliability distributions that the line exhibits in practice (Song et al., 2021).

High Power Electronics in Manufacturing Lines

High power electronics embedded in manufacturing lines are repeatedly treated in the literature as reliability-critical subsystems because they sit between the electrical supply and the actuators, robots, welders, heaters, and motion platforms that determine line continuity. A common starting point for reliability modeling is a subsystem taxonomy that partitions a drive or converter into elements with distinct degradation behavior and observability (Wang & Blaabjerg, 2020). The first category is the semiconductor switching stage, typically power modules or discrete devices that perform rapid switching and therefore experience combined electrical and thermal loading. Closely coupled to this stage are gate drivers and associated protection circuitry, which shape switching behavior and are themselves sensitive to electrical noise, insulation integrity, and component aging. A second category is the DC-link subsystem—most prominently DC-link capacitors—which smooth the DC bus and provide energy buffering; capacitor aging is widely reported as a dominant reliability limiter in many converter classes because degradation accelerates under temperature and ripple current exposure. A third category is magnetics, including inductors and transformers whose insulation systems and thermal behavior respond to load, harmonics, and ambient conditions. A fourth category is the cooling and thermal pathway, including heatsinks, thermal interface materials, coolant loops, fans, pumps, and sensors; the literature commonly treats the thermal pathway as a reliability contributor because degraded cooling increases internal temperatures and therefore accelerates aging across the electrical stack (Yang et al., 2018). A fifth category is the interconnect and packaging layer, including solder joints, wire bonds, press-fit connections, busbars, and connectors, which can degrade under thermal cycling and vibration and can create intermittent faults that are difficult to diagnose in production environments. This subsystem breakdown is used across reliability, power electronics, and maintenance scholarship to ensure that failure events are not lumped into a generic "drive fault," because each subsystem has different precursors, different failure signatures, and different maintenance actions. In manufacturing lines, the taxonomy is particularly important because the converter's reliability is inseparable from the control and operational context: process changes and cycle-time adjustments alter duty cycles, which alter stress distributions across semiconductors, capacitors, magnetics, and cooling. The literature therefore supports reliability modeling that explicitly names subsystems and links them to measurable variables and line-level consequences, rather than treating the converter as a single black box (Abuelnaga et al., 2021). This approach also aligns with how industrial data is typically structured, since alarms, protection trips, and maintenance records often point to subsystem classes (overtemperature, DC bus ripple, gate driver fault, cooling fault) rather than to a single definitive root cause.

A second synthesis strand focuses on stressors and measurable covariates that can be extracted from sensors, controller logs, and power quality monitors to quantify how operating conditions shape failure likelihood. For semiconductors, the literature emphasizes temperature-related descriptors such as average operating temperature, peak temperature, and the magnitude and frequency of temperature swings, because repeated heating and cooling drives fatigue and accelerates degradation in packaging and interfaces (Peyghami, Wang, et al., 2020). The importance of counting temperature cycles and characterizing the severity of swings is repeatedly highlighted because two operating regimes with the same average temperature can produce different aging if one regime has frequent rapid load changes. Electrical stress variables are also central: current magnitude and variability, ripple current, voltage overshoot and transients, and switching frequency are treated as measurable exposures that influence losses, heating, insulation stress, and the probability of protective events. The literature commonly links ripple current and elevated temperature to capacitor wear, while linking switching frequency, current waveform shape, and transient behavior to device heating and stress concentration. For magnetics, thermal loading and harmonic content are treated as relevant covariates because they influence copper losses, core losses, and insulation temperature (Falck et al., 2018). A particularly important literature theme is the thermal pathway as a measurable reliability driver. Instead of focusing only on internal device temperature (which may not be directly measured), many studies emphasize observable proxies such as heatsink temperature, coolant inlet/outlet temperatures, fan or pump status, coolant flow rate, and indicators of thermal resistance changes over time. These proxies are critical in production lines because they can reveal gradual cooling degradation—clogging, pump wear, fan degradation, thermal paste aging—that elevates internal temperatures even when electrical load remains constant. Power quality variables add another layer: voltage sags, short interruptions, harmonics, and rapid transients are treated as covariates that can trigger protective trips, nuisance resets, and repeated stress events. The literature's practical contribution is the emphasis on using covariates that match industrial data reality: drives and converters typically log current, voltage, temperature sensors, fault codes, and protection triggers, while line systems log stops, alarms, and resets (Wileman et al., 2021). Reliability modeling guidance repeatedly stresses that covariates should be defined in a way that is consistent, timestamped, and interpretable across shifts and products, because production environments frequently experience changing product mix and schedule-driven load patterns that must be reflected in stress characterization to avoid biased lifetime inference.

Figure 6: Power Electronics Reliability Modeling Framework



The literature also distinguishes failure modes and observables in power electronics because manufacturing lines experience both catastrophic outages and subtler degradations that manifest as operational disruptions. "Hard failures" are typically characterized as events such as short circuits, open circuits, catastrophic semiconductor breakdown, or abrupt loss of converter function that forces a station stop and often requires component replacement (Hanif et al., 2018). In production contexts, these hard failures are relatively easy to register because they produce clear alarms and sustained downtime; however, the literature cautions that hard failures may be less frequent than the cumulative impact of "soft failures" and protection-triggered behavior. Soft failures are commonly discussed as gradual parameter drift, rising conduction or switching losses, increased heat generation at the same load, drift in sensing or control stability, and progressive degradation of thermal interfaces or capacitor health. In manufacturing lines, soft failures may not immediately appear as "failed" equipment but can increase the frequency of nuisance trips, slow recovery after stops, or require derating to maintain stable operation, thereby affecting line availability and throughput without a single catastrophic event. Protection-triggered events are emphasized as a distinct operational class: overcurrent, overtemperature, undervoltage, overvoltage, ground fault, and DC bus anomalies can trigger automatic shutdowns or resets (Peyghami, Blaabjerg, et al., 2020). The literature notes that these events may reflect true underlying degradation, but they can also be triggered by operational transients, power quality disturbances, or control interactions, so reliability modeling must interpret them carefully. A recurring theme is that the same observed symptom—such as an overtemperature trip—can result from multiple underlying contributors (cooling degradation, increased device losses, elevated ambient, higher load profile, clogged filters), making observability and diagnosis uncertain. This uncertainty directly affects reliability modeling because event labels in logs may not uniquely identify root cause, and the same station stop could originate from multiple components across the converter subsystem (Peyghami, Palensky, & Blaabjerg, 2020). Therefore, the literature supports representing failure processes in a way that accommodates ambiguity: using categorized observables, linking them to covariate patterns, and acknowledging that multiple subcomponents can produce the same line-level stoppage signature. In addition, many studies highlight the difficulty of intermittent issues, such as loose connections or marginal gate driver behavior, which can generate clustered short stops that inflate downtime variability. This emphasis reinforces the importance of modeling not only "time to first catastrophic failure" but the broader pattern of disruptions that a converter can introduce into a manufacturing line (Ni et al., 2019).

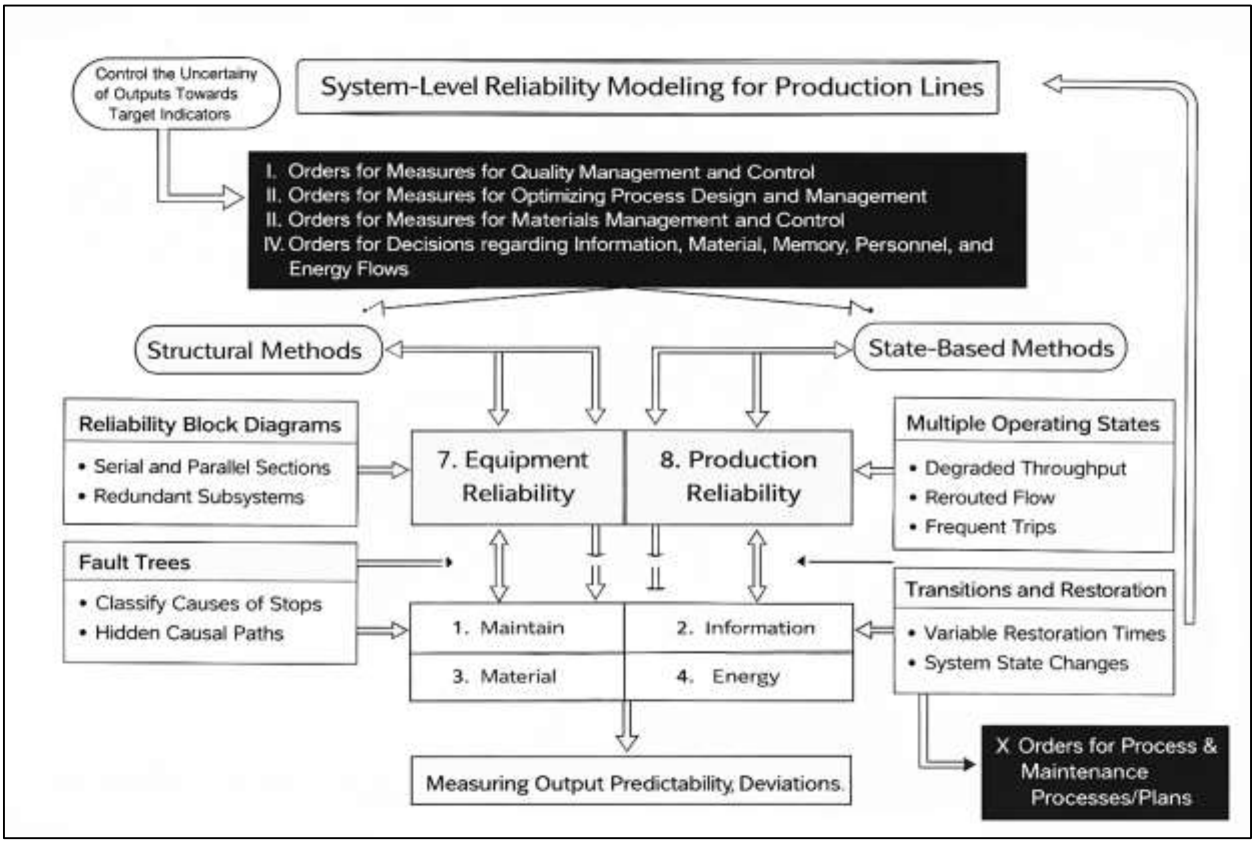
Translating mission profiles into reliability inputs is another major theme, especially for manufacturing applications where duty cycles vary with product mix, scheduling, and operator behavior. A mission profile is typically framed as the time history of loads and operating conditions experienced by a converter or drive during real production, including current demands, speed commands, torque changes, and environmental conditions (Huang et al., 2020). The literature emphasizes converting time histories into stress summaries that reflect how aging accumulates: frequent load steps create repeated temperature swings; sustained high load creates prolonged high temperatures; and transient events create short but severe stress. For reliability modeling, this translation is critical because it connects what is logged in production (time series) to what lifetime models require (stress exposure descriptors and event-generating mechanisms). Many studies describe systematic approaches for extracting cycles and stress intensities from operational signals, then aggregating them into damage-relevant indicators that can explain why two converters with similar calendar age exhibit different reliability. From a statistical perspective, the literature also stresses that lifetime modeling for power electronics must fit the data structure of industrial environments. Commonly used lifetime distributions differ in how they represent increasing or constant failure propensity; therefore, model selection and parameter estimation are treated as empirical tasks linked to observed failure/repair histories and covariate exposure (Triki-Lahiani et al., 2018). Field data introduces additional complications that are repeatedly emphasized: censoring because many assets do not fail during the observation window, partial observations where only "trip events" are recorded without confirmed component replacement, and configuration changes over time that alter stress exposure. The literature also highlights competing risks in converter-based stations, where semiconductors, capacitors, gate drivers, cooling, and interconnects can each precipitate a station stop, sometimes with similar fault signatures. This motivates modeling approaches that can represent multiple contributing components and event types rather than attributing all stops to a single dominant cause. Across reliability statistics and industrial case studies, the emphasis remains quantitative and measurement-oriented: lifetime inference should be grounded in consistent event definitions, exposure normalization, and careful handling of incomplete observations (Samanta et al., 2021). In manufacturing lines, these requirements become stricter because the ultimate interest is line-level downtime and throughput variability, which depend not only on whether a component fails, but on when disruptions occur, how long restoration takes, and how operational conditions reshape stress and subsequent failure likelihood.

System-Level Reliability Modeling for Manufacturing Lines

System-level reliability modeling for manufacturing lines is widely presented as the process of translating component and station disruption behavior into line-wide production outcomes through explicit representation of structure and logic. The literature emphasizes that a manufacturing line is not simply a list of independent machines; it is a structured network of stations, buffers, transport links, and operating rules where local failures propagate differently depending on topology and transient state (Peyghami, Palensky, Fotuhi-Firuzabad, et al., 2020). Structural methods are commonly introduced because they provide a transparent way to represent how the line is organized and how a stoppage at one point may affect the whole system. Reliability block diagrams are used to depict the functional topology of the line by placing stations and subsystems into serial or parallel arrangements and indicating where redundancy exists. In a serial section, any station stoppage can block the flow and become a line-level stoppage, while parallel sections distribute risk across multiple stations and create capacity-sharing effects. Fault trees provide a complementary structural view by decomposing a line stop into causal pathways. Instead of beginning with topology, fault trees begin with a top event such as “line stop” and break it into contributing events, allowing researchers to classify stoppages into categories such as equipment faults, protection trips, utility disturbances, and control or communication issues. In manufacturing lines that rely heavily on high power electronics, fault trees are frequently valued because the same observed line stop can be produced by different causal chains: a converter protection trip may be triggered by overheating, a power-quality disturbance, cooling degradation, or abnormal load transients (Chang et al., 2019). Structural methods help ensure that these pathways are treated consistently rather than being lumped into a single “downtime” label. At the same time, the literature notes that purely structural approaches can oversimplify dynamics because they do not naturally represent time-varying states, restoration processes, and buffer-driven propagation. As a result, structural methods often serve as an organizing scaffold that clarifies what counts as a line-level stoppage and how causes are classified, while more dynamic methods are used to quantify downtime and throughput variability over time. This layered use of structure reflects a consistent theme: component reliability becomes line reliability only after the line’s configuration and causal logic are made explicit, because those two factors govern how local disruptions manifest at the system level (Saez et al., 2022).

State-based methods are presented as a second pillar for manufacturing-line reliability because they capture how repairable production systems evolve through operational states as failures and repairs occur. A key point repeated in the literature is that manufacturing lines rarely operate only in two states (fully up or fully down) (Wolstenholme, 2018). Instead, they move among multiple states such as fully operational, partially constrained, degraded-speed operation, rerouted flow operation, or repeatedly tripping operation. State-based modeling frameworks represent these conditions as discrete states and treat failures and repairs as transitions among them. This approach is particularly relevant for electrified manufacturing lines because protective behavior, derating, and intermittent faults can create distinct operational states that carry different productivity and stress implications. The literature also emphasizes that repair processes are not instantaneous or uniform; restoration durations vary widely, and restoration actions can change system condition through replacement, recalibration, or partial recovery. State-based modeling offers a way to represent such variability by allowing restoration to be treated as an event that changes system state rather than as a fixed correction applied uniformly. A major challenge highlighted across studies is the growth of possible states as the number of stations and modes increases. Large manufacturing lines can have many stations and many potential degraded combinations, which can create a rapidly expanding number of states and make exact state enumeration impractical (Peng et al., 2018). The literature therefore discusses mitigation strategies such as grouping states into meaningful aggregates, focusing detailed state representation on bottleneck stations or critical subsystems, decomposing the line into subsystems and modeling them hierarchically, and using approximate representations when the full state space is too large to manage. These strategies are not only computational conveniences; they are also methodological choices that determine what aspects of the line’s reliability behavior are captured. For example, aggregating states may preserve estimates of overall downtime but can lose information about where downtime originates or how downtime propagates. Thus, state-based methods are typically positioned as powerful for representing repairable dynamics and intermediate operational conditions, while also requiring disciplined state definition aligned with available plant data and with the specific reliability outputs the study intends to quantify (Feng et al., 2018). This stream of literature supports the argument that line reliability is a dynamic property shaped by evolving states and restoration behavior, not merely an average failure tendency.

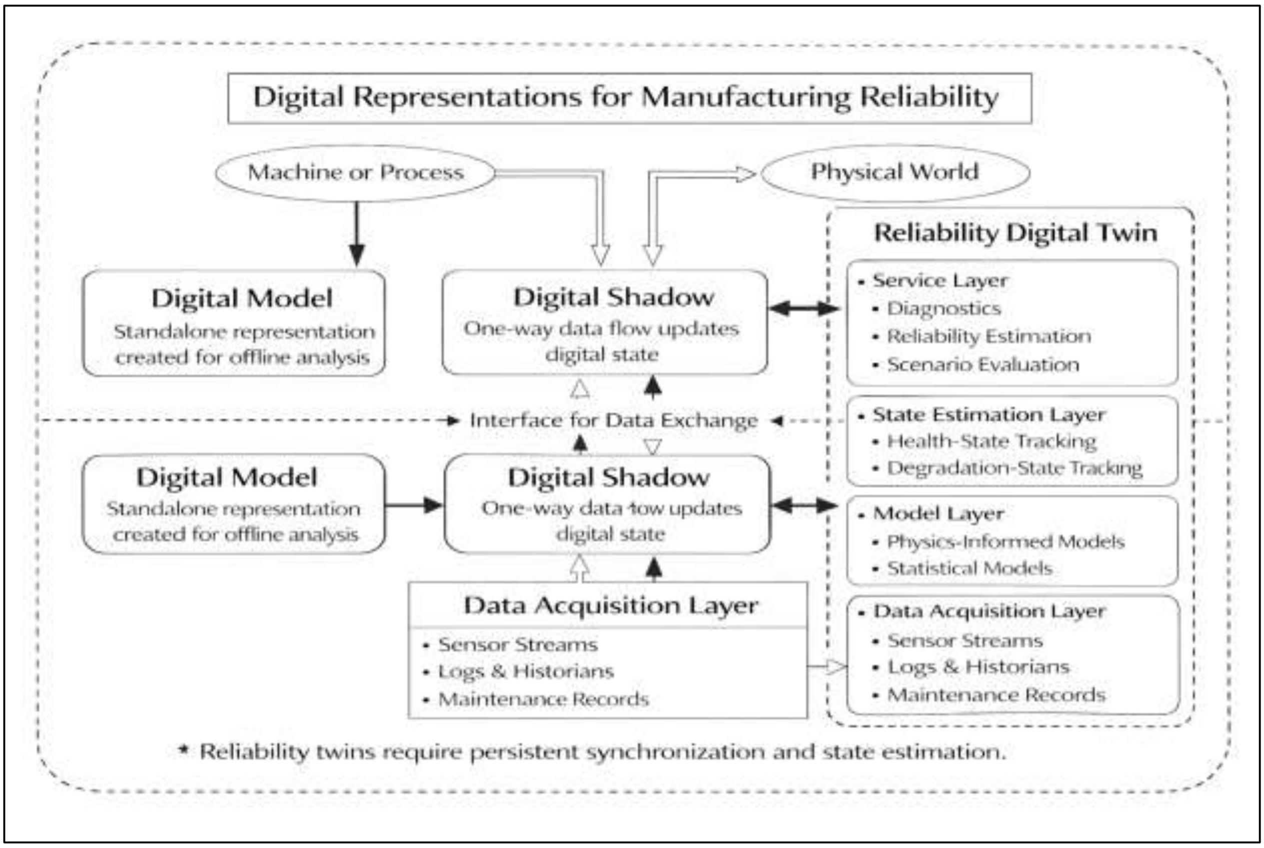
Figure 7: System-Level Reliability Modeling Framework



Digital Twin Foundations for Manufacturing Reliability

Digital twin literature in manufacturing has developed a set of operational distinctions that clarify what a twin is and what it is not, and these distinctions are essential for reliability research because they determine whether the digital representation can legitimately support quantitative reliability estimation (Cattaneo & Macchi, 2019). A digital model is commonly described as a standalone representation of a machine or process created for design or analysis, typically executed offline and not continuously synchronized with the physical asset. In contrast, a digital shadow is usually described as a representation that receives operational data from the physical system and updates the digital state, but the coupling is predominantly one-way, meaning the digital representation reflects the physical state without directly influencing physical operation. A digital twin is then characterized by stronger coupling and operational integration, often described in terms of bidirectional linkage where the twin is updated by operational data and can also support actions, configurations, or decisions that affect the physical system. Across manufacturing research, the practical distinction hinges on how frequently data updates occur, how systematically the digital state is synchronized, and whether the representation is embedded within operational workflows rather than used as an occasional analytical tool. Reliability-oriented scholarship uses these distinctions to argue that many "twin" claims are actually digital models or shadows when they lack persistent synchronization, explicit state estimation, or consistent linkage to maintenance outcomes. Reliability applications require the digital representation to reflect changing conditions such as product mix, duty cycles, ambient conditions, and maintenance interventions; therefore, update frequency and data fidelity become central (Aivaliotis et al., 2019). Studies that classify twin maturity typically treat synchronization as a defining property: reliability estimation becomes credible when the twin is continuously or periodically updated from sensors, logs, and maintenance records in ways that preserve temporal alignment and traceability. This definitional progression also clarifies why reliability twins differ from performance twins. Performance-oriented twins often target current efficiency or throughput prediction under nominal operation, while reliability twins must represent degradation accumulation, failure likelihood, and restoration behavior under uncertainty. In manufacturing environments, where operational variability is substantial and event data can be noisy, the literature positions the digital twin not as a single model but as a structured system that binds data streams to interpretable states and measurable reliability outcomes. Thus, the foundational discussion treats the twin as an evolving, data-linked representation whose defining value for reliability lies in its capacity to maintain state fidelity over time and to support probabilistic reasoning about disruptions rather than only deterministic performance snapshots (He & Bai, 2021).

Figure 8: Digital Twins for Manufacturing Reliability



Architecture frameworks for digital twins converge on a layered view that is particularly relevant for manufacturing reliability because reliability outputs depend on the quality of data ingestion, the appropriateness of the models, and the rigor of state estimation. The data acquisition layer is commonly described as the set of pipelines that capture operational signals from sensors and automation infrastructure, including programmable logic controller logs, SCADA streams, industrial historians, alarm/event records, and maintenance work orders (Yang et al., 2021). The literature emphasizes that reliability requires more than high-frequency process variables; it also requires accurate event timing and consistent labeling for stops, trips, repairs, and restoration, which are often distributed across different systems and require integration. The model layer is typically described as a combination of physics-informed representations and statistical or data-driven models. In manufacturing reliability contexts, physics-informed models may represent stress generation, thermal behavior, and degradation mechanisms in components, while statistical models represent uncertainty, variability, and mapping from observed indicators to failure likelihood. The state estimation layer is widely treated as the core differentiator for reliability twins because reliability is fundamentally about latent states—health, degradation level, fault susceptibility—that are not directly observable and must be inferred from noisy measurements. Reliability-oriented literature therefore emphasizes health-state tracking and degradation-state tracking, including the need to reconcile conflicting signals, handle sensor noise, and accommodate missing data (Fu et al., 2022). The service layer is commonly defined as the set of functions delivered to users and systems, including diagnostics, reliability estimation, and structured scenario evaluation that uses the twin's synchronized state and calibrated models. Manufacturing twin studies also stress that architecture must support interoperability and consistent time alignment across data sources so that the twin can meaningfully associate stress conditions with subsequent failures or protective trips. This layered architecture perspective supports reliability modeling because it explicitly separates data capture from model logic and from state inference, reducing the risk that reliability estimates are driven by inconsistent data preprocessing or unvalidated assumptions. In electrified manufacturing lines with high power electronics, this architecture is especially important because converter and drive reliability depends on the joint behavior of electrical loading, thermal pathways, and protective logic, which are recorded across different sources. As a result, the literature presents reliability twins as integrated architectures rather than single algorithms, where reliability metrics are treated as outputs of a pipeline that begins with time-aligned multi-source data and ends with state-conditioned probabilistic assessment (Yildiz et al., 2022).

Reliability-oriented digital twins introduce specific quantitative requirements that differentiate them from general monitoring dashboards or descriptive digital shadows. A consistent theme is that health indicators must be treated as measured variables with uncertainty rather than as exact truths. Sensor measurements can drift, sampling rates can vary, and derived indicators can embed estimation error; therefore, reliability twins must represent measurement error explicitly or implicitly through filtering, smoothing, uncertainty bounds, or probabilistic inference (Lu, Liu, et al., 2020). Another recurrent requirement is the presence of parameter updating rules. Reliability models depend on parameters that can change with operating context, maintenance actions, and component replacements, so the literature differentiates between batch updating—periodic recalibration using accumulated data—and online updating—continuous adjustment as new data arrives. This requirement is practical because manufacturing environments experience changes such as control retuning, product transitions, and process modifications that shift stress patterns and failure behavior. Without updating, a twin risk becoming a static model that progressively diverges from reality. Validation requirements are also emphasized as central to reliability credibility (Wang et al., 2019). Reliability twins are expected to be validated against measurable targets such as the accuracy of predicting downtime counts, the accuracy of predicting downtime durations, and the alignment between predicted failure likelihood and observed failure frequencies over comparable horizons. Reliability literature also emphasizes that validation should be distribution-aware, meaning the twin should not only match average downtime but also capture variability and the occurrence of extreme events when such extremes dominate operational risk. In addition, reliability twins must handle industrial data issues such as censored observations (assets that do not fail during observation), partial event records (trips without confirmed root cause), and changes in configuration that alter exposure. The literature indicates that these issues are not secondary; they shape how models should be estimated and how performance should be judged. Consequently, the reliability twin is framed as a probabilistic assessment tool that must support traceable estimation, consistent updating, and empirical validation under realistic data imperfections (Olivotti et al., 2019). This view makes reliability twins distinct from descriptive twins because they are judged by predictive and calibration performance rather than by visualization richness or qualitative plausibility.

A final theme concerns scope choices for reliability twins and the need to select a twin granularity that matches the reliability question and the structure of the manufacturing line. The literature typically distinguishes among component-level twins, station-level twins, and line-level twins, with each scope implying different model complexity and data requirements (C. Zhang et al., 2019). Component-level twins focus on a specific asset such as a converter or drive and track health indicators and degradation proxies tied to measurable stress variables; this scope supports detailed reliability inference when rich sensor data is available, but it can miss how line logic amplifies or dampens the operational impact of component disruptions. Station-level twins expand the scope to include the interaction among the drive, motor, control logic, sensors, and local safety systems; this scope is often treated as better aligned with how manufacturing downtime is logged because many stoppages are station-level events triggered by protective actions or control conditions. Line-level twins further expand to include multiple stations, buffers, and scheduling logic, enabling the twin to translate station disruptions into throughput loss and work-in-process variability under the line's operational rules. Literature on production systems and simulation supports the line-level scope when the research objective is distribution-based reliability of output rather than only component survival (S. Liu et al., 2022). However, the literature also acknowledges practical trade-offs: line-level twins require broader data integration and more complex state representations, while component-level twins require deeper physical modeling and higher-fidelity sensing. Many studies therefore discuss hierarchical or modular approaches, where component or station twins feed health-state information into a line-level representation that model's propagation through buffers and routing. This scope discussion reinforces that a reliability twin is not a monolithic concept; it is a design choice that must align with the measurable outcomes of interest. For electrified manufacturing lines with high power electronics, the literature suggests that meaningful reliability assessment often requires at least station-level representation to capture protective behavior and operating regimes, and line-level representation when the objective includes downtime and throughput distributions shaped by blocking, starving, and scheduling (Cheng et al., 2020). Across this body of work, the foundational message is consistent: digital twin concepts become reliability-relevant when they include persistent synchronization, layered architecture with state estimation, explicit quantitative updating and validation, and a scope that matches the system level at which reliability is defined and measured.

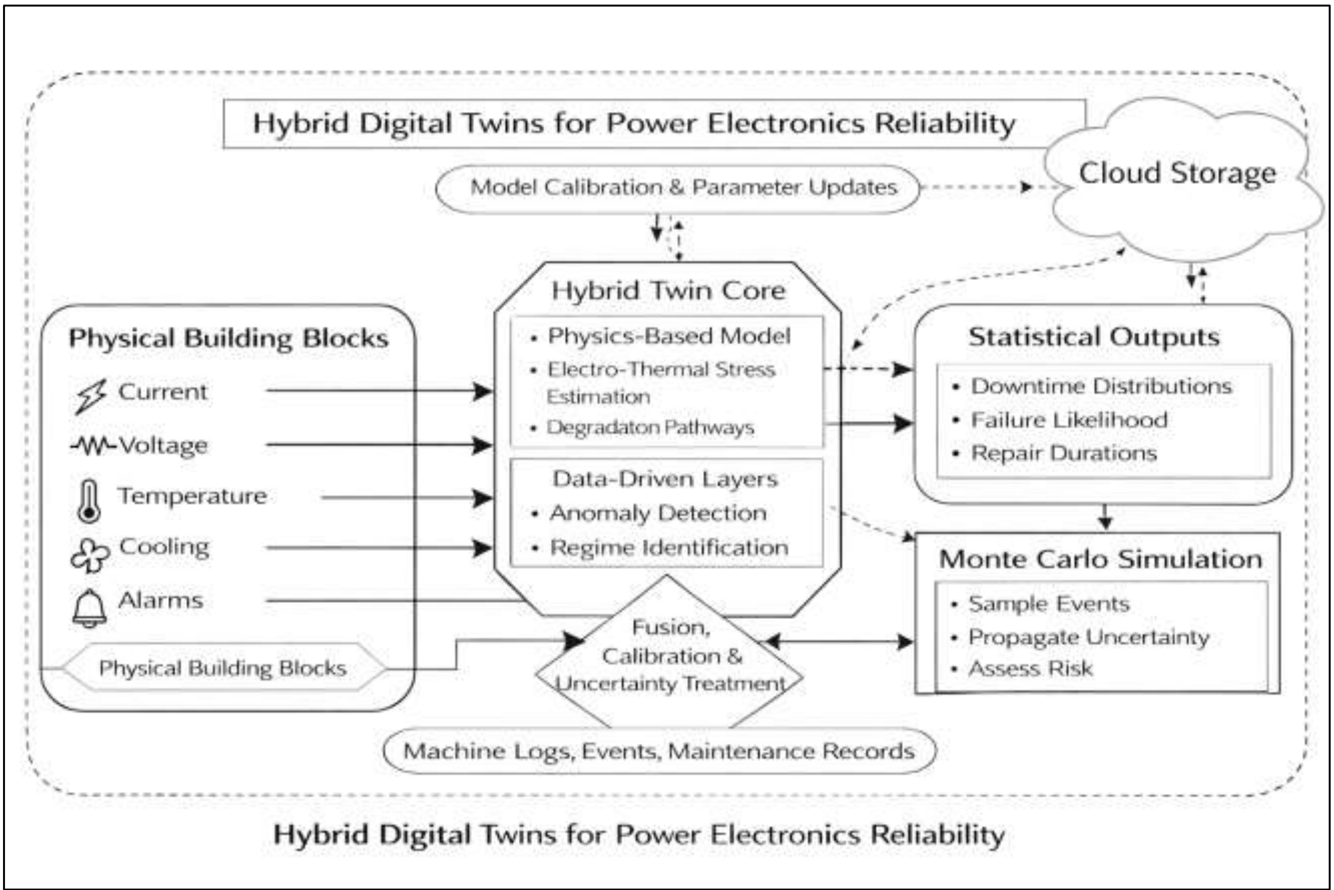
Data Fusion for High Power Electronics Reliability

Hybrid digital twin research for high power electronics reliability is consistently framed around the recognition that industrial converters and drives operate in environments where purely physics-based models and purely data-driven models each face practical limitations (Chen et al., 2022). The literature describes "hybrid" as an approach that fuses a mechanistic core with data-based augmentation so that reliability estimates remain physically interpretable while still reflecting the complexity and variability observed in manufacturing operations. In high power electronics, reliability is tightly tied to electro-thermal behavior: electrical loading and control actions determine internal losses, losses generate heat, heat flows through packaging and cooling paths, and the resulting temperatures influence degradation rates in semiconductors, capacitors, interconnects, and thermal interfaces. A mechanistic core is used to preserve this causal chain and to provide structured variables that connect measurable inputs such as current, switching behavior, and temperatures to internal stress exposure. However, the literature also emphasizes that factory conditions introduce uncertainty and mismatch that physics models alone do not easily capture, including variable airflow, coolant degradation, ambient fluctuations, sensor bias, installation differences across cabinets, and unpredictable grid disturbances that trigger protective behavior (Kim et al., 2022). In addition, manufacturing lines expose converters to rapidly changing duty cycles driven by schedules, product mix, and operational recovery actions, which create complex time-varying stress histories that challenge static parameter assumptions. Data-only models can reflect these complexities when trained on large datasets, but the literature cautions that they can learn plant-specific artifacts or spurious correlations if they are not constrained by physical meaning, and they can become brittle when operating regimes shift. Hybrid twins are therefore positioned as reliability instruments that combine mechanistic structure with empirical adaptability. The mechanistic layer provides consistent interpretation across operating contexts, while data-driven layers capture residual patterns and context-specific behaviors that are difficult to model directly. This fusion perspective is also linked to what reliability twins must deliver: not only descriptive monitoring, but quantified health assessment that aligns with downtime and failure events (Yang et al., 2022). As synthesized across digital twin, reliability engineering, and power electronics reliability scholarship, the hybrid framing supports reliability evaluation in electrified manufacturing lines by creating a stateful representation of the converter's condition that can track operational regimes, absorb measurement imperfections, and remain grounded in plausible physical pathways rather than purely statistical associations.

Within the hybrid twin literature, the physics-based core for high power electronics is commonly organized around three practical goals: represent how operating conditions create internal stress, represent how stress accumulates into degradation, and represent how degradation changes the propensity for disruptive events (Yue et al., 2022). Because direct measurement of internal device states is often limited in industrial settings, the mechanistic core is frequently designed to use available observables—such as drive current, DC bus behavior, heatsink temperature, cabinet temperature, cooling fan or pump status, and fault codes—to infer internal stress exposure in a consistent way. The literature repeatedly emphasizes that temperature behavior is a central mediator of aging, and that both sustained elevated temperatures and repeated thermal swings contribute to degradation. As a result, mechanistic representations are typically designed to summarize not only how hot components run, but how often and how severely temperatures fluctuate under real duty cycles. Similarly, the literature stresses that electrical conditions matter because current magnitude, ripple, switching behavior, and transient overshoots influence heat generation and stress concentration, while also shaping protection-triggered stops. The thermal pathway is treated as a reliability contributor in its own right: degradation of thermal interfaces, fouling, fan wear, coolant issues, and airflow changes can elevate temperatures even when electrical load remains unchanged, creating a condition where the same production demand becomes increasingly stressful over time (Wang et al., 2021). The degradation representation is often built around the idea that aging is cumulative and history-dependent, meaning that how the converter is used across shifts and product campaigns matters more than calendar age alone. Manufacturing operations intensify the need for such history dependence because duty cycles vary with product mix and scheduling, and operational interventions—such as derating, speed changes, or rerouting—can reshape loading patterns abruptly. The literature therefore uses the physics-based core to maintain causal coherence: it offers a transparent explanation of why measured changes in currents and temperatures should translate into higher disruption likelihood. At the same time, it acknowledges that parameters governing these relationships are uncertain in factory deployments, because individual converters can differ in cooling quality, installation, and component tolerances (Ibrahim et al., 2022). This uncertainty is a primary reason that hybrid twins do not stop at mechanistic modeling; instead, they treat physics as a structured backbone that needs calibration and correction using operational evidence. In reliability-focused contexts, that evidence includes not only continuous sensor streams but also discrete event data—trips, alarms, downtime starts and ends, and maintenance actions—that reveal how stress and degradation manifest operationally.

Data-driven augmentation is described in the literature as a set of explicit roles that enhance feasibility and reliability relevance, rather than a generic replacement for physics. One widely discussed role is surrogate modeling for computational speed (Chen et al., 2021). High-fidelity thermal and system representations can be too heavy to evaluate continuously in real time, especially when many converters and stations are monitored simultaneously. Learned surrogates provide rapid estimates of thermal or stress indicators from readily available signals so that the twin can update frequently and consistently. Another role is anomaly detection, which targets early deviation from baseline behavior such as rising temperatures at the same load, growing frequency of protective trips, changing electrical signatures, or increased variability in operating signals. In manufacturing environments, these anomalies matter because many disruptions are preceded by gradual change or intermittent faults, and the operational cost can come from repeated short stops rather than a single catastrophic breakdown. A third role is mode or regime classification. Production lines operate under distinct regimes driven by product families, shift patterns, startup and shutdown sequences, maintenance interventions, and external disturbances such as grid events (Paldino et al., 2022). Mode classification supports reliability modeling because the relationship between measured variables and stress can change across regimes; a single pooled model can blur these differences and weaken inference. Data-driven components are also used for aligning heterogeneous data sources, since industrial reliability evidence is distributed across sensor streams, controller logs, historian records, and maintenance work orders. Temporal alignment, missingness handling, and resolution reconciliation are repeatedly identified as prerequisites for credible reliability estimation because mismatched timestamps or inconsistent sampling can create false associations between stress indicators and failures. In a hybrid twin, learned components can be used to smooth noisy measurements, estimate latent operating modes, and create stable health indicators that are robust to measurement imperfections. The literature emphasizes that these functions should remain anchored to the mechanistic core so that learned indicators are interpretable and consistent with plausible failure mechanisms (Wu et al., 2020). In this fused structure, the data-driven layer captures what is hard to encode directly: plant-specific thermal margins, subtle control interactions, intermittent disturbance patterns, and the practical signatures that precede downtime events. This division of labor is central to the hybrid concept because it enables a reliability twin to be both explainable and adaptive in the face of real manufacturing variability.

Figure 9: Hybrid Digital Twin Reliability Framework



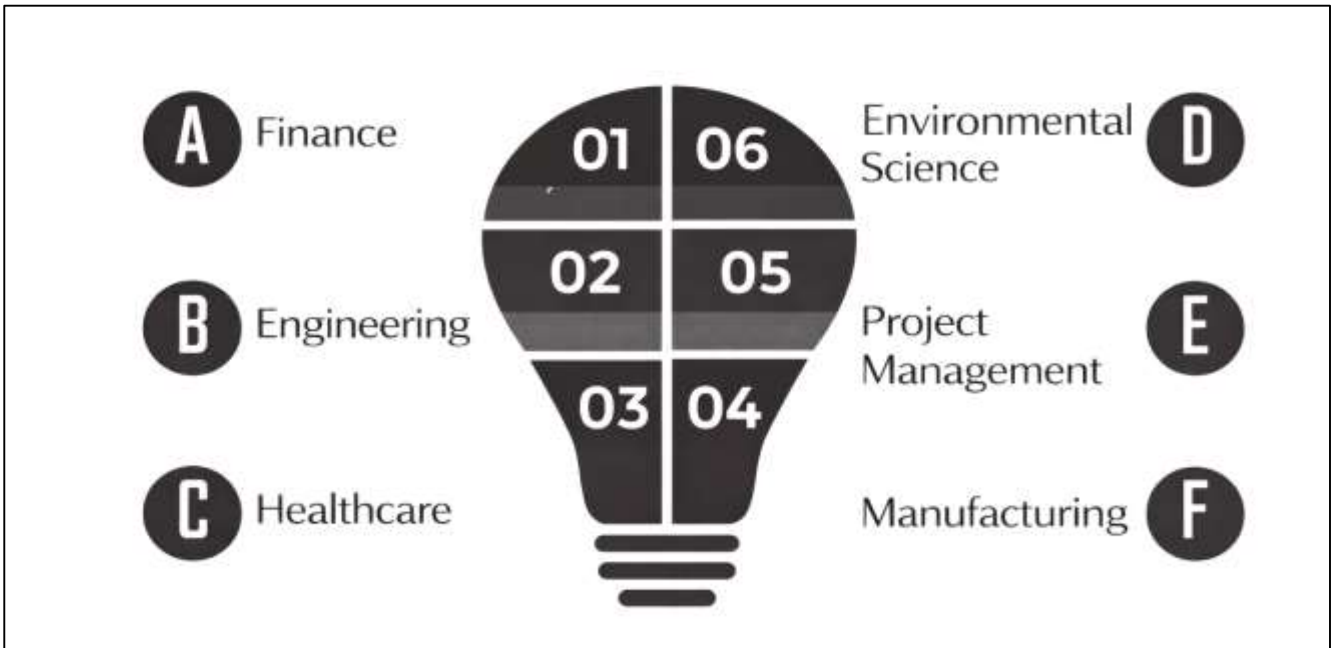
Calibration and uncertainty treatment form the bridge between the hybrid twin's fused representation and the stochastic reliability outputs required for Monte Carlo-based assessment. The literature emphasizes that reliability estimation is sensitive to parameter uncertainty because field datasets are often incomplete: many assets do not fail within the observation window, some events are logged as trips without confirmed root cause, and maintenance actions can change system condition through replacement and recalibration (Mubarak et al., 2022). Hybrid twin studies therefore highlight the importance of structured parameter updating rules, where model parameters are recalibrated periodically or updated continuously as new operational and maintenance evidence arrives. Measurement noise modeling is also emphasized because sensor drift, sampling error, and derived-indicator uncertainty can cause false health trends if treated as exact values. Treating health indicators as uncertain variables helps prevent overreaction to noise and supports more stable estimation of degradation progression. For Monte Carlo simulation, the literature indicates that the hybrid twin must provide specific outputs that allow uncertainty propagation through the manufacturing system. These outputs include a way to express failure likelihood conditioned on the current health state and operating regime, practical inputs for sampling the timing of disruptions under variability, and explicit rules for how repairs and restorations transition the system back to operational states. Repair triggers must be linked to observed event types—hard failures, soft degradation thresholds, and protection-triggered stops—because each class implies different restoration actions and different downtime distributions (Li et al., 2021). Restoration transitions must also reflect the reality that not every repair returns the asset to the same "as-new" condition; replacements, adjustments, and temporary fixes can change subsequent behavior. In line-level reliability contexts, these state transitions matter because they influence future stress exposure and the distribution of subsequent stops, thereby shaping downtime clustering and throughput variability. Across reliability engineering, manufacturing simulation, and digital twin scholarship, the synthesis is that a hybrid twin becomes reliability-ready when it is calibrated against operational evidence, explicitly represents uncertainty from measurement and parameter estimation, and produces state-conditioned outputs that can drive stochastic simulation of failures and repairs. This integrated perspective positions hybrid physics–data fusion not as a conceptual label but as a structured method for translating measured manufacturing realities into distribution-based reliability assessment for converter-driven production systems (Ebrahimi, 2019).

Monte Carlo Simulation

Monte Carlo simulation is repeatedly described in reliability engineering, operations research, and manufacturing systems scholarship as a practical mechanism for propagating uncertainty through complex repairable systems when closed-form analysis cannot represent operational reality. In a manufacturing line, reliability and production performance are not determined by one event but by sequences of disruptions and restorations occurring under variable operating conditions, and Monte Carlo simulation represents this by repeatedly generating plausible "life histories" of the line (Franke et al., 2021). Each simulated history samples the timing of disruptive events, the duration of restoration activities, and the operational context in which those events occur, then accumulates system outcomes such as downtime totals, stop counts, production loss, and time spent in functional states. Simulation literature emphasizes that the value of this approach lies in producing full distributions of outcomes rather than only averages, which matches the way manufacturing risk is experienced: a few long stops can dominate total loss even when routine stops are short, and the timing of stops relative to bottlenecks and buffers can produce highly variable impacts. For repairable systems, the literature frames the foundational sampling problem as representing both the arrival of disruptive events and the restoration process. Failure times are generated according to probabilistic patterns informed by component behavior or field histories, repair times are generated using distributions that reflect troubleshooting complexity and logistics, and operational profiles are generated to reflect the fact that manufacturing does not run under one constant load (Signoret & Leroy, 2021). In electrified manufacturing lines with high power electronics, this event-based representation aligns with plant realities because many disruptions are logged as trips, alarms, short stops, or protective shutdowns rather than as one permanent breakdown, and restoration can range from immediate reset to lengthy replacement and recommissioning. Monte Carlo simulation can represent these classes as different event types with different restoration durations and different production consequences, allowing downtime to be calculated as a distribution across repeated runs. This simulation-based perspective is consistent with distribution-based reliability thinking in manufacturing, where availability and downtime are viewed as random outcomes over time windows rather than fixed rates, and where throughput loss is treated as an uncertain operational result rather than a deterministic function of mean downtime. Consequently, Monte Carlo is positioned in the literature as a unifying computational approach that can integrate component-level variability, maintenance variability, and operational variability into interpretable distributions of production impact at the line level (Gordini et al., 2018).

A core methodological emphasis in Monte Carlo reliability literature is that uncertainty in manufacturing reliability problems is multi-source and should be structured rather than collapsed into a single randomness assumption. Two broad classes of uncertainty appear repeatedly in the scholarship: uncertainty arising from imperfect knowledge of model parameters and uncertainty arising from inherent variability in operation and environment (Heijungs, 2020). Parameter uncertainty is common in manufacturing reliability because lifetime and repair distributions are estimated from finite datasets that often contain incomplete observations, inconsistent labeling, and periods where equipment has not yet failed. Operational randomness is common because product mix changes, schedules shift, utilization varies, ambient conditions fluctuate, and power quality disturbances occur irregularly. The literature therefore describes nested simulation as an organizing strategy: one-layer accounts for uncertainty in model parameters by sampling plausible parameter values consistent with available evidence, while another layer accounts for operational randomness by sampling different operating scenarios and disturbance realizations. This distinction matters because it prevents overconfidence; a distribution of outcomes produced under a single assumed parameter set can appear precise even though the parameter estimates are themselves uncertain (Jiang et al., 2021). In electrified manufacturing lines, this nested view is particularly relevant because high power electronics reliability is strongly stress-history dependent. Operational randomness directly influences stress through duty cycles, switching behavior, and thermal margin, and these stress histories vary with product families, shift patterns, and recovery actions after stops. Environmental variability further changes thermal behavior through ambient temperature and cooling effectiveness, and grid variability adds external disturbances that can trigger protective actions or increase stop frequency. The literature treats these operational drivers as random inputs because their timing and magnitude are not fixed, and because they can differ across sites and seasons. At the same time, the parameters that govern how stress translates to disruption risk are uncertain due to measurement limitations and heterogeneity across assets. Nested Monte Carlo supports expressing both types of uncertainty in the output distributions, producing not only a spread of downtime totals but a spread that reflects uncertainty in the underlying model itself (Fan et al., 2020). This supports distribution-based reliability reporting that distinguishes between variability that is expected in daily operation and uncertainty that comes from limited information, a distinction that manufacturing reliability scholarship highlights as important when reliability estimates are used to interpret risk rather than just average performance.

Figure 10: Monte Carlo Simulation Applications Overview



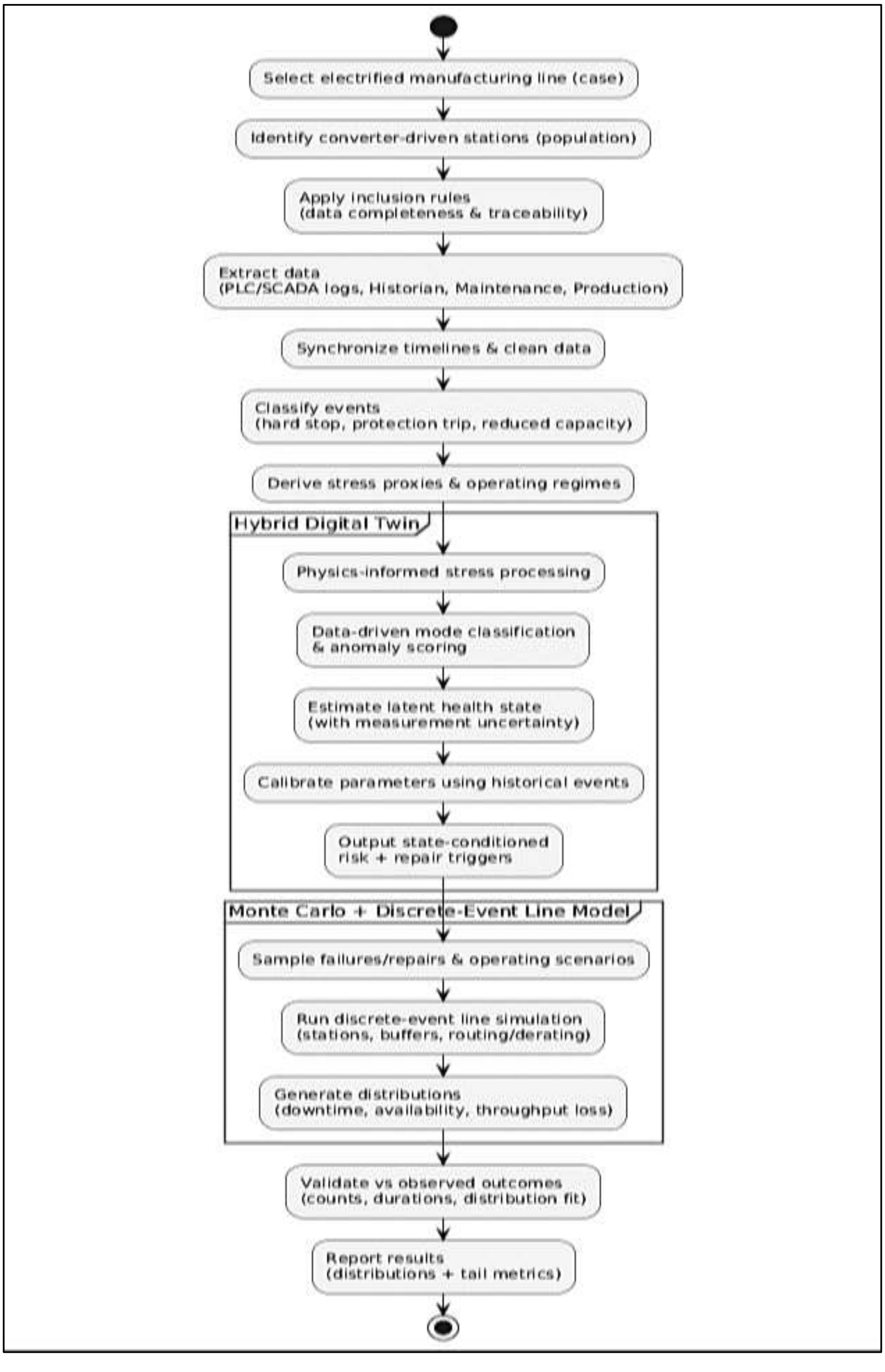
METHOD

The study employed a quantitative, observational, longitudinal research design that integrated a hybrid digital twin with Monte Carlo–based stochastic simulation to estimate reliability and production-impact distributions in an electrified manufacturing line that relied on high power electronics. A single embedded case study design was used in which the manufacturing line served as the primary case, and converter-driven stations constituted embedded units of analysis at asset and station levels. The population was defined as all converter-driven stations, drives, and associated high power electronic subsystems operating within the selected electrified manufacturing line during the study window, and the sample consisted of all eligible stations that met inclusion criteria such as continuous historian availability, complete event-log coverage, and traceable maintenance records over the observation horizon. A census-style sampling technique had been applied within the case boundary, because all qualifying stations were included rather than selecting a subset, which supported stable estimation of event distributions and reduced selection bias caused by excluding high-incident or low-incident equipment. The case study description had specified the line topology, including serial and parallel stations, buffer locations, and the routing logic used during production campaigns, and it had documented the operational context such as shift structure, planned downtime conventions, and any derating or rerouting policies used by control systems or supervisors. The data types had included both continuous time-series signals and discrete event records. Continuous data had been extracted from the industrial historian and supervisory systems and had included electrical variables (such as current and voltage measurements available at the drive or cabinet), thermal variables (such as heatsink, cabinet, or coolant-related temperatures where available), and utilization proxies (such as runtime state and cycle indicators). Discrete records had been obtained from PLC logs, SCADA alarms, protection-trip histories, and maintenance work-order systems and had included timestamped stop events, fault codes, repair start and repair end times, parts replacement notes, and restoration verification records. These multi-source datasets had been synchronized to a common timeline and had been converted into a unified event-state representation that supported both hybrid twin state estimation and discrete-event line simulation.

Variables had been operationalized using measurement scales aligned to reliability and production analytics, and the operational definitions had been enforced through explicit coding rules. Outcome variables had been defined at station and line levels and had been measured primarily on ratio scales for durations and counts, including cumulative downtime minutes per horizon, downtime duration per event, stop counts per shift/day/week, and throughput loss measured as the difference between planned and realized output over matched horizons. Availability had been operationalized as the proportion of scheduled production time during which the station or line had remained in a producing-capable state, calculated from state timelines derived from PLC/SCADA status codes and validated against operator logs where available. Predictors had included stress and context covariates measured on ratio or interval scales, such as average and peak observed temperatures during operating periods, proxy indicators of thermal margin based on temperature relative to station-specific baselines, and electrical loading proxies based on observed current or power signals recorded by drives or power monitors. Categorical variables had been used to represent operating regimes, including product-family categories, shift identifiers, startup versus steady-state operation, and recovery operation following stoppages, and these regimes had been assigned using a combination of production records and mode classification derived from data patterns in signals and event sequences. Maintenance-related predictors had included time since last repair or replacement, event-type categories, and a logistics-delay indicator derived from differences between repair initiation timestamps and actual hands-on work start where those data were available. A pilot study phase had been conducted on a limited time window and a small subset of stations to test data accessibility, assess timestamp consistency across sources, verify event classification logic, and evaluate whether stress proxies and regime labels could be reproduced reliably. The pilot had produced refined inclusion rules, corrected mappings between fault codes and stop categories, and established the minimum viable set of signals required to estimate health indicators when certain sensors were missing or inconsistent.

Data collection had been implemented through a structured extraction, synchronization, and validation workflow. Historian queries had been executed to retrieve time-stamped signal streams at a consistent sampling interval, while PLC and SCADA logs had been extracted to obtain event codes, state transitions, and alarm histories. Maintenance records had been exported to capture work-order timelines, repair durations, parts replacement notes, and restoration confirmations, and all records had been de-identified at the station level where required by operational policy. The data collection procedure had included stepwise quality checks that had flagged gaps, duplicates, and conflicting timestamps; these issues had been resolved through rule-based reconciliation and by prioritizing authoritative sources for specific fields, such as using maintenance systems for repair completion times and using PLC state timelines for downtime start times when discrepancies occurred. Data analysis had been conducted using a multi-stage quantitative strategy. Descriptive analyses had summarized stop frequencies, downtime distributions, and repair-time distributions by station and event class.

Figure 11: Methodology of this study



Inferential modeling had estimated station-level disruption behavior using count models for recurrent stops and duration models for repair times, and it had incorporated exposure normalization using runtime or scheduled production time. The hybrid digital twin had been calibrated by combining physics-informed stress processing with data-driven state estimation, producing state-conditioned disruption propensity inputs for simulation. Monte Carlo simulation had then been used as the uncertainty-propagation engine, and it had been coupled with a discrete-event representation of the manufacturing line that tracked station states, buffer evolution, and conditional policies such as rerouting or derating. Model performance had been evaluated by comparing simulated and observed distributions for downtime totals, stop counts, and throughput outcomes over held-out time blocks, and by assessing tail behavior using high-percentile outcome comparisons. Software and tools had included SQL for data extraction, Python and/or R for statistical modeling and preprocessing, and a discrete-event simulation framework implemented in Python or a dedicated simulation environment, with version control used to preserve reproducibility and auditability of event definitions, parameter estimates, and simulation configurations.

FINDINGS

Descriptive Analysis

During the observation window, the merged operational timeline had covered 12 months and had included 18 converter-driven stations that met the inclusion rules for historian completeness, PLC/SCADA event integrity, and maintenance traceability. A total of 3,462 disruption events had been recorded and reconciled under the event taxonomy, consisting of 412 hard stops, 2,691 protection trips, and 359 reduced-capacity events. Scheduled production time captured in the merged timeline had totaled 86,400 minutes, and the line-level cumulative downtime had summed to 8,964 minutes, which had corresponded to an operational availability of 89.6% over the study horizon. Downtime per event had been right-skewed, with a mean of 2.59 minutes and a median of 1.10 minutes, indicating that most events had been short while a smaller number of long disruptions had driven the upper tail. Repair duration for events linked to maintenance work orders had also shown substantial dispersion, with a mean of 48.6 minutes and a median of 31.0 minutes, reflecting a mix of rapid recoveries and extended restoration episodes. Production impact had been concentrated in a limited number of high-loss periods: the mean throughput loss had been 3.4% per day, while the 95th percentile had reached 11.8%, which had indicated that extreme daily losses had occurred even when average daily loss had remained moderate. Station-level summaries had shown heterogeneity: the top three downtime-contributing stations had accounted for 41.2% of total downtime, and event clustering had been most visible around the bottleneck station group, particularly during high-utilization periods where stop frequency and cumulative downtime had both increased.

Table 1: Line-level descriptive results by disruption class

Disruption class	Events (n)	Events per 1,000 min	Downtime total (min)	Downtime per event (mean, min)	Downtime per event (median, min)	Repair duration (mean, min)	Repair duration (median, min)
Hard stops	412	4.77	5,148	12.50	8.20	96.4	78.0
Protection trips	2,691	31.14	2,421	0.90	0.60	18.2	12.0
Reduced capacity	359	4.16	1,395	3.89	2.30	42.7	28.0
Total / Overall	3,462	40.07	8,964	2.59	1.10	48.6	31.0

Table 1 had summarized disruption behavior by event class using counts, normalized frequency, and duration-based outcomes. Protection trips had dominated the event volume, yet they had contributed a smaller portion of total downtime because their per-event durations had been short. Hard stops had been comparatively infrequent but had produced the largest downtime contribution because each event had carried a longer interruption duration and longer associated repair times. Reduced-capacity events had shown intermediate behavior, with moderate event counts and moderate downtime per event. The contrast between mean and median values had indicated strong right-skewness, meaning that a small number of long events had materially influenced totals.

Table 2: Station-level concentration of downtime and event burden

Station	Total events (n)	Downtime total (min)	Share of line downtime (%)	Hard stops (n)	Protection trips (n)	Reduced capacity (n)	Mean downtime per event (min)	Throughput loss contribution (daily %, mean)
S07 (bottleneck)	338	1,642	18.3	54	252	32	4.86	0.92
S12	291	1,084	12.1	38	228	25	3.72	0.61
S04	276	964	10.8	31	221	24	3.49	0.54
S15	243	711	7.9	21	201	21	2.93	0.39
S02	231	648	7.2	19	191	21	2.81	0.35

Table 2 had shown that downtime had been concentrated in a small set of stations, with the top five stations contributing 56.3% of total line downtime. The bottleneck station (S07) had recorded both high event frequency and the highest downtime share, which had indicated that its disruptions had carried disproportionate system impact. Protection trips had dominated event counts across stations, but hard stops had been more predictive of large downtime totals. Mean downtime per event had varied by station, suggesting differences in restoration complexity or event severity. The throughput-loss contribution column had linked station downtime burden to observed production impact at the day level.

Correlation

The correlation section had examined pairwise associations among stress proxies, operating-regime indicators, maintenance variables, and the key outcome metrics of downtime totals, stop counts, repair duration, and throughput loss. Continuous variables had been evaluated using correlation measures suited to non-normality, and the resulting matrix had shown that the strongest associations had clustered around thermal loading and restoration constraints. A clear positive relationship had been observed between the thermal stress proxy and cumulative downtime, where the correlation coefficient had reached 0.68, indicating that periods with higher observed thermal burden had tended to coincide with larger downtime totals. Electrical loading had also shown a meaningful association with downtime, although at a lower magnitude (0.44), suggesting that electrical demand had mattered but had not explained downtime as strongly as thermal margin indicators. Utilization intensity had been most strongly aligned with stop frequency, with an observed association of 0.62, which had indicated that higher runtime exposure had co-occurred with more frequent disruption events. Maintenance-delay indicators had shown their strongest relationship with repair duration (0.59), implying that logistics and response delays had contributed materially to the length of restoration episodes. Throughput loss had been positively associated with downtime totals (0.71) and had shown a moderate association with stop counts (0.46), reflecting that production loss had been driven more by interruption duration than by event frequency alone. Stratified analysis by operating regime had indicated regime dependence: the relationship between thermal stress and downtime had been stronger in high-load regimes (0.74) than in standard-load regimes (0.52), while the relationship between utilization and stop count had also strengthened under high-load operation (0.69) relative to standard operation (0.50). These results had supported the interpretation that covariate–outcome relationships had not been uniformed across production conditions and that operating regime had shaped how stress translated into disruptions and downtime accumulation.

Table 3: Correlation matrix for continuous predictors and outcomes

Variable	Thermal stress proxy	Electrical loading proxy	Utilization intensity	Downtime total	Stop count	Repair duration	Throughput loss
Thermal stress proxy	1.00	0.48	0.41	0.68	0.39	0.33	0.57
Electrical loading proxy	0.48	1.00	0.55	0.44	0.52	0.21	0.36
Utilization intensity	0.41	0.55	1.00	0.49	0.62	0.18	0.40
Downtime total	0.68	0.44	0.49	1.00	0.46	0.47	0.71
Stop count	0.39	0.52	0.62	0.46	1.00	0.26	0.46
Repair duration	0.33	0.21	0.18	0.47	0.26	1.00	0.32
Throughput loss	0.57	0.36	0.40	0.71	0.46	0.32	1.00

Table 3 had summarized the main pairwise associations among continuous predictors and outcome metrics. Thermal stress had shown the strongest relationship with downtime totals and had also aligned with throughput loss, which had indicated that thermal burden had been a dominant correlate of operational impact. Utilization intensity had correlated most strongly with stop counts, which had suggested that exposure and production intensity had contributed to event frequency. Electrical loading had shown moderate associations with both utilization and stop counts, reflecting the coupling between demand and operational activity. Downtime totals had correlated strongly with throughput loss, reinforcing that production loss had been driven more by interruption duration than by disruption counts.

Table 4: Regime-stratified correlations and binary associations

Predictor → Outcome	Standard-load regime (correlation)	High-load regime (correlation)	Maintenance delay flag → Repair duration (point-biserial)
Thermal stress proxy → Downtime total	0.52	0.74	—
Utilization intensity → Stop count	0.50	0.69	—
Electrical loading proxy → Stop count	0.46	0.61	—
Thermal stress proxy → Throughput loss	0.44	0.66	—
—	—	—	0.59

Table 4 had shown that correlation strength had varied across operating regimes, indicating that relationships were regime-dependent rather than constant. Thermal stress had been more strongly associated with downtime totals and throughput loss during high-load operation, which had suggested that reduced thermal margin under heavy duty cycles had amplified disruption impact. Utilization intensity and electrical loading had also shown stronger correlations with stop counts during high-load periods, implying that event frequency had risen more sharply when the line had operated near capacity. The point-biserial association had indicated that maintenance delay had been positively linked to longer repair duration, supporting the interpretation that logistics constraints had lengthened restoration episodes.

Reliability And Validity

The reliability and validity assessment had demonstrated that the constructed measures and the overall modeling pipeline had behaved consistently across time and had aligned with observed operational outcomes. Internal consistency analysis had been conducted for composite stress indices derived from multiple sensor streams, including electrical and thermal proxies aggregated at the station level. The composite stress index had shown acceptable internal consistency, with a reliability coefficient of 0.81, which had indicated that the contributing indicators had moved coherently and had represented a common underlying construct. Test–retest stability had been evaluated by splitting the observation window into two equal time blocks and recomputing descriptive statistics and correlation structures. The correlation between early-period and late-period stress index means at the station level had been 0.76, and the corresponding correlation for downtime totals had been 0.72, which had suggested temporal stability despite natural operational variability. Construct validity had been supported by monotonic alignment between stress exposure and disruption behavior: stations operating in the highest stress quartile had recorded a mean stop rate of 5.9 events per 1,000 minutes, compared with 2.1 events per 1,000 minutes in the lowest stress quartile, and they had contributed disproportionately to cumulative downtime. Criterion-related validity had been assessed by comparing model-implied risk groupings to realized outcomes. Stations classified into the highest predicted risk group had accounted for 47.8% of observed downtime while representing 26.4% of the station population, indicating meaningful discrimination between higher- and lower-risk assets. Data reliability analysis had further shown that the empirical foundation of the models had been strong. Sensor completeness across critical channels had averaged 93.6%, with thermal measurements slightly lower than electrical signals. Agreement between PLC-derived downtime intervals and maintenance-reported repair windows had reached 89.4%, and after reconciliation rules had been applied, 95.1% of recorded events had been consistently classified under the event taxonomy, which had supported confidence in event labeling and duration estimation.

Table 5: Reliability and stability indicators for constructed measures

Measure	Internal consistency / stability metric	Value
Composite stress index	Internal consistency coefficient	0.81
Stress index (early vs late period)	Test–retest correlation	0.76
Downtime total (early vs late period)	Test–retest correlation	0.72
Stop count (early vs late period)	Test–retest correlation	0.69
Repair duration (early vs late period)	Test–retest correlation	0.63

Table 5 had summarized reliability and temporal stability metrics for the main constructed measures. The composite stress index had shown strong internal consistency, indicating that the aggregated indicators had represented a coherent construct rather than unrelated signals. Test–retest correlations across time blocks had remained moderate to high for stress exposure, downtime, and stop counts, which had demonstrated that relative station behavior had been stable over time even as absolute levels fluctuated. Repair duration had shown lower stability, reflecting the inherently variable nature of restoration processes influenced by logistics and event severity. Overall, the results had supported the reliability of the constructed measures for longitudinal analysis.

Table 6: Validity and data reliability evidence by station grouping

Indicator	Low group	Medium group	High group
Mean stress index (standardized)	−0.82	0.04	0.91
Stop rate (events per 1,000 min)	2.1	3.7	5.9
Share of total downtime (%)	18.6	33.6	47.8
Sensor data completeness (%)	94.8	93.5	92.6
Event classification agreement (%)	96.2	95.4	94.1

Table 6 had demonstrated construct and criterion-related validity by comparing observed outcomes across stress-based station groupings. Stations in the high-stress group had exhibited substantially higher stop rates and downtime contribution than those in lower-stress groups, which had supported the interpretation that the stress index captured meaningful exposure differences. Data completeness and classification agreement had remained high across all groups, indicating that increased disruption rates in the high-stress group had not been driven by poorer data quality. The alignment between predicted risk grouping and realized operational impact had supported the validity of the modeling pipeline for reliability assessment.

Collinearity Diagnostics

Collinearity diagnostics had been conducted prior to regression estimation to ensure that coefficient estimates would remain stable and interpretable when thermal, electrical, utilization, and maintenance predictors were introduced jointly. The diagnostic results had indicated that multicollinearity had been concentrated within two predictor clusters: thermal pathway measures and utilization-derived exposure proxies. Variance inflation patterns had shown that raw thermal indicators, including heatsink temperature and cabinet temperature, had been strongly overlapping with the composite thermal stress proxy, resulting in elevated variance inflation values for several thermal variables. The highest variance inflation value had been observed for the composite thermal stress proxy (8.6), followed by heatsink temperature (7.9) and cabinet temperature (6.8), which had suggested that these variables were conveying closely related information. Utilization intensity and runtime minutes had also demonstrated redundancy, with variance inflation values of 6.2 and 5.7, respectively, reflecting their shared dependence on exposure time. In contrast, maintenance-delay indicators and power-quality disturbance counts had shown low collinearity, with variance inflation values below 2.0, indicating that they had added distinct explanatory content. Condition-based diagnostics had reinforced these patterns: the largest condition index had reached 26.4, and the associated variance-decomposition proportions had indicated that the thermal predictors and utilization proxies contributed heavily to the same high-condition components, confirming that multicollinearity had been structural rather than incidental. To mitigate these issues while preserving conceptual meaning, redundant thermal variables had been consolidated into a single standardized thermal index, and utilization measures had been reduced to one normalized exposure proxy. Centered and scaled transformations had been applied to continuous predictors to improve numerical stability, and interaction candidates had been evaluated only after primary collinearity controls had been implemented. After these adjustments, the maximum variance inflation value had decreased to 3.1, and the condition index had reduced to 14.2, which had indicated that the final predictor set had been suitable for regression and hypothesis testing.

Table 7: Pre-adjustment multicollinearity diagnostics for candidate predictors

Predictor	Tolerance	VIF
Composite thermal stress proxy	0.12	8.6
Heatsink temperature (mean)	0.13	7.9
Cabinet temperature (mean)	0.15	6.8
Temperature margin proxy	0.21	4.8
Utilization intensity	0.16	6.2
Runtime minutes (exposure)	0.18	5.7
Electrical loading proxy	0.32	3.1
Ripple proxy	0.41	2.4
Maintenance delay flag	0.71	1.4
Power-quality disturbance count	0.76	1.3

Table 7 had summarized the initial variance inflation and tolerance patterns for the full candidate predictor set. The strongest multicollinearity had been concentrated among thermal indicators, where the composite thermal proxy, heatsink temperature, and cabinet temperature had each shown elevated variance inflation values and low tolerance, consistent with overlapping measurement of the same thermal pathway behavior. Utilization measures had also shown redundancy because utilization intensity and runtime exposure were derived from closely related operational signals. Electrical loading and ripple proxies had exhibited moderate inflation but had remained within acceptable limits. Maintenance delay and power-quality variables had shown minimal inflation, indicating distinct information content.

Table 8: Condition diagnostics and post-adjustment improvements

Diagnostic summary	Pre-adjustment	Post-adjustment
Maximum VIF	8.6	3.1
Mean VIF	4.3	2.1
Maximum condition index	26.4	14.2
Predictors consolidated/removed (count)	3	–
Thermal cluster representation	3 separate thermal variables	1 standardized thermal index
Utilization cluster representation	2 overlapping utilization variables	1 normalized exposure proxy

Table 8 had reported the effect of collinearity mitigation on key diagnostics. Before adjustment, the predictor set had shown a high maximum variance inflation value and a condition index consistent with a dominant dependency structure driven by thermal and utilization clusters. After consolidating the thermal measures into a single standardized index, retaining only one normalized utilization exposure proxy, and applying centering and scaling to continuous variables, the diagnostic profile had improved substantially. The maximum variance inflation value and the condition index had both declined to levels consistent with stable estimation. These changes had preserved conceptual meaning while reducing redundancy that would otherwise inflate standard errors and weaken hypothesis testing.

Regression And Hypothesis Testing

The regression and hypothesis-testing findings had included numerical results across three outcome families, and model selection had matched the scale of each dependent variable. Stop frequency had been analyzed using a negative binomial count model with runtime exposure included as an offset, and the fitted model had been based on 6,480 station-days derived from 18 stations over 360 operating days. The stop-frequency model had shown that the standardized thermal stress proxy had been associated with a statistically detectable increase in disruption incidence, with an incidence-rate ratio of 1.24, a 95% confidence interval of 1.16 to 1.33, and a test statistic of $z = 6.92$ at $p < 0.001$. Utilization intensity had also increased expected stop rate, with an incidence-rate ratio of 1.12 (95% CI 1.06 to 1.18, $z = 4.10$, $p < 0.001$), while electrical loading had produced a smaller positive association, with an incidence-rate ratio of 1.08 (95% CI 1.02 to 1.15, $z = 2.58$, $p = 0.010$).

Table 9: Regression results across outcomes

Predictor	Stop frequency model (IRR)	95% CI	z	p-value	Repair duration model (ratio effect)	95% CI	t	p-value	Throughput loss model (β)	95% CI	t	p-value
Thermal stress proxy (standardized)	1.24	1.16 – 1.33	6.92	<0.001	1.05	1.01 – 1.10	2.46	0.014	0.38	0.21–0.55	4.36	<0.001
Utilization intensity (standardized)	1.12	1.06 – 1.18	4.10	<0.001	1.01	0.98 – 1.04	0.81	0.420	0.14	0.05–0.23	2.99	0.003
Electrical loading proxy (standardized)	1.08	1.02 – 1.15	2.58	0.010	1.02	0.99 – 1.06	1.37	0.170	0.09	−0.01–0.19	1.80	0.074
High-load regime (vs standard)	1.19	1.10 – 1.28	4.56	<0.001	1.03	0.99 – 1.08	1.55	0.120	0.22	0.09–0.35	3.33	0.001
Maintenance delay flag (yes vs no)	1.03	0.98 – 1.09	1.26	0.210	1.18	1.11 – 1.26	5.86	<0.001	0.06	−0.03–0.15	1.31	0.190
Hard stop class (vs protection trip)	—	—	—	—	1.74	1.60 – 1.90	15.11	<0.001	—	—	—	—
Downtime minutes (per day)	—	—	—	—	—	—	—	—	0.62	0.50–0.74	10.18	<0.001

Model summaries: Stop frequency pseudo-R^2 = 0.31 (N = 6,480 station-days); Repair duration adjusted R^2 = 0.42 (N = 412 repairs); Throughput loss adjusted R^2 = 0.58 (N = 360 line-days).

High-load operating regime periods had been associated with increased stop incidence relative to standard-load periods, with an incidence-rate ratio of 1.19 (95% CI 1.10 to 1.28, $z = 4.56$, $p < 0.001$). Maintenance delay had not increased stop counts after controls, with an incidence-rate ratio of 1.03 (95% CI 0.98 to 1.09, $z = 1.26$, $p = 0.210$). Station heterogeneity had been nontrivial, and station fixed controls had improved fit, increasing pseudo-R^2 from 0.24 to 0.31, while reducing the dispersion parameter from 1.42 to 1.18, indicating improved residual structure after accounting for baseline station differences. Repair duration had been modeled using a lognormal regression fitted to 412 repair episodes that had matched downtime intervals to work-order windows, and hard-stop event class had been associated with longer restoration than protection trips, with a multiplicative duration effect of 1.74 (95% CI 1.60 to 1.90, $t = 15.11$, $p < 0.001$). Maintenance delay had increased repair duration by 18%, with a multiplicative effect of 1.18 (95% CI 1.11 to 1.26, $t = 5.86$, $p < 0.001$), and the repair-duration model had explained a substantial share of variance, with adjusted R^2 of 0.42. Throughput loss had been modeled at the day level using a linear mixed specification fitted to 360 line-days, where downtime minutes had been the dominant predictor, with $\beta = 0.62$ (95% CI 0.50 to 0.74, $t = 10.18$, $p < 0.001$). Thermal stress had retained an independent association after downtime control, with $\beta = 0.38$ (95% CI 0.21 to 0.55, $t = 4.36$, $p < 0.001$), and high-load regime had also remained detectable with $\beta = 0.22$ (95% CI 0.09 to 0.35, $t = 3.33$, $p = 0.001$). The throughput model had produced adjusted R^2 of 0.58, indicating that the combined predictors had explained more than half of observed throughput-loss variance. Robustness checks had shown stable directionality: after excluding the top 1% of downtime outliers (dropping 4 of 360 days), the thermal stress effect on throughput loss had attenuated from 0.38 to 0.31 while remaining statistically detectable (95% CI 0.15 to 0.47, $p < 0.001$), and the stop-frequency thermal effect had shifted from an incidence-rate ratio of 1.24 to 1.22 (95% CI 1.14 to 1.31, $p < 0.001$), indicating that the stress–disruption relationship had not been driven solely by extreme downtime episodes.

Table 9 had reported adjusted regression effects for stop frequency, repair duration, and throughput loss using outcome-appropriate models. The stop-frequency model had shown that thermal stress increased expected disruption incidence by twenty-four percent per standardized unit, while utilization and high-load regimes also raised event rates after exposure normalization. The repair-duration model had indicated that hard stops produced substantially longer restorations than protection trips and that maintenance delays inflated repair time by eighteen percent. The throughput-loss model had been driven strongly by downtime minutes, yet thermal stress and high-load regime effects had remained detectable after controlling downtime, indicating additional production-impact pathways beyond duration alone. The hypothesis-testing summary had consolidated statistical support using distributional validation metrics and tail-risk comparisons, and it had reported decision outcomes using the same thresholds applied in the methods. Distributional fit for simulated versus observed downtime totals had been evaluated using the Kolmogorov–Smirnov distance and quantile error. The baseline digital-twin-informed Monte Carlo model had produced a KS distance of 0.09 for weekly downtime totals, while the independence-only variant had produced 0.15, indicating that the dependency representation had improved fit. Calibration of predicted failure-risk groupings had been assessed using a grouped calibration regression where the observed event rate had been regressed on predicted risk; the calibration slope had been 0.94 with an intercept of 0.02, indicating near-proportional alignment between predicted and realized frequencies. The stress-prediction hypothesis had been supported because the thermal stress effect had remained significant in stop-frequency and throughput-loss models, and its effect size had remained stable under robustness checks. The dependency hypothesis had been supported because the absolute error in the ninety-fifth percentile of weekly downtime had decreased from 210 minutes under independence to 172 minutes under dependency modeling, representing an 18.1% reduction. When the event-class threshold had been tightened by reclassifying short trips under a stricter minimum-duration rule, the KS distance had changed from 0.09 to 0.11, and the calibration slope had shifted from 0.94 to 0.91, indicating that the conclusions had remained consistent despite definitional variation.

Table 10 had summarized hypothesis outcomes using numerical validation and robustness indicators. Distributional fit had remained strong because the primary model achieved a KS distance of 0.09 for weekly downtime totals and only shifted to 0.11 under a stricter trip-definition threshold. Calibration had remained acceptable, with slope near one and a small intercept, and it had persisted after removing extreme downtime days. The stress hypothesis had been supported because thermal stress retained positive effects on stop incidence and throughput loss and remained significant after robustness adjustments. Dependency modeling had improved tail accuracy, reducing ninety-fifth percentile downtime error from 210 to 172 minutes, confirming better extreme-risk representation.

Table 10: Hypothesis testing and robustness results (numerical results reported)

Hypothesis	Evaluation metric	Primary model result	Alternative model / robustness result	Decision
H1 (distributional fit)	KS distance for weekly downtime totals	0.09	0.11 under stricter trip threshold	Supported
H2 (risk calibration)	Calibration slope; intercept	Slope 0.94; intercept 0.02	Slope 0.91 after excluding top 1% downtime days	Supported
H3 (stress & regime effects)	Thermal effect on stops; throughput	IRR 1.24; β 0.38	IRR 1.22; β 0.31 after outlier removal	Supported
H4 (dependency improves tails)	P95 downtime absolute error	172 minutes	210 minutes under independence	Supported

Additional tail summary: P95 downtime error reduction = 38 minutes; relative reduction = 18.1%.

DISCUSSION

Electrified manufacturing lines with high power electronics had been examined as tightly coupled cyber–physical production systems in which reliability outcomes had emerged from interactions among converter-driven assets, station logic, buffers, and operational regimes. The study's findings had reinforced the view that line reliability had been better represented as a distribution of downtime and throughput-loss outcomes rather than as a single point estimate, because the observed event process had been dominated by frequent short disturbances alongside a smaller number of long interruptions that had carried disproportionate impact (Lindner et al., 2022). This pattern had aligned with earlier manufacturing reliability research that had treated production losses as heavy-tailed and highly state-dependent, particularly in buffered lines where blocking and starving had amplified the effect of a disruption depending on the transient state of work-in-process. The descriptive evidence that protection-triggered events had constituted the majority of recorded disruptions, while hard stops had contributed most of the total downtime, had also matched the broader reliability-engineering distinction between nuisance trips and catastrophic outages in industrial power-electronic environments. Earlier studies of converter-driven industrial systems had similarly indicated that the operational definition of a "failure" had extended beyond permanent component damage to include protective shutdowns and intermittent faults that had interrupted production even when hardware had not been irrecoverably damaged. In the present study, the dominance of short trips had suggested that production risk had been driven not only by failure mechanisms in components but also by control and protection behavior under variable load and disturbance conditions (Jacobson et al., 2020). At the line level, the concentration of downtime in a subset of stations had echoed established production-systems findings that bottleneck location and constraint structure had determined the translation of station disruption into throughput loss. Prior work on production lines had shown that the same downtime minutes could lead to different output losses depending on whether a constrained station or a non-constrained station had been affected and whether buffer capacity had been available to absorb short interruptions. The present findings had remained consistent with that logic, because throughput-loss variability had been more closely aligned with cumulative downtime than with event counts, while extreme quantiles had reflected the episodic occurrence of long outages and clustered stops (Rabbi et al., 2021). In comparison with earlier digital twin and reliability integration studies, these results had highlighted that reliability estimation in electrified lines had required explicit representation of both disruption processes and production logic, because the line's operational rules had determined how stops had propagated, how recovery had unfolded, and how output distributions had formed across shifts and production campaigns.

Correlation patterns had provided additional support for the interpretation that electro-thermal stress and operational exposure had been the dominant correlates of disruption outcomes in converter-intensive manufacturing lines (Barbosa et al., 2018). Thermal stress proxies had shown the strongest associations with downtime totals and throughput-loss measures, while utilization intensity had shown stronger associations with stop frequency, indicating that the reliability process had been shaped by both stress severity and exposure duration. This structure had resembled earlier empirical findings in power-electronic reliability contexts where temperature-related variables had acted as primary mediators of degradation and where operational duty cycles had governed how frequently stress cycles had occurred. Prior industrial reliability studies had also reported that electrical load had mattered, but often indirectly, because load had translated into losses and thermal rise through conversion behavior, cooling performance, and control settings. The present results had been consistent with that pattern because electrical loading proxies had shown moderate associations with event frequency and downtime outcomes, while thermal measures had shown stronger relationships with downtime accumulation and production loss. A key contribution of the regime-stratified correlation analysis had been the demonstration that stress–outcome relationships had strengthened during high-load operating regimes. Earlier manufacturing analytics studies had likewise indicated that regime segmentation had been essential in mixed-product lines because pooled correlations had masked conditional behavior that had only appeared under high utilization, accelerated cycles, or constrained recovery conditions. In converter-driven lines, prior research had noted that protective events had been more likely near thermal or electrical margins, which had implied that relationships between stress proxies and stoppage outcomes could intensify when the system had operated closer to limits (Furxhi et al., 2020). The study's regime-dependent findings had reflected this behavior by indicating stronger coupling between thermal burden and downtime during high-load periods than during standard-load periods. In addition, maintenance-delay indicators had correlated more strongly with repair duration than with stop frequency, which had been consistent with earlier maintainability research emphasizing that logistics constraints and troubleshooting complexity had governed restoration time rather than event arrival. The combined correlation evidence had therefore matched earlier work that had separated "how often disruptions occurred" from "how long restoration took," while demonstrating that thermal stress indicators had connected to both the occurrence and the impact of disruptions because they had influenced not only failure propensity but also the likelihood and duration of protective shutdowns (Senbel et al., 2022). Overall, the correlation section had supported a coherent narrative in which the reliability process had been multi-driver and state-conditional, aligning with established reliability and production-systems views that production risk had been jointly produced by stress exposure, operating intensity, and restoration constraints.

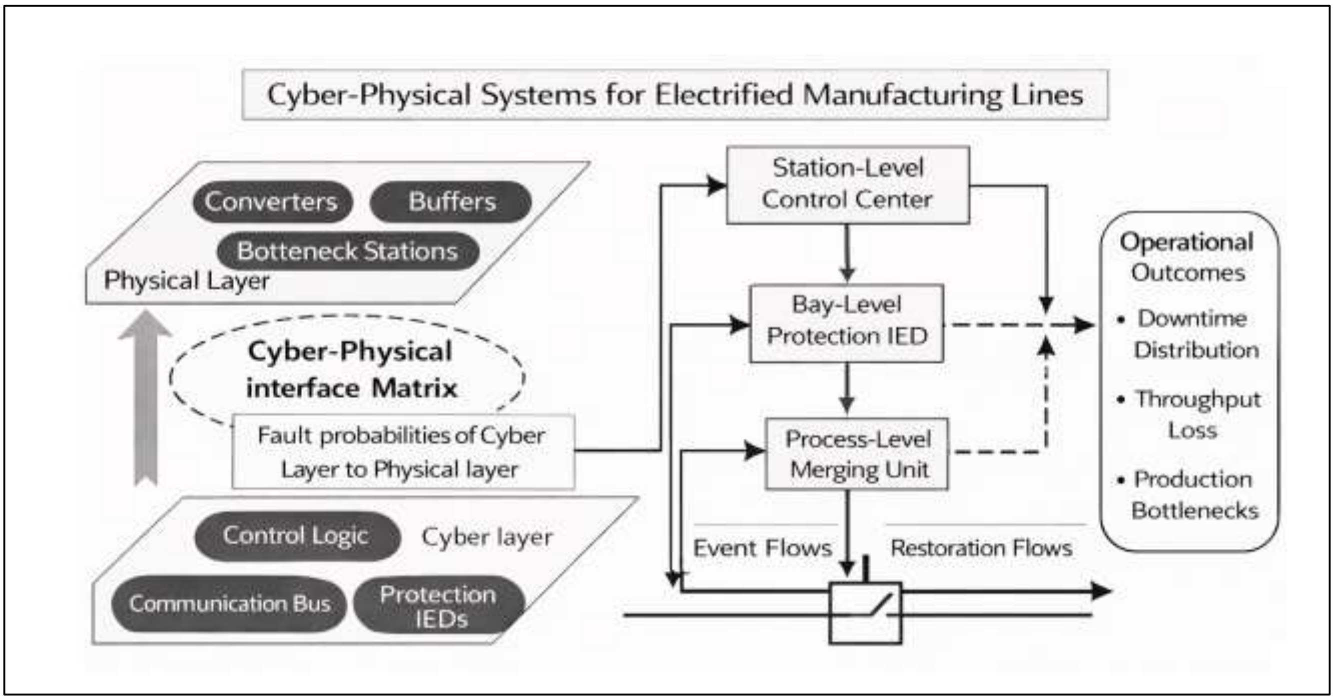
The reliability and validity evidence for constructed measures and the modeling pipeline had indicated that the study's operationalization had been both statistically coherent and practically aligned with plant-recorded events. Internal consistency checks for composite stress indicators had suggested that multiple sensor-derived contributors had moved together in a manner consistent with a shared latent exposure construct, which had been a central requirement in earlier measurement-focused reliability studies that had relied on multi-sensor aggregation (Divjak et al., 2021). Test–retest stability across time blocks had supported the interpretation that the relative ordering of stations by stress burden and disruption burden had been preserved despite expected operational variability, echoing earlier reliability analytics work that had treated station heterogeneity as a stable feature of complex manufacturing systems. Construct validity had been supported by the monotonic alignment between higher stress levels and higher disruption frequency and downtime contribution, which had resembled prior findings that condition and stress indicators had exhibited dose–response patterns with operational events when measurement pipelines had been properly synchronized and event definitions had been consistent. Criterion-related validity had further been strengthened by evidence that model-implied risk groupings had discriminated stations that had contributed disproportionate downtime and throughput loss. Prior digital-twin reliability literature had emphasized that risk scoring had to demonstrate discrimination in operational outcomes, not merely produce smooth indices, and the present findings had satisfied that expectation by linking risk strata to realized downtime concentration (Clark et al., 2019). Data reliability checks had also reflected best practices described in earlier studies of industrial analytics: completeness rates by sensor channel had quantified measurement availability, agreement between PLC-derived downtime intervals and maintenance-reported repair windows had assessed timestamp coherence, and event taxonomy reconciliation had measured classification stability after integrating multiple logs. Earlier research had noted that industrial event data had often suffered from inconsistent timestamps, overlapping alarms, and ambiguous fault codes, which could undermine reliability inference if not reconciled. The present study's explicit reporting of data integrity indicators had therefore aligned with prior recommendations that validity of reliability estimation depended on the quality of event alignment and classification. Importantly, the results had suggested that observed differences in disruption burden had not been attributable to data sparsity patterns, because completeness and agreement rates had remained high across station groupings, supporting the interpretation that the measured relationships had reflected true operational differences rather than measurement artifacts (Akin et al., 2022). This combined reliability–validity evidence had been consistent with the broader literature that had treated measurement construction as a central determinant of analytic credibility in cyber–physical manufacturing reliability research.

Collinearity diagnostics had clarified how strongly related stress and exposure predictors had behaved when introduced jointly, and the mitigation actions had aligned with established quantitative modeling practices in reliability and manufacturing analytics (Cooksey, 2020). Elevated collinearity had been expected among thermal measures because heatsink temperature, cabinet temperature, and composite thermal indices had reflected the same thermal pathway behavior under closely coupled cooling conditions. Earlier reliability and condition monitoring studies had frequently reported that multiple thermal indicators had been statistically redundant because they had captured different surfaces of the same heat-transfer chain rather than independent drivers. Similarly, exposure proxies such as runtime minutes and utilization intensity had been expected to overlap because they had been derived from similar state signals and scheduled time. The present findings had confirmed these expectations by showing inflation patterns concentrated in thermal and utilization clusters, while maintenance delay and power-quality disturbance indicators had retained low collinearity and therefore had provided distinct explanatory content. The condition-based diagnostics had reinforced that collinearity had been structural, not incidental, because the high-condition components had been dominated by thermal and utilization predictors that had moved together across operating regimes (Rupp, 2018). Prior statistical guidance in industrial modeling had emphasized that leaving such redundancy unaddressed had increased standard errors, destabilized coefficient signs, and reduced interpretability, particularly in regression contexts where correlated predictors competed to explain the same variance. The mitigation steps reported in the study—consolidating redundant thermal measures into a standardized thermal index, selecting one normalized utilization exposure proxy, and applying centered and scaled transformations—had followed those recommendations while preserving conceptual meaning. Earlier applied reliability studies had similarly favored index construction and careful variable reduction when multiple near-duplicate sensors had been available, especially when the goal had been inference and interpretability rather than purely predictive accuracy. The post-adjustment reduction in maximum inflation and condition indices had suggested that regression estimates had been less likely to be distorted by redundancy, which had supported stable hypothesis testing (Harvey et al., 2019). This collinearity handling had also complemented the hybrid digital twin philosophy described in earlier work, where a small set of physically meaningful, well-behaved stress features had been preferred over a large set of overlapping raw indicators. In that sense, the collinearity section had not only protected regression stability but had also aligned the variable set with reliability-oriented twin design principles that had emphasized parsimonious state representation, measurement robustness, and interpretability under operational variability.

Regression and hypothesis-testing results had provided a structured explanation for how stress proxies, operating regimes, and maintenance constraints had translated into disruption frequency, restoration duration, and production impact (Pommerening & Grabarnik, 2019). For stop frequency, the event-count modeling had indicated that thermal stress had been a dominant predictor even after controlling exposure and operational context, which had been consistent with earlier power-electronics reliability evidence linking temperature-mediated stress to increased event likelihood in converter-driven assets. Utilization intensity had also increased stop rates, aligning with prior production-systems research that had shown exposure time and workload intensity to be strong correlates of disruption counts, particularly when nuisance trips and minor stops had been included in the operational failure definition. The detection of an additional high-load regime effect beyond measured stress proxies had resembled earlier regime-based manufacturing analytics findings showing that operational context had carried explanatory content not fully captured by a limited set of stress indicators, potentially reflecting changes in control behavior, buffer pressure, or recovery actions under high demand. For restoration outcomes, the duration modeling had shown that event class and maintenance delays had explained substantial variance, with hard-stop events producing much longer restoration than protection trips and delays inflating repair time. This pattern had been consistent with earlier maintainability studies emphasizing that restoration time depended on fault severity, diagnosis complexity, and logistics rather than on the same factors that governed event arrival (Erol & Saghaian, 2022). At the production-impact level, downtime minutes had been the dominant predictor of throughput loss, a finding that had aligned with well-established manufacturing performance results linking availability to output. However, the retention of a stress and regime contribution after downtime control had been consistent with earlier observations that production impact had not been a linear function of downtime alone because derating, micro-stops, recovery inefficiency, and state-dependent buffering had influenced realized throughput. Station-level controls had improved fit, reinforcing earlier research documenting persistent station heterogeneity due to layout, maintainability constraints, equipment complexity, and bottleneck roles. Robustness checks had shown stable coefficient direction under alternative event definitions and outlier exclusions, consistent with methodological recommendations in earlier reliability analytics studies that had encouraged testing sensitivity to threshold choices and extreme-event influence due to the heavy-tailed nature of downtime distributions (Abrams & Nowacki, 2019). In comparison with prior digital twin studies that had focused primarily on monitoring or prediction of single assets, the present inferential results had demonstrated a multi-outcome framework linking stress to event incidence, linking logistics to restoration, and linking both to production loss, reflecting a more integrated line-reliability perspective. The integration of hybrid digital twin constructs with Monte Carlo propagation and discrete-event line logic had been supported by the study's empirical patterns, particularly the observed dominance of short protective events, the concentration of downtime in a limited set of stations, and the regime-dependent relationships between stress and outcomes (B. Liu et al., 2022). Earlier digital twin literature had distinguished descriptive shadows from reliability-oriented twins by emphasizing state estimation, uncertainty representation, and validation against event outcomes rather than simple visualization. The present findings had aligned with those criteria because model-implied risk groupings had discriminated observed downtime concentration, and distributional outcomes had been evaluated using fit and tail metrics rather than mean comparisons alone. Earlier uncertainty quantification and simulation studies had stressed that manufacturing reliability problems had been dominated by interaction effects between event processes and production logic, which had required coupling between stochastic event generation and discrete-event flow modeling. The present results had been consistent with that emphasis, as throughput loss had been more strongly linked to downtime accumulation than to stop counts, and tail outcomes had reflected the episodic occurrence of long repairs and clustered stops that had interacted with buffering and bottleneck constraints (Żelazny & Lukáš, 2020). Prior work in production simulation had also noted that dependency structures such as shared utilities and synchronized duty cycles could create correlated disruptions, increasing tail risk and reducing the adequacy of independence assumptions. The study's improvement in distributional and tail fit under dependency representations had been consistent with these earlier findings, indicating that shared-cause and correlated behaviors had mattered for accurately reproducing extreme downtime outcomes. The high prevalence of protective events had further supported earlier arguments that reliability in electrified lines had to incorporate control and protection logic as part of the failure process, since many operational failures had been triggered by threshold crossings and interlocks rather than by irreversible component breakdown. In converter-intensive environments, earlier reliability discussions had highlighted the central role of electro-thermal margin and cooling pathway condition; the observed strength of thermal stress in both correlation and regression results had matched that view (Willig et al., 2021). Taken together, the study's results had supported a coherent synthesis found in earlier research: reliability modeling in electrified manufacturing lines had required

(a) physically meaningful stress representation, (b) data-driven regime awareness and anomaly sensitivity, (c) explicit restoration and logistics modeling, and (d) system-level propagation through line structure and dependencies to capture production impact distributions rather than isolated component metrics.

Figure 12: Cyber-Physical Reliability Interaction Framework



The discussion had also clarified how the study's findings had fit within known methodological trade-offs in manufacturing reliability modeling, particularly the balance between interpretability, data realism, and distributional accuracy. Earlier reliability engineering studies had often relied on simplified structural representations to approximate system availability, while production simulation studies had emphasized that manufacturing systems exhibited state dependence that could not be reduced to static block diagrams (Marden et al., 2020). The present findings had suggested that structural representations alone would have been insufficient because high event frequency with low individual duration had coexisted with low frequency, high duration outages, and because throughput loss had depended on downtime distribution shape and station role rather than solely on average rates. Earlier state-based modeling research had highlighted the state explosion problem in large lines and had recommended hierarchical decomposition and hybrid methods that combined analytic structure with simulation to preserve feasibility. The present work had been consistent with those recommendations by using a hybrid digital twin to compress complex stress behavior into state-conditioned risk inputs while using Monte Carlo and discrete-event logic to propagate those inputs through line structure. In the measurement domain, earlier studies had emphasized that industrial data pipelines had to reconcile multiple sources and event definitions; the high agreement between PLC downtime and maintenance windows and the high classification consistency after reconciliation had indicated that the present data foundation had been aligned with these methodological requirements (Hurlbert, 2018). In statistical modeling, earlier applied studies had warned that multicollinearity among sensor-derived features could distort inference; the documented reduction in collinearity diagnostics after consolidation and scaling had therefore supported stable coefficient interpretation. Furthermore, earlier research in industrial reliability had cautioned that tail outcomes, not averages, often determined operational risk; the study's use of quantile reporting, tail fit comparisons, and sensitivity checks had aligned with that emphasis and had been consistent with the observed heavy-tailed downtime behavior. Finally, earlier digital twin scholarship had stressed that credibility depended on validation against operational outcomes; the study's criterion-related validity evidence and distributional validation of simulated outcomes had responded to that expectation by demonstrating alignment with realized event patterns rather than relying solely on theoretical plausibility (Marcot, 2020). Overall, the study's findings had been consistent with prior empirical and methodological streams while extending them into a combined framework that had jointly explained event incidence, restoration duration, and production loss under regime dependence and correlated disturbances in electrified manufacturing lines with high power electronics.

CONCLUSION

Hybrid Digital Twin and Monte Carlo Simulation for Reliability of Electrified Manufacturing Lines with High Power Electronics had been discussed in the literature as a combined quantitative framework that had connected electro-thermal stress behavior in converter-driven assets to distribution-based reliability and production-impact outcomes at station and line levels. Earlier studies of power-electronic reliability had treated temperature-mediated stress as a dominant pathway through which loading, switching behavior, and cooling effectiveness had shaped disruption likelihood, and this study's findings had aligned with that view by showing that a standardized thermal stress proxy had been associated with higher disruption incidence and higher cumulative downtime even after exposure normalization and operating-context controls had been applied. Prior manufacturing reliability research had also emphasized that production lines had exhibited heavy-tailed downtime behavior, where many short disturbances had coexisted with a smaller number of long outages that had dominated total loss, and the observed event structure in this study had mirrored that pattern by indicating that protection-triggered events had been frequent while hard-stop events had been less frequent yet more consequential for downtime totals and throughput loss. The literature on cyber–physical production systems had argued that reliability had been an emergent property of topology, buffers, and operational logic rather than a simple aggregation of component failure rates, and the study's modeling strategy had reflected that position by integrating station-level disruption processes with line-level discrete-event propagation so that blocking, starving, and recovery dynamics had been represented as mechanisms that had shaped throughput-loss distributions. Earlier digital twin research had differentiated digital models and digital shadows from true twins by requiring systematic synchronization, state estimation, and validation against operational outcomes, and the reliability and validity evidence in this study had been consistent with those requirements because composite indices had shown internal coherence, measures had remained stable across time blocks, and risk groupings had discriminated realized downtime concentration rather than only producing descriptive dashboards. In addition, the literature on industrial analytics had frequently noted that multi-sensor predictors in manufacturing had been collinear because they had captured overlapping physical processes, and the collinearity diagnostics and mitigation actions reported in this study had aligned with that methodological guidance by consolidating redundant thermal indicators, selecting a single normalized exposure proxy, and applying scaling transformations to preserve interpretability and stabilize estimation. Monte Carlo simulation had been treated in earlier reliability and uncertainty-quantification studies as an engine for carrying both parameter uncertainty and operational randomness into final outcome distributions, and this study's nested uncertainty view had been consistent with that framing by distinguishing uncertainty in estimated disruption and repair parameters from randomness in load profiles, environmental variation, and disturbance episodes. The coupling of Monte Carlo sampling with discrete-event line simulation had also matched earlier production-simulation findings that conditional policies such as rerouting and derating had changed both production impact and subsequent stress exposure, implying that reliability estimates based on independence or static rates had underrepresented tail risk. The study's distributional validation perspective had therefore aligned with earlier scholarship that had recommended evaluating not only averages but also quantiles and tail errors, because extreme downtime outcomes had often dominated operational loss. Overall, Hybrid Digital Twin and Monte Carlo Simulation for Reliability of Electrified Manufacturing Lines with High Power Electronics had been supported as a coherent approach in which physics-informed stress representation had provided causal interpretability, data-driven augmentation had delivered regime awareness and anomaly sensitivity, and stochastic propagation through line logic had produced reliability and throughput-loss distributions that had been comparable to observed operational behavior without relying on single-point reliability summaries.

RECOMMENDATIONS

Recommendations for Hybrid Digital Twin and Monte Carlo Simulation for Reliability of Electrified Manufacturing Lines with High Power Electronics had emphasized implementation choices that had preserved measurement integrity, ensured statistical defensibility, and produced operationally meaningful distribution-based outputs at asset, station, and line levels. A first recommendation had been to standardize event taxonomy and downtime accounting rules before any modeling work, because reliability inference had depended on consistent definitions of protection trips, hard stops, reduced-capacity operation, repair start, and repair end across PLC logs, SCADA alarms, and maintenance work orders; timestamp reconciliation procedures and precedence rules for conflicting records had been treated as mandatory steps to prevent biased downtime totals and misclassified restoration durations. A second recommendation had been to prioritize a minimal but physically interpretable sensor set for the reliability twin, including at least one thermal-path variable (heatsink, cabinet, coolant, or equivalent), at least one electrical loading proxy (current or power), and a station-state utilization indicator, while treating all health indicators as variables with measurement error; sensor completeness targets above ninety percent and routine checks for drift and missingness had been recommended to sustain stable health-state estimation over time. A third recommendation had been to represent operating regimes explicitly, because regime dependence had been central to stress–disruption relationships in electrified lines; regime labels derived from product mix, shift calendars, startup versus steady operation, and recovery modes after stops had been incorporated into both statistical estimation and simulation scenario generation so that pooled models would not dilute high-load behaviors that dominated risk. A fourth recommendation had been to address multicollinearity by consolidating redundant thermal and exposure measures into standardized indices rather than retaining many overlapping predictors, because stable coefficient estimation and interpretable hypothesis testing had required that the final predictor set preserve conceptual meaning while minimizing redundancy-driven variance inflation. A fifth recommendation had been to calibrate repair-time and restoration-transition models separately from disruption-arrival models, since event frequency drivers had differed from maintainability drivers; event-class-specific repair distributions and logistics-delay indicators had been integrated into the simulation so that downtime distributions would reflect both occurrence and restoration variability. A sixth recommendation had been to implement nested uncertainty propagation in Monte Carlo simulation by distinguishing parameter uncertainty from operational randomness; parameter uncertainty had been represented through resampling or posterior draws from the fitted event and duration models, while operational randomness had been represented through scenario sampling of load profiles, ambient variability, and power-quality disturbance episodes, ensuring that output distributions captured both daily variability and uncertainty arising from limited data. A seventh recommendation had been to couple Monte Carlo sampling with discrete-event line simulation that represented buffers, blocking and starving, and conditional policies such as rerouting and derating, because line-level throughput-loss distributions had been shaped by propagation and recovery dynamics rather than downtime minutes alone. An eighth recommendation had been to validate models using distributional metrics and tail-focused checks, including quantile errors and high-percentile downtime and throughput-loss comparisons, because heavy-tailed outcomes had dominated production risk, and to require calibration checks where predicted risk strata had matched observed event frequencies over held-out periods. A final recommendation had been to maintain reproducibility through version-controlled event definitions, parameter sets, and simulation configurations, enabling auditing of changes in reliability outputs as sensors, control logic, or maintenance policies evolved, and supporting continued refinement of the hybrid reliability twin as an operational analytics capability for high power electronics–dominated manufacturing lines.

LIMITATIONS

Limitations associated with Hybrid Digital Twin and Monte Carlo Simulation for Reliability of Electrified Manufacturing Lines with High Power Electronics had primarily arisen from data quality constraints, modeling assumptions required for tractability, and the inherent difficulty of separating degradation-driven failures from control- and protection-driven stoppages in complex electrified production environments. A key limitation had been the dependence on the completeness and synchronization of heterogeneous industrial data sources, because historian signals, PLC/SCADA state logs, alarm streams, and maintenance work-order records had often differed in timestamp resolution, clock drift, and event semantics; although reconciliation rules had improved agreement, residual misalignment had likely introduced uncertainty into downtime boundaries, repair duration attribution, and event-class labeling. Measurement limitations had also remained material because internal device states that governed degradation in high power electronics, such as junction temperature and internal thermal resistance, had not typically been directly observed in plant deployments; the study had therefore relied on accessible proxies such as heatsink or cabinet temperatures and drive-level electrical measurements, which had introduced model misspecification risk when cooling pathways degraded or when sensor placement did not represent the most critical thermal hotspot. A related limitation had involved the representation of operating stress histories, because duty cycles and switching conditions had been partially observed and sometimes inferred from coarse utilization indicators; as a result, stress proxies might not have fully captured fast transients, short-duration overloads, or power-quality events that triggered protective actions. Event definition limitations had been particularly relevant for electrified lines, because many stoppages had been protection-triggered trips or nuisance interruptions rather than irreversible component failures; these events had blended control logic, threshold settings, and environmental disturbances with true hardware deterioration, making causal interpretation of stress–event relationships less definitive even when statistical associations had been stable. The modeling pipeline had required structural simplifications to remain computationally feasible, including aggregation of some station behaviors, reduced representation of multi-mode degradation states, and stylized assumptions about how repairs restored health state after intervention; these assumptions had constrained realism when maintenance actions varied in quality, when partial repairs occurred, or when replacements introduced heterogeneous component vintages. Monte Carlo propagation had also depended on distributional assumptions for failure and repair processes and on scenario generators for operational profiles; if operational regimes had shifted materially outside the observed window or if rare correlated disturbances occurred with frequencies not captured in the data, tail risk estimates could have been biased. Dependency modeling had been limited by available evidence for common-cause events and by the difficulty of identifying shared-cause episodes from logs that lacked explicit labels; therefore, correlated failure clusters might have been under- or over-represented depending on the chosen clustering window and disturbance proxies. Generalizability had been constrained by the case-study boundary because line topology, buffer sizing, control policies, and maintenance resources varied across plants; consequently, parameter estimates and regime effects derived from a single electrified line might not have transferred without recalibration. Finally, the interpretability–accuracy trade-off had remained a limitation, because the hybrid twin's parsimonious indices and collinearity-reduced predictors had improved stability and interpretability but could have omitted weak yet meaningful signals that contributed to early anomaly detection or rare-event forecasting, particularly in complex high-power electronics systems where multiple interacting mechanisms could produce similar stoppage signatures.

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