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Stochastic Digital Twin Frameworks for Uncertainty Quantification in Industrial Operations

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ABSTRACT

Industrial digital twins increasingly support monitoring, simulation, optimization, and decision-making across manufacturing, energy systems, logistics, infrastructure, and quality control. However, many implementations still depend on deterministic assumptions that treat system inputs, model parameters, and operating conditions as fixed. This limits their reliability in real industrial environments where uncertainty arises from sensor noise, demand fluctuation, machine degradation, environmental variability, model abstraction, and supply chain disruption. This review synthesizes stochastic digital twin frameworks for uncertainty quantification in industrial operations. It examines how aleatory, epistemic, data-quality, model, and prediction uncertainties enter digital twin pipelines and propagate through virtual models into operational decisions. The review evaluates key modelling and computational approaches, including Bayesian updating, Monte Carlo simulation, stochastic processes, Markov models, polynomial chaos expansion, Gaussian process emulators, probabilistic machine learning, reduced-order models, and hybrid physics-data architectures. It also maps major industrial applications in predictive maintenance, production scheduling, supply chain risk management, energy optimization, and process quality control. The analysis shows that stochastic digital twins improve decision quality by replacing single-point predictions with probability distributions, confidence bounds, failure probabilities, risk metrics, and scenario-sensitive outputs. Yet practical deployment remains constrained by computational cost, data quality, calibration difficulty, real-time latency, multi-level integration, and lack of standardized implementation protocols. Future progress requires adaptive learning, uncertainty-aware artificial intelligence, scalable distributed computing, and interoperable digital twin ecosystems. Stochastic digital twins will not eliminate industrial uncertainty, but they can make it measurable, interpretable, and actionable for resilient industrial decision-making..

1. Introduction

Industrial operations across manufacturing, energy systems, and logistics networks increasingly rely on digital twins to mirror physical systems through real-time data and predictive models (Rasheed et al., 2020; Huang et al., 2021). A digital twin serves as a virtual replica of a physical entity, integrating multi-physics, multi-scale simulation with sensor updates to support monitoring, optimization, and decision-making throughout a system's lifecycle (Rasheed et al., 2020; Vitalis et al., 2024). These tools have found broad adoption in sectors ranging from smart manufacturing and advanced robotics (Huang et al., 2021), to energy systems (Kamyabi et al., 2022) and production scheduling (Negri et al., 2020). Digital twins enable real-time production planning, scheduling, execution, and control with reduced complexity (Guo et al., 2020), and they support forecasting of optimal network design, inventory management, and logistics operations (Igbokwe et al., 2025). Despite this progress, most deployed digital twins rely on deterministic assumptions, treating system inputs, parameters, and model structures as fixed (Okeagu et al., 2024; Chavoshi et al., 2021). This is problematic because uncertainty is intrinsic to industrial environments, arising from demand variability, machine degradation, environmental conditions, supply chain disruptions, and human intervention (Bakon et al., 2022; Nwamekwe et al., 2025). Ignoring these uncertainties leads to overconfident predictions and suboptimal decisions (Bakon et al., 2022). This limitation has driven the emergence of stochastic digital twin frameworks that explicitly incorporate uncertainty into modelling and analysis (Nwamekwe et al., 2024; Okpala et al., 2025).

1.1 Problem Framing

Traditional digital twins provide point estimates of system states and performance without quantifying the range of possible outcomes or the likelihood of extreme events (Cotoarbă et al., 2025; Chavoshi et al., 2021). In high-stakes industrial settings, decisions must account for risk and variability, making deterministic outputs insufficient (Chavoshi et al., 2021; Bakon et al., 2022). Uncertainty arises at multiple levels within digital twin frameworks. Input uncertainty reflects variability in external conditions such as fluctuating demand and environmental factors (Bakon et al., 2022; Negri et al., 2020). Parameter uncertainty captures incomplete knowledge of system characteristics, including manufacturing tolerances and degradation rates (Park et al., 2022; Chidiebube et al., 2025). Structural uncertainty relates to model assumptions and simplifications that introduce discrepancies between simulated and actual behaviour (Emeka et al., 2025; Onyeka et al., 2024). These uncertainties propagate through the digital twin and influence outputs in ways that demand systematic treatment (Nwamekwe et al., 2025; Chidiebube et al., 2025). Methods such as Monte Carlo simulation, Bayesian inference, polynomial chaos expansion, and interval analysis have been applied to quantify and propagate these uncertainties (Nwamekwe et al., 2025; Moghadam et al., 2021; Cotoarbă et al., 2025). Existing approaches often address these uncertainty sources in isolation, and there remains a lack of unified frameworks that integrate stochastic modelling, real-time data assimilation, and decision support within digital twins (Onyeka et al., 2025; Nwamekwe et al., 2024).

1.2 Objective of the Review

This review synthesizes stochastic digital twin frameworks for uncertainty quantification in industrial operations. It examines modelling approaches that range from frequentist statistical techniques and Bayesian updating to Monte Carlo propagation methods. It also considers integration strategies that combine physics-based models with data-driven approaches to create hybrid digital twins capable of operating under real-world variability. The review identifies challenges related to scalability, data requirements, computational cost, and real-time implementation that constrain the deployment of stochastic digital twins in practice. By mapping the current state of research across manufacturing, energy, and infrastructure domains, this work aims to provide a structured foundation for advancing uncertainty-aware digital twin frameworks in industrial operations.

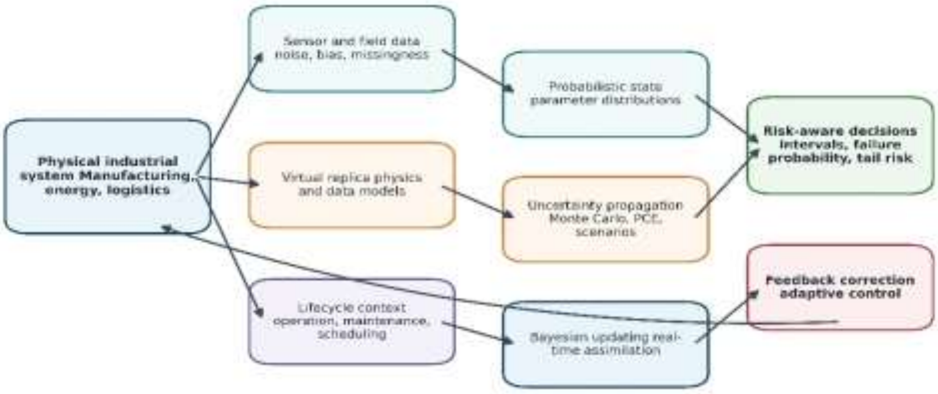

Figure 1: Conceptual Architecture of Stochastic Digital Twin for Uncertainty-Aware Industrial Operations

Figure 1 converts the study's conceptual argument into an end-to-end stochastic digital twin architecture. It shows how field data, virtual models, probabilistic states, Bayesian updating, uncertainty propagation, risk-aware decisions, and feedback correction operate as one adaptive loop.

2. Conceptual Foundations of Stochastic Digital Twins

2.1 Digital Twin Architecture under Uncertainty

A conventional digital twin consists of three core elements: a physical entity, a virtual replica, and the data connections linking them (Rasheed et al., 2020; Huang et al., 2021). NASA's early definition described the digital twin as "an integrated multi-physics, multiscale, probabilistic simulation" that mirrors the life of its physical counterpart (Juarez et al., 2021; Kamyabi et al., 2022). A stochastic digital twin extends this architecture by embedding probabilistic representations at each layer of the system. At the data acquisition layer, sensor measurements carry noise, intermittent connectivity issues, and processing biases that introduce uncertainty into the twin's inputs (Negri et al., 2020; Guo et al., 2020). At the model layer, system parameters are treated as random variables rather than fixed constants, reflecting incomplete knowledge and natural variability (Igbokwe et al., 2025; Cotoarbă et al., 2025). At the output layer, predictions take the form of probability distributions rather than single point estimates, enabling the twin to communicate both expected behaviour and the range of plausible outcomes (Chavoshi et al., 2021; Bakon et al., 2022). Cotoarbă et al. (2021) proposed a probabilistic digital twin (PDT) framework that provides a structured approach to integrating all sources of uncertainty and propagating them throughout the entire modelling process. This layered probabilistic structure transforms the digital twin from a deterministic mirror into a risk-aware decision support tool (Negri et al., 2020; Nwamekwe et al., 2025).

2.2 Types of Uncertainty in Industrial Systems

Uncertainty in industrial digital twins falls into two fundamental categories. Aleatory uncertainty refers to inherent randomness in the system that cannot be reduced through additional data collection, such as demand fluctuations, stochastic machine failures, and environmental variability (Chavoshi et al., 2021; Okpala et al., 2024). Epistemic uncertainty arises from incomplete knowledge, including unknown model parameters, limited calibration data, and simplifications in model structure (Chavoshi et al., 2021; Park et al., 2022). Chavoshi et al. (2021) explicitly distinguish aleatoric, data, model, and prediction uncertainties within their PDT framework for geotechnical applications. Negri et al., (2020) identify sensor noise, intermittent connectivity, data processing biases, and model abstractions as primary uncertainty sources in smart manufacturing digital twins. Park et al. (2022) note that uncertainty and variability in structural integrity assessments arise from lack of knowledge, modelling approximations, and differences between as-manufactured and as-operated components. Bakon et al. (2022) observe that separating aleatory from epistemic uncertainty within a digital twin is a challenging problem in practice, and propose generative models as a basis for twins that estimate both types simultaneously. Both categories must be addressed for accurate uncertainty quantification, as ignoring either leads to overconfident or unreliable predictions (Negri et al., 2020; Chavoshi et al., 2021).

2.3 Representation of Stochastic Processes

Industrial systems exhibit variables that evolve randomly over time, and representing these variables requires stochastic process models. Demand processes, machine failure processes, and environmental variations are common examples in manufacturing and energy systems (Chidiebube et al., 2025; Emeka et al., 2025). Augustyn et al. (2021) model equipment failure probability in real time using data-driven statistical models within a digital twin framework synchronized with field sensor data. Shields et al. (2019) describe how stochastic degradation of products is modelled using failure rate functions or stochastic processes such as Markov processes, Wiener processes, or gamma processes. Moghadam et al. (2021) construct digital twins using hidden Markov models, where the model component forms a Markov chain encapsulating system dynamic through discrete states and transition probabilities, while the simulation component recreates phenomena using Monte Carlo simulation. Liang et al. (2025) integrate Gaussian mixture models with hidden Markov models within a digital twinning framework to dynamically predict disassembly waste generation under uncertainty. These stochastic representations allow the digital twin to capture temporal variability and random disruptions that deterministic models overlook (Negri et al., 2020; Chidiebube et al., 2025).

2.4 Uncertainty Propagation Mechanisms

Once uncertainties are characterized at the input and parameter levels, they must be propagated through the digital twin's model equations to quantify their effect on outputs. Monte Carlo simulation is the most widely adopted propagation technique, offering flexibility in handling complex, nonlinear systems with multiple uncertainty sources (Negri et al., 2020; McAfee et al., 2022; Nwamekwe et al., 2024). Battula et al. (2024) employ a Monte Carlo uncertainty propagation method to establish the distribution of fatigue damage in offshore wind substructures based on updated digital twin parameters. Polynomial chaos expansion (PCE) provides an alternative approach that represents random variables using orthogonal polynomial functions, offering computational efficiency for systems where Monte Carlo sampling becomes prohibitively expensive (Igbokwe et al., 2024; Huang et al., 2021). Campean et al. (2019) report the use of generalized polynomial chaos expansion within digital twins of power electronic converters to improve performance characterization. Scenario-based analysis represents a third approach, where discrete sets of plausible future conditions are simulated to assess system response under different operating regimes (Chidiebube et al., 2025; Cotoarbă et al., 2025). McAfee et al. (2022) emphasize that reduced-order uncertainty propagation techniques, including polynomial chaos and surrogate modelling approaches, need further development for stochastic digital twins to remain computationally tractable. The choice of propagation method depends on the system's complexity, the number of uncertain parameters, and the computational budget available (Negri et al., 2020; Igbokwe et al., 2025).

2.5 Metrics for Uncertainty Quantification

Quantifying uncertainty in digital twin outputs requires well-defined metrics that communicate risk and variability to decision-makers. Variance and standard deviation of output quantities provide basic measures of spread around expected values (Negri et al., 2020; Nwamekwe et al., 2025). Confidence intervals and prediction intervals offer probabilistic bounds on future observations, as demonstrated by Battula et al. (2024), who use updated uncertainty distributions to compute structural reliability indices for offshore wind turbine joints. Probability of failure is a direct risk metric used in structural and reliability engineering contexts, where Park et al. (2022) discuss its computation through Level 3 Monte Carlo analyses and Latin hypercube sampling. Ma et al. Baumgartner et al. (2022) propose a novel anomaly measure based on the first Wasserstein distance to characterize entire flight datasets for gas turbine engines, applying thresholds to detect anomalous behaviour within a probabilistic digital twin. Value-at-risk and related tail-risk measures capture the likelihood of extreme outcomes, which is relevant for high-stakes industrial decisions involving supply chain disruptions or catastrophic equipment failures (Cotoarbă et al., 2025; Okpala et al., 2025). Chen et al. (2024) introduce user-prescribed bounds on quantities of interest within an adaptive Monte Carlo framework, maintaining predictive error within specified tolerances to ensure trustworthy prognostic forecasts. The selection of appropriate metrics depends on the decision context and the consequences of prediction errors in the specific industrial application (Negri et al., 2020; Park et al., 2022).

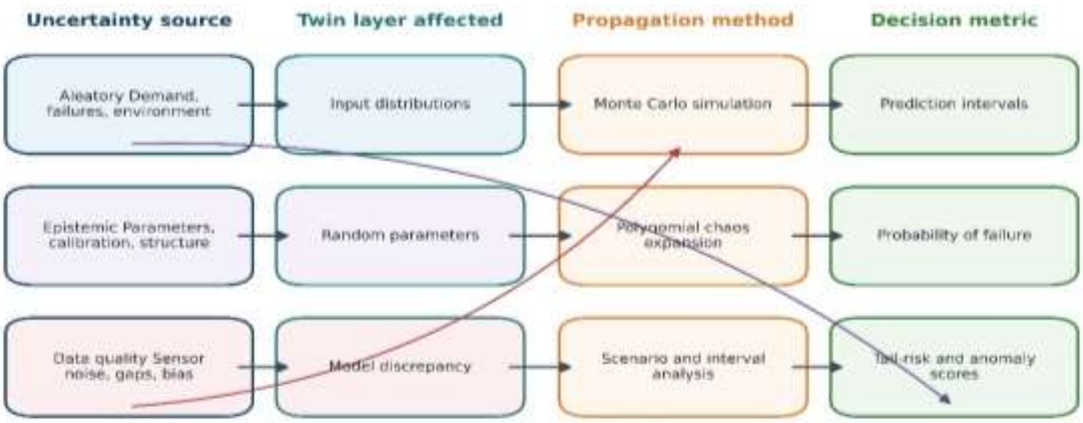

Figure 2: Uncertainty Sources and Propagation Pathways in Stochastic Digital Twin Systems

Figure 2 separate aleatory, epistemic, and data-quality uncertainty, then traces how each source affects input distributions, model parameters, simulation methods, and decision metrics. It clarifies why uncertainty must be managed across the whole twin pipeline.

3. Modelling Frameworks and Computational Architectures

3.1 Probabilistic Modelling Approaches

Stochastic digital twins rely on probabilistic models to represent the uncertain behaviour of physical systems. Bayesian models form a core approach for parameter estimation, where prior distributions on model parameters are updated with observed data to yield posterior distributions that reflect both existing knowledge and new evidence (Nwamekwe et al., 2024; Cotoarbă et al., 2025). Kapteyn et al. (2020) demonstrate this by combining a library of component-based reduced-order models with Bayesian state estimation, treating the digital twin as a discrete random variable with a probability mass function given by the posterior distribution. Markov processes represent another class of probabilistic models suited to systems with discrete state transitions. Ghosh et al. (2019) construct digital twins using hidden Markov models where the model component forms a Markov chain encapsulating system dynamic through discrete states and transition probabilities. Chen et al. (2024) apply dynamic Bayesian networks, a temporal extension of Bayesian networks, for fatigue crack propagation prediction within a digital twin framework, noting that the dynamic Bayesian network is "among the most widely applied probabilistic methods" for representing and managing uncertainties in physical models. For continuous dynamic systems, stochastic differential equations offer a natural formulation. Møller and Goranović (2024) describe stochastic grey box models that use stochastic differential equations with a diffusion term for uncertainty quantification, forming the basis of data-driven digital twins that account for random changes and process uncertainties. Ganguli and Adhikari (2020) formalize the equation of motion of a stochastic multiple-degrees-of-freedom digital twin, where mass, damping, and stiffness functions carry uncertainties that must be propagated through the system. The selection among these probabilistic approaches depends on the nature of the system, the type of uncertainty present, and the available data (Nwamekwe et al., 2024; Chavoshi et al., 2021).

3.2 Data Assimilation and Bayesian Updating

Real-time data assimilation is a defining feature that distinguishes a digital twin from a static simulation model (Cotoarbă et al., 2025; Kochunas & Huan, 2021). Bayesian updating provides the mathematical foundation for incorporating new sensor observations into the digital twin's probabilistic state, reducing epistemic uncertainty over time (Nwamekwe et al., 2025; Ezeanyim et al., 2025). Cotoarbă et al. (2025) describe a probabilistic digital twin framework where the digital state evolves dynamically as new data are obtained and decisions are made, with Bayesian updates performed by evaluating likelihood functions for every sample and computing normalized sample weights followed by resampling. Augustyn et al. (2021) present a probabilistic framework in which digital twin information is used to update the uncertainties associated with structural dynamics and load modelling parameters in fatigue damage accumulation for offshore wind substructures. Their results show that updating soil stiffness significantly affects the reliability of joints close to the mudline, while updating wave loading affects joints in the splash zone (Chidiebube et al., 2025). Kochunas and Huan (2021) discuss how sequential Bayesian inference encompasses well-known methods such as the Kalman filter, ensemble Kalman filter, and particle filter for state estimation problems where uncertain states evolve over time. Kessels et al. (2024) propose probabilistic Bayesian neural networks for real-time parameter updating, inferring probability distributions for updating parameter values instead of point estimates obtained from traditional deterministic neural networks. This continuous assimilation of field data enables adaptive digital twins that improve prediction accuracy as operational experience accumulates (Cotoarbă et al., 2025; Ezeanyim et al., 2025).

3.3 Simulation-Based Frameworks

Simulation methods generate multiple system trajectories under uncertainty, providing a distribution of possible outcomes rather than a single deterministic prediction. Monte Carlo simulation is the most established sampling-based technique for this purpose (Nwamekwe et al., 2025; Ganguli & Adhikari, 2020). Ghosh et al. (2019) employ discrete event Monte Carlo simulation as the simulation component of their hidden Markov model-based digital twin, recreating manufacturing phenomena through repeated random sampling. Murray et al. (2023) present an adaptive Monte Carlo framework for prognostic digital twins in smart manufacturing, where a closed-loop architecture controls the quality of uncertainty forecasting by defining application-specific quantities of interest and associated bounds on forecasting error. Their approach addresses a limitation of traditional open-loop Monte Carlo propagation, which requires guessing the simulation size a priori and only estimates forecast accuracy after completion (Murray et al., 2023). Felsberger et al. (2019) apply Monte Carlo simulation within a digital reliability twin paradigm for power converter maintenance optimization, drawing stochastic input parameters from normal distributions to propagate parameter uncertainty to the simulation engine. Gérard et al. (2022) use Monte Carlo simulation to propagate uncertainties onto project bankability assessment for green hydrogen facilities, calculating opportunity indices and internal rates of return under varying input assumptions. Scenario simulation complements sampling-based methods by exploring specific extreme or boundary conditions. Augustyn et al., (2021) propose a simheuristics framework combining genetic algorithms with discrete event simulation for robust scheduling under uncertain scenarios, synchronized with the field through a digital twin (Chidiebube et al., 2025). The computational cost of these simulation-based approaches remains a practical constraint, particularly when thousands or millions of samples are needed for convergence (Ganguli & Adhikari, 2020; Murray et al., 2023).

3.4 Hybrid Deterministic-Stochastic Models

Hybrid models combine deterministic system dynamics with stochastic components to balance computational efficiency and modelling realism. Tsialiamanis et al. (2021) propose a framework where physics-based stochastic finite element models are coupled with data-driven conditional generative adversarial networks, demonstrating that for structures with material nonlinearities and uncertainties, the data-driven model outperforms the physics-based approach alone, while a hybrid combination of both yields improved results. Kapteyn et al. (2020) combine physics-based reduced-order models with data-driven Bayesian state estimation, where the reduced-order models provide computational speed while the Bayesian framework handles uncertainty quantification and model adaptation. Chakraborty et al. (2021) explore the use of Gaussian process emulators within digital twin technology, noting that Gaussian processes are probabilistic surrogate models immune to overfitting and capable of quantifying uncertainty due to limited and noisy data. Their results show that with increasing noise levels, the uncertainty captured by the Gaussian process also increases, providing decision-makers with a realistic picture of prediction confidence (Chakraborty et al., 2021). Kim et al. (2023) propose a physics-informed data-driven digital twin for federated optimization in manufacturing, incorporating known uncertainty from physics-based models and learning unknown uncertainty on-the-fly through Bayesian linear regression from sensor measurements. This hybrid deterministic-stochastic strategy is particularly relevant for industrial digital twins where purely physics-based models are too slow for real-time use and purely data-driven models lack physical interpretability (Tsialiamanis et al., 2021; Ezeanyim et al., 2025).

3.5 Scalable Computational Architectures

Large-scale stochastic simulations demand high-performance computing resources, and scalability is a persistent challenge for deploying stochastic digital twins in industrial settings (Ganguli & Adhikari, 2020; Wagg et al., 2020). Ganguli and Adhikari (2020) identify the need for reduced-order uncertainty propagation techniques, including polynomial chaos and surrogate modelling approaches, to make stochastic digital twins computationally tractable for complex systems. Kapteyn et al. (2020) address scalability through component-based reduced-order models that decompose large systems into modular components, noting that this approach compared to traditional monolithic model reduction techniques. Wagg et al. (2020) discuss the computational challenges of propagating uncertainties through a digital twin for engineering dynamics applications, emphasizing that for complex structures, determining how uncertainties propagate remains an active area of research. Cloud-based platforms and parallel processing architectures provide the infrastructure needed to run thousands of Monte Carlo samples or scenario simulations concurrently (Nwamekwe et al., 2024; Murray et al., 2023). Murray et al. (2023) demonstrate an adaptive Monte Carlo platform that controls simulation size dynamically, reducing unnecessary computational expenditure by terminating simulations once prescribed error tolerances are met. Surrogate models, including Gaussian processes and neural network emulators, offer another path to scalability by replacing expensive physics-based simulations with fast approximations trained on simulation data (Chakraborty et al., 2021; Ganguli & Adhikari, 2020).

3.6 Integration with Real-Time Systems

Stochastic digital twins must operate within the time constraints of industrial decision-making to deliver actionable insights (Nwamekwe et al., 2020; Kochunas & Huan, 2021). Battula et al. (2024) emphasize that uncertainty quantification at its core involves real-time adaptive control in dynamically changing environments, leveraging state awareness towards responsive action within predictive control models and feedback systems. Chavoshi et al. (2021) note that real-time updating is the key characteristic distinguishing a digital twin from regular simulations, and that the best available knowledge of digital twin properties should be provided as probability distributions so that risk-informed decisions follow. Kapteyn et al. (2020) demonstrate near-real-time model adaptation for an unmanned aerial vehicle digital twin, where reduced-order models in the model library accelerate the Bayesian inference problem to make it tractable for online operation. Kim et al. (2023) propose an uncertainty-aware digital twin for CNC machining that updates on-the-fly via Bayesian regression, achieving federated optimization under servo error constraints in real time. Birk et al. (2022) discuss the need for self-correction and update mechanisms operating autonomously as a prerequisite for long-term value creation from digital twins in process industrial systems. Achieving real-time performance with stochastic models requires efficient algorithms, low-latency data pipelines, and often a trade-off between model fidelity and computational speed (Ezeanyim et al., 2025; Wagg et al., 2020).

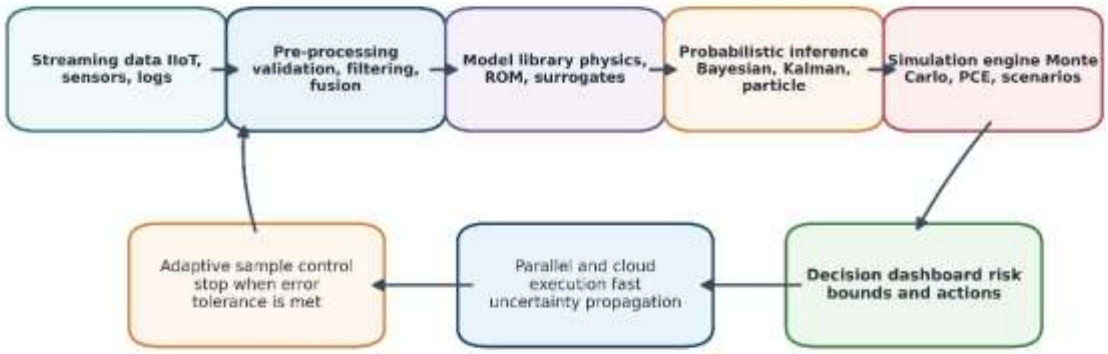

Figure 3: Computational Architecture for Real-Time Stochastic Digital Twin Simulation and Updating

Figure 3 presents the computational architecture required for real-time stochastic digital twins. It links streaming data, pre-processing, model libraries, probabilistic inference, simulation engines, adaptive sample control, parallel execution, and decision dashboards into a closed-loop system.

4. Applications in Industrial Operations

4.1 Predictive Maintenance under Uncertainty

Stochastic digital twins provide a structured approach to modelling machine degradation and failure probabilities, enabling risk-based maintenance scheduling that accounts for the inherent randomness in equipment behaviour. Rasheed et al. (2020) identify predictive maintenance for robotics in flexible manufacturing environments as a primary use case, where wear uncertainties in components need to be monitored over time and model predictive control systems use digital twin simulations to optimize production quality under process variability. Huang et al. (2021) apply a digital reliability twin paradigm to power converter maintenance optimization, drawing stochastic input parameters from normal distributions to propagate parameter uncertainty through a simulation engine. Their results show that either reactive or preventive maintenance is more cost-effective depending on the operating conditions, a distinction that deterministic models fail to capture (Huang et al., 2021). Augustyn et al. (2021) present a probabilistic framework where digital twin information updates the uncertainties associated with structural dynamics and load modelling parameters in fatigue damage accumulation for offshore wind substructures. Their findings demonstrate that updating soil stiffness significantly affects the reliability of joints close to the mudline, while updating wave loading affects joints in the splash zone (Juarez et al., 2021). Murray et al. (2022) develop an adaptive Monte Carlo framework for prognostic digital twins in smart manufacturing, specifically targeting cutting tool wear in CNC machines, where a closed-loop architecture controls the quality of uncertainty forecasting by maintaining predictive error within user-prescribed tolerances. These applications demonstrate that incorporating stochastic models into maintenance planning leads to more informed decisions about when and how to intervene, reducing both unplanned downtime and unnecessary preventive actions (Rasheed et al., 2020; Juarez et al., 2021).

4.2 Production Planning and Scheduling

Uncertainty-aware digital twins improve production planning decisions by accounting for variability in demand, processing times, and equipment availability. Negri et al. (2020) propose a simheuristics framework for robust scheduling applied to a flow shop scheduling problem, where a digital twin synchronized with the field employs an equipment prognostics and health management module to compute failure probability in real time using data-driven statistical models. Their framework combines genetic algorithms for schedule optimization with discrete event simulation, demonstrating the viability of uncertainty-aware scheduling in a laboratory environment (Negri et al., 2020). Bakon et al. (2020) review how uncertainties in increasingly complex production and supply chains should be addressed in scheduling tasks, noting that uncertainty management is particularly important in Industry 5.0 solutions requiring close integration of operators and technical systems. Guo et al. (2021) present a Graduation Intelligent Manufacturing System enabled by Industrial Internet of Things and digital twin technology, achieving real-time production planning, scheduling, execution, and control with reduced complexity and uncertainty. Akçay et al. (2025) describe the construction of manufacturing digital twins for wafer fabrication plants, where historical data for stochastic events modelling is incorporated and verification, validation, and uncertainty quantification of the digital twin model and supporting data must be performed throughout the twin's lifecycle. Huang et al. 2021) report that digital twin-based production planning and scheduling represent active areas of AI-driven digital twin research in Industry 4.0, covering both conventional metal machining and emerging techniques. These studies collectively show that embedding stochastic elements into production scheduling digital twins leads to more robust plans that perform well across a range of plausible operating conditions (Negri et al., 2020; Guo et al., 2020).

4.3 Supply Chain Risk Management

Digital twins simulate disruption scenarios and evaluate mitigation strategies, enhancing supply chain resilience under uncertainty. Ivanov and Dolgui (2022) present the digital supply chain twin as a contemporary instrument for stress testing supply chain resilience, where disruption events and supply chain parameters are updated automatically from external databases to create a real-time digital twin enhanced by end-to-end supply chain visibility. Their framework uses any logistic supply chain simulation and optimization software to model ripple effects during crises such as the COVID-19 pandemic (Bakon et al., 2022). Abideen et al. (2024) review how digital twin simulation modelling applies to supply chain and logistics, noting that simulation modelling and the digital twin approach have been applied extensively to study and analyse various operations of production and supply chain systems. Tang et al. (2022) propose a digital twin-assisted collaborative capability optimization model for smart manufacturing systems, building a multi-objective optimization model to enhance the value of the shared supply chain while helping collaborative manufacturing enterprises respond to market environments and reduce the loss of manufacturing resources. Liu et al. (2022) investigate digital twins for industrial symbiosis networks in the Norwegian wood supply chain, noting that the difficulty of digital twin construction in supply chains stems from the great uncertainty inherent in supply chain operations. Gérard et al. (2021) use Monte Carlo simulation within a digital twin to propagate uncertainties onto project bankability assessment for green hydrogen facilities, calculating opportunity indices and internal rates of return under varying input assumptions. These applications confirm that stochastic digital twins provide supply chain managers with a structured way to anticipate disruptions and evaluate response strategies before committing resources (Bakon et al., 2022; Nwamekwe et al., 2025).

4.4 Energy Systems and Process Optimization

Stochastic models within digital twins capture variability in energy demand and supply, enabling efficient and reliable operation of energy systems. Moghadam et al. (2019) review digital twin applications in power systems, covering wind turbines, solar panels, power electronic converters, and shipboard electrical systems, noting that digital twins provide a technique to assess and analyse system performance while merging with intelligent algorithms for supervisory and optimization activity. Kamyabi et al. (2019) describe how data science-based digital twin models of renewable energy system technologies developed in a real-time data-rich environment help develop better decisions and predictions, contributing to effective and reduced cost-based power system control at the localized level. Augustyn et al. (2021) demonstrate the value of probabilistic digital twins in the offshore wind energy sector, where updated uncertainty distributions for soil stiffness and wave loading directly affect structural reliability estimates used for operation and maintenance optimization. Bowman et al. (2021) discuss digital twin applications in the nuclear sector, where automated and integrated uncertainty quantification is applied to define appropriate boundaries of processes, critical safety parameters, allowable tolerances, and appropriate safety margins using the best estimate plus uncertainty approach. Mane et al. (2025) examine digital twins in the chemical industry, reporting that digital twins help optimize energy usage by identifying opportunities to reduce consumption without compromising production output. These energy sector applications demonstrate that stochastic digital twins address a critical need: managing the inherent variability of renewable sources, load fluctuations, and degradation processes that deterministic models treat inadequately (Emeka et al., 2025; Juarez et al., 2021).

4.5 Quality Control and Process Variability

Uncertainty quantification within digital twins helps identify sources of variability and improve process stability in manufacturing operations. Huang et al. (2021) report that at the quality control stage, classical supervised machine learning models such as artificial neural networks, decision trees, and support vector machines are deployed within digital twin frameworks to detect or predict potential deformations and surface deviations in production. Battula et al. (2020) emphasize that uncertainty quantification allows the collaboration of human and machine, giving early warnings on anomalies and risks that enhance visibility and foster coordination during disruptive situations in manufacturing. Ghosh et al. (2022) construct a digital twin of surface roughness created by successive grinding operations using hidden Markov models, where the model component encapsulates the dynamics underlying the phenomenon through discrete states and transition probabilities, and the simulation component recreates the phenomenon using Monte Carlo simulation. Wright and Davidson (2024) note that a digital twin approach for manufacturing allows monitoring the supply chain by linking mechanical properties of raw materials to end product quality, using quality assessment data to estimate material properties and adjust process settings. Chakraborty et al. (2021) explore Gaussian process emulators within digital twin technology, showing that with increasing noise levels, the uncertainty captured by the Gaussian process also increases, providing decision-makers with a realistic picture of prediction confidence for quality-related variables. Tsialiamanis et al. (2019) demonstrate that for structures with material nonlinearities and uncertainties, a hybrid combination of physics-based stochastic finite element models and data-driven conditional generative adversarial networks yields improved results for predicting structural response variability. These studies indicate that stochastic digital twins offer a systematic path to understanding and controlling process variability, moving quality management from reactive inspection toward proactive prediction and intervention (Rasheed et al., 2020; Chavoshi et al., 2021).

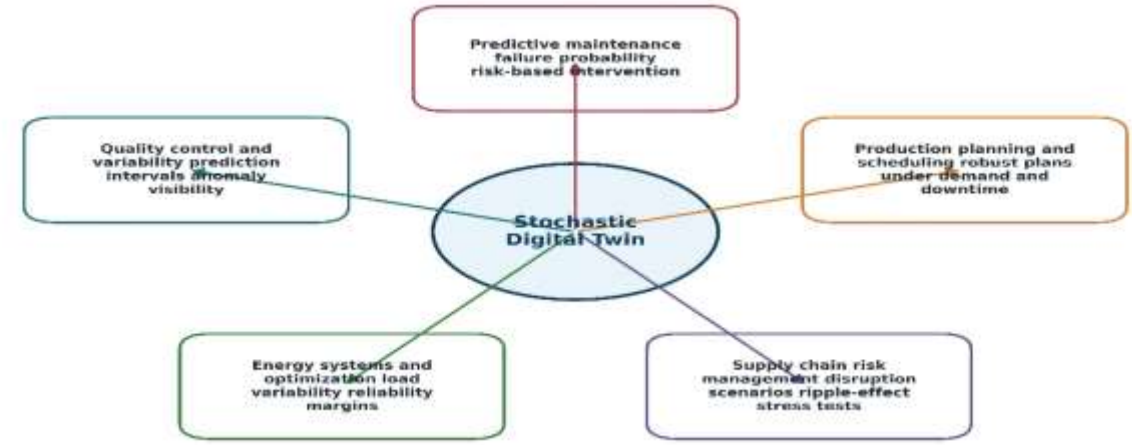

Figure 4: Industrial Application Domains of Stochastic Digital Twin Frameworks

Figure 4 map the study's five industrial application domains: predictive maintenance, production scheduling, supply chain risk, energy optimization, and quality control. It shows the specific uncertainty-aware value mechanism attached to each domain.

5. Key Challenges and Research Gaps

5.1 Computational Complexity

Stochastic simulations demand significant computational resources, and this burden grows rapidly with system size and the number of uncertain parameters. Ganguli and Adhikari (2020) formalize the equation of motion of a stochastic multiple-degrees-of-freedom digital twin and identify the need for reduced-order uncertainty propagation techniques, including polynomial chaos and surrogate modelling approaches, to keep stochastic digital twins computationally tractable. Monte Carlo simulation, the most widely adopted propagation method, requires thousands or millions of samples for convergence in complex nonlinear systems (Huang et al., 2021; Juarez et al., 2021). Murray et al. (2021) address this limitation through an adaptive Monte Carlo framework that dynamically controls simulation size, terminating once prescribed error tolerances are met, thereby reducing unnecessary computational expenditure. Wagg et al. (2022) discuss the computational challenges of propagating uncertainties through a digital twin for engineering dynamics applications, emphasizing that for complex structures, determining how uncertainties propagate remains an active area of research. Kapteyn et al. (2020) tackle scalability through component-based reduced-order models that decompose large systems into modular components, noting that this approach "scales efficiently to large complex systems" compared to traditional monolithic model reduction techniques. Chakraborty et al. (2020) explore Gaussian process emulators as surrogate models within digital twin technology, offering a faster alternative to full physics-based simulations while retaining the ability to quantify uncertainty. Despite these advances, the computational cost of running stochastic digital twins at industrial scale, particularly for systems with hundreds of uncertain parameters and tight time constraints, remains a barrier to widespread deployment (Rasheed et al., 2020; Kamyabi et al., 2022).

5.2 Data Requirements and Quality

Accurate uncertainty quantification depends on high-quality data, and gaps or noise in the data directly reduce the reliability of stochastic digital twin outputs. Battula et al. (2021) identify sensor noise, intermittent connectivity, biases from data processing, and model abstractions as primary uncertainty sources in smart manufacturing digital twins, all of which originate from data quality issues. Chakraborty et al. (2020) demonstrate through numerical experiments that with increasing noise levels, the uncertainty captured by a Gaussian process emulator also increases, providing a realistic picture of prediction confidence but simultaneously widening the bounds on useful predictions. Rasheed et al. (2021) note that data quality, including completeness, consistency, and timeliness, is a critical enabler for digital twins, and that poor data infrastructure limits the fidelity of virtual replicas. Akçay et al. (2025) describe the construction of manufacturing digital twins for wafer fabrication plants, where historical data for stochastic events modelling must be carefully curated and verified throughout the twin's lifecycle. Birk et al. (2021) discuss the challenge of obtaining sufficient and representative data for model learning and updating in process industrial systems, noting that data availability varies across different stages of a plant's life. Kochunas and Huan (2022) observe that for nuclear power applications, the availability of operational data for calibrating and validating digital twin models is often limited due to the nature of the systems involved. These observations confirm that data scarcity, noise, and inconsistency pose persistent obstacles to building reliable stochastic digital twins across industrial domains (Huang et al., 2021; Igbokwe et al., 2024).

5.3 Model Calibration and Validation

Validating stochastic models presents unique challenges because outputs are distributions rather than single values, and ground truth for probabilistic predictions is difficult to establish. Cotoarbă et al. (2024) describe the validation challenge within their probabilistic digital twin framework for geotechnical applications, where the digital state evolves dynamically as new data are obtained and Bayesian updates must be verified against field observations that themselves carry uncertainty. Wagg et al. (2022) identify verification and validation as a key open research problem for digital twins in engineering dynamics, noting that the progression from system identification to data-augmented modelling requires careful assessment at each stage. Chavoshi et al. (2022) discuss pertinent issues on convergence testing, required number of trials, sensitivity analysis, and verification of individual analyses in probabilistic structural integrity assessments, highlighting that extremely small failure probabilities are particularly difficult to validate. Tsialiamanis et al. (2022) compare physics-based stochastic finite element models with data-driven conditional generative adversarial networks and find that for structures with material nonlinearities and uncertainties, the data-driven model outperforms the physics-based approach, raising questions about which model to trust when both produce different uncertainty estimates. Kessels et al. (2021) propose probabilistic Bayesian neural networks for parameter updating but acknowledge that the user must assess how certain the neural network is about inferred parameter values and adjust decision-making accordingly. The absence of standardized validation protocols for stochastic digital twin outputs makes it difficult to compare results across studies and build confidence in model predictions Kamyabi et al., 2022; Okpala et al., 2024).

5.4 Real-Time Implementation Constraints

Balancing computational cost and real-time responsiveness remains a major challenge for deploying stochastic digital twins in operational settings. Battula et al. (2021) emphasize that uncertainty quantification at its core involves real-time adaptive control in dynamically changing environments, requiring state awareness and responsive action within predictive control models and feedback systems. Kapteyn et al. (2020) demonstrate near-real-time model adaptation for an unmanned aerial vehicle digital twin, where reduced-order models in the model library accelerate the Bayesian inference problem to make it tractable for online operation. Kim et al. (2019) propose an uncertainty-aware digital twin for CNC machining that updates on-the-fly via Bayesian regression, achieving feed rate optimization under servo error constraints in real time. Their experimental results show cycle time reductions of up to 38% while staying close to error tolerances (Emeka et al., 2025). Negri et al. (2019) synchronize a digital twin with the field through an equipment prognostics and health management module that computes failure probability in real time using data-driven statistical models. Kochunas and Huan (2022) note that for nuclear power applications, the computational demands of forward uncertainty propagation and inverse uncertainty quantification create tension with the need for timely decision support. The trade-off between model fidelity and computational speed forces practitioners to make compromises, often simplifying the stochastic model or reducing the number of samples to meet time constraints, which in turn affects the quality of uncertainty estimates (Rasheed et al., 2020; Negri et al., 2020).

5.5 Integration Across System Levels

Industrial systems operate across multiple scales, from individual components to entire supply chains, and integrating stochastic models across these levels introduces significant complexity. Huang et al. (2021) outline a route for AI-integration in multiscale and multi-fidelity digital twins with multiscale and multi-fidelity data sources in Industry 4.0, acknowledging that bridging different levels of abstraction remains a practical challenge. Rasheed et al. (2021) discuss the modularity of multi-disciplinary systems and the need to tackle fundamental barriers not addressed by current evolutionary modelling practices when constructing digital twins that span multiple physical domains. Liang et al. (2025) elaborate on the potential of hybrid digital twinning for smart infrastructures throughout all stages of their life cycle, noting that modern infrastructures are cyber-physical systems comprising heterogeneous data of diversified granularity alongside models that carry information on system behaviour at different scales. Ivanov and Dolgui (2022) present the digital supply chain twin as an instrument for stress testing supply chain resilience, where disruption events propagate across multiple tiers and the twin must capture interactions between production, logistics, and demand at different organizational levels. Augustyn et al. (2024) demonstrate that updating parameters at the component level, such as soil stiffness for individual joints, affects system-level reliability estimates for entire offshore wind substructures. Connecting stochastic models at the component, subsystem, and system levels while maintaining consistency in uncertainty representation is an open problem that limits the applicability of current frameworks to large, multi-tiered industrial operations (Igbokwe et al., 2025; Moghadam et al., 2021).

5.6 Lack of Standardized Frameworks

There is no unified methodology for stochastic digital twins, and this absence limits adoption, comparability, and reproducibility across industrial sectors. Juarez et al. (2021) note that as there are several uses of digital twins in the existing literature, the understanding of the concept and its functioning remains diffuse, making standardization difficult. Battula et al. (2021) provide best practices, insights, and guidelines on the application of uncertainty quantification across modelling, control strategies, and collaborative workflows, but acknowledge that these represent recommendations rather than an established standard. Wagg et al. (2022) identify the lack of a common workflow for digital twin construction and maintenance as an open research problem, noting that different research groups adopt different approaches to verification, validation, and uncertainty management. Birk et al. (2021) propose a way forward to enable automatic generation and updating of digital twins for process industrial systems, but observe that the required research and development activities span multiple disciplines and lack a coordinating framework. Cotoarbă et al. (2024) propose a probabilistic digital twin framework tailored to geotechnical design and construction, but their framework is domain-specific and does not transfer directly to other industrial sectors. Kochunas and Huan (2022) find that current digital twin concepts are amenable to nuclear power systems but benefit from modifications and enhancements specific to that domain. This fragmentation across sectors and research groups means that practitioners face a steep learning curve when attempting to implement stochastic digital twins, and results from one application are difficult to benchmark against another (Huang et al., 2021; Kamyabi et al., 2022; Huang et al., 2021).

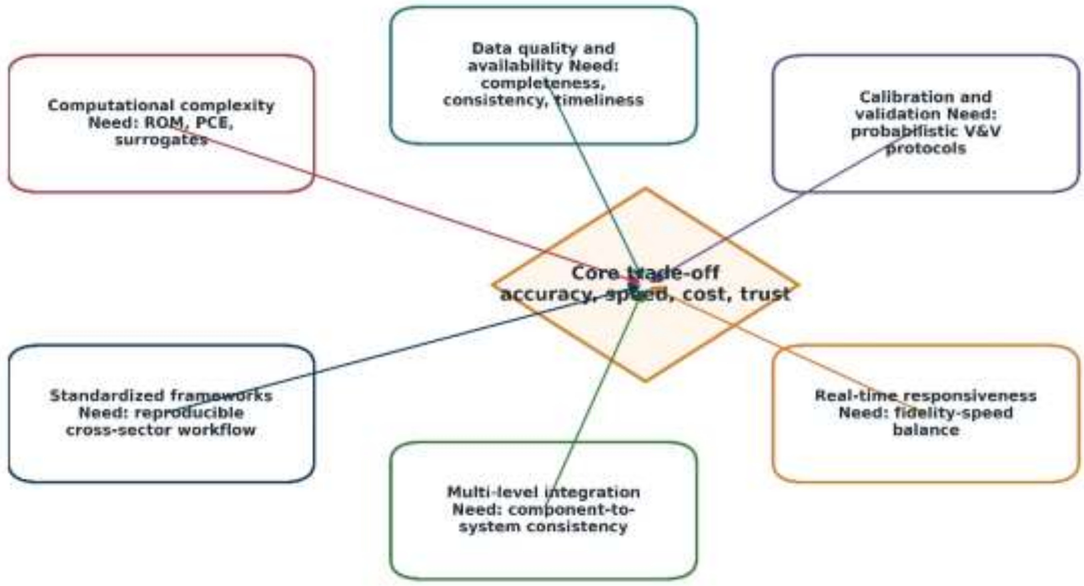

Figure 5: Key Challenges and Trade-offs in Stochastic Digital Twin Implementation

Figure 5 summarizes the main implementation barriers identified in the manuscript. It frames computational complexity, data quality, calibration, real-time speed, multi-level integration, and standardization as linked trade-offs around accuracy, cost, trust, and speed.

6. Future Directions and Conclusion

6.1 Adaptive and Learning Digital Twins

Future stochastic digital twins must move beyond static probabilistic models toward adaptive systems that learn continuously from operational data. Industrial conditions rarely remain stable. Machine degradation, demand shifts, sensor drift, material variability, environmental fluctuations, and human intervention alter system behaviour over time. A useful stochastic twin must therefore update its assumptions as these changes occur. This requires stronger integration of Bayesian updating, online learning, recursive state estimation, and adaptive Monte Carlo control within the digital twin pipeline. The next research priority is to reduce epistemic uncertainty through continuous learning while preserving aleatory uncertainty as a measurable feature of the operating environment. This distinction is important. More data can improve parameter knowledge, model calibration, and prediction confidence, but it cannot remove inherent randomness from machine failures, demand volatility, or external disruptions. Adaptive digital twins should therefore separate reducible uncertainty from irreducible variability and report both in decision-ready formats. This will make industrial decisions more transparent, especially in predictive maintenance, quality control, energy optimization, and production scheduling.

6.2 Integration with AI and Advanced Analytics

Artificial intelligence will play a central role in the next generation of stochastic digital twins, but its value will depend on how well it supports uncertainty-aware reasoning. Machine learning models can improve prediction, anomaly detection, fault diagnosis, surrogate modelling, and decision optimization. However, deterministic AI outputs are insufficient for high-risk industrial settings. Future work should prioritize probabilistic machine learning methods such as Bayesian neural networks, Gaussian process emulators, dynamic Bayesian networks, probabilistic graphical models, and generative models that produce uncertainty bounds rather than isolated point estimates. AI should also support causal and explainable decision-making. In industrial operations, managers need to know why a risk signal emerged, which uncertainty source drives the prediction, and what intervention offers the best risk-adjusted outcome. This requires models that connect prediction with mechanism. Physics-informed learning, hybrid deterministic-stochastic modelling, and interpretable surrogate models offer a practical route. These methods can reduce computational burden while retaining physical meaning, auditability, and operational trust.

6.3 Digital Twin Ecosystems

Future industrial systems will require interconnected digital twins rather than isolated asset-level models. Current frameworks often focus on individual machines, components, processes, or facilities. Yet industrial uncertainty propagates across levels. A machine fault can affect production schedules. A supply disruption can alter inventory, energy demand, and quality outcomes. A change in environmental conditions can shift process capability and maintenance risk. This means stochastic digital twins must evolve into multi-level ecosystems that connect component, process, plant, and supply chain models. Such ecosystems should support system-wide uncertainty propagation. They should also allow local updates to influence global reliability estimates. For example, updating the failure probability of one critical asset should affect maintenance planning, production throughput, delivery risk, and cost exposure. This direction will require consistent uncertainty taxonomies, interoperable data structures, shared risk metrics, and governance rules for linking models across organizational boundaries. Without this integration, digital twins will remain useful for local optimization but weak for enterprise-level resilience.

6.4 Scalable and Distributed Frameworks

Scalability remains a major condition for practical adoption. Stochastic digital twins often depend on Monte Carlo simulation, scenario analysis, Bayesian inference, and high-dimensional uncertainty propagation. These methods can become computationally expensive when applied to large industrial systems with many uncertain parameters and real-time decision requirements. Future research should therefore focus on scalable architectures that combine distributed computing, edge processing, cloud platforms, parallel simulation, adaptive sampling, and reduced-order modelling. Surrogate models will become essential in this direction. Gaussian processes, neural emulators, polynomial chaos expansion, reduced-order physics models, and hybrid simulation engines can reduce computational time without fully sacrificing uncertainty resolution. Adaptive simulation control should also become standard. Instead of fixing the number of simulations in advance, stochastic digital twins should stop or refine sampling based on error tolerance, convergence behaviour, and decision sensitivity. This will make uncertainty quantification more efficient and more aligned with real operational timeframes.

6.5 Concluding Insight

This review shows that stochastic digital twin frameworks provide a rigorous pathway for uncertainty quantification in industrial operations. Their main contribution lies in changing the digital twin from a deterministic replica into a probabilistic decision-support system. This shift is critical because industrial systems operate under uncertainty from multiple sources, including input variability, parameter imprecision, model structure, sensor noise, degradation, demand fluctuation, and external disruption. The reviewed literature confirms that Monte Carlo simulation, Bayesian inference, Markov models, stochastic processes, polynomial chaos expansion, probabilistic machine learning, and hybrid physics-data models offer useful tools for representing and propagating uncertainty. These methods strengthen predictive maintenance, production scheduling, supply chain risk management, energy optimization, and quality control. They also allow decision-makers to evaluate risk, confidence, failure probability, prediction intervals, and tail events instead of relying on single-value forecasts. However, the field still faces critical barriers. Computational complexity limits real-time deployment. Data quality affects model reliability. Calibration and validation remain difficult because stochastic outputs are distributions rather than fixed predictions. Multi-level integration remains underdeveloped. Standardized implementation protocols are still lacking. These barriers explain why many digital twin applications remain conceptually strong but operationally constrained. Future progress will depend on four linked priorities: adaptive learning, uncertainty-aware AI, ecosystem-level integration, and scalable computing. A mature stochastic digital twin should update continuously, quantify uncertainty transparently, support risk-informed intervention, and operate within the time limits of industrial decision-making. Such a framework will not eliminate uncertainty. Instead, it will make uncertainty measurable, interpretable, and actionable. That is the central value of stochastic digital twins for resilient, intelligent, and trustworthy industrial operations.

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