Model-Based Systems Engineering in Manufacturing Systems: A Survey

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Abstract

Model-Based Systems Engineering (MBSE) is revolutionizing manufacturing systems by transitioning from traditional document-centric approaches to model-centric frameworks, crucial for managing complexities in Industry 4.0. This survey explores MBSE's integration with digital twins, industrial automation, and systems integration, highlighting its transformative potential in enhancing operational efficiency, collaboration, and decision-making across manufacturing environments. The survey underscores MBSE's capacity to integrate technologies like Cyber-Physical Systems (CPS) and the Internet of Things (IoT), addressing variability and reconfiguration needs in high-mix, low-volume facilities. It emphasizes the role of digital twins in predictive maintenance and operational optimization, supported by advancements in modeling tools and methodologies. Challenges such as system interoperability, integration, and model calibration are discussed, alongside solutions like surrogate modeling and semantic interoperability frameworks. The survey identifies future research directions, including meta model refinement, self-supervised learning in digital twins, and dynamic holonic architectures, poised to enhance MBSE's applicability. Concluding, MBSE, digital twins, and systems integration are pivotal in advancing digital transformation, ensuring manufacturing systems remain adaptable, resilient, and capable of meeting evolving industrial demands.

1 Introduction

1.1 Concept of MBSE and Its Relevance

Model-Based Systems Engineering (MBSE) signifies a shift from document-centric methodologies to a model-centric framework, essential for navigating the complexities of contemporary manufacturing systems. This shift is particularly relevant in the context of Industry 4.0, where the integration of advanced technologies demands a robust framework for managing dynamic and reconfigurable systems [1]. MBSE enables the development of digital twins, which serve as accurate virtual representations of physical systems, enhancing decision-making and operational efficiency throughout the lifecycle of manufacturing systems [2].

MBSE's significance in manufacturing is underscored by its ability to integrate technologies such as Cyber-Physical Systems (CPS) and the Internet of Things (IoT) into cohesive operational frameworks, addressing challenges posed by variability and the need for frequent system reconfiguration, thereby ensuring efficient and reliable manufacturing processes [3, 4]. For instance, in semiconductor High Mix Low Volume (HMLV) facilities, precise modeling is crucial for managing high variability, highlighting MBSE's importance in complex manufacturing environments [5].

Furthermore, MBSE aids in automating supervisory controller implementation in Flexible Manufacturing Systems (FMS), reducing manual labor and errors, which enhances process efficiency [6]. Its capability to manage complex and evolving business workflows through description-driven systems (DDS) further emphasizes its relevance in modern manufacturing contexts [7].

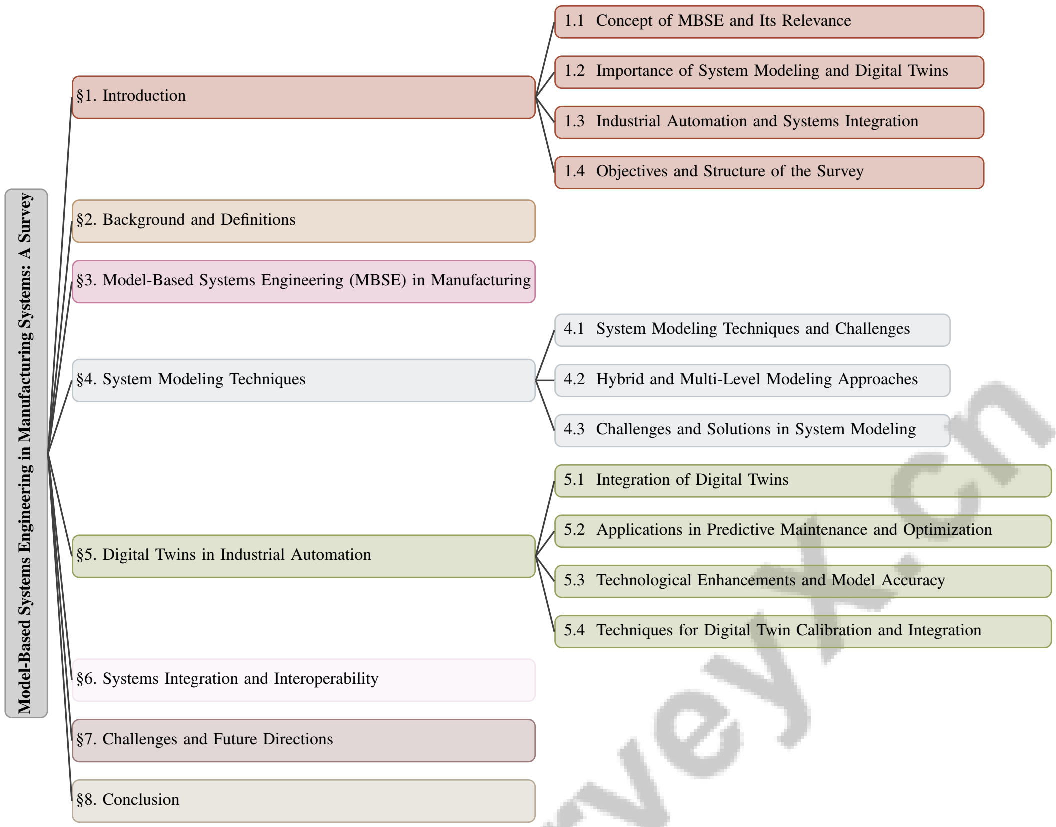

Figure 1: chapter structure

The evolution of control architectures, particularly the adoption of the holonic paradigm, illustrates the conceptual advancements facilitated by MBSE, supporting the development of flexible and adaptive control systems essential for competitiveness in a rapidly changing manufacturing landscape [8]. As manufacturing systems evolve, MBSE's role in fostering seamless integration and interoperability among diverse components becomes increasingly critical, enabling adaptation to emerging trends and technologies.

Moreover, MBSE addresses the creation of scalable digital twins for Cyber-Physical Production Systems (CPPS) by integrating heterogeneous models with online data, thus overcoming limitations of existing high-fidelity models [9]. This integration is vital for accurately modeling Digital Twin-Oriented Complex Networked Systems (DT-CNSs), enhancing adaptability and resilience in manufacturing systems through increased heterogeneity of node features and interaction rules [10, 11].

1.2 Importance of System Modeling and Digital Twins

System modeling and digital twins play a crucial role in advancing manufacturing processes by providing robust frameworks for simulation, optimization, and real-time decision-making. As virtual counterparts of physical systems, digital twins optimize performance, enhance predictive maintenance, and deliver real-time operational insights. Their integration with existing manufacturing systems is essential for minimizing downtime and enhancing operational efficiency, providing effective monitoring and control interfaces [12].

The adoption of Domain-Specific Modeling Languages (DSML) significantly improves modeling clarity and integration, addressing the complexities inherent in manufacturing systems [13]. Digital twin technology has broad applicability across industrial sectors, facilitating virtual representations for design, analysis, and behavior prediction. The incorporation of methodologies such as surrogate modeling and machine learning enhances these processes, aiding in generating synthetic data crucial for improving automatic AI model selection.

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Additionally, new methodologies like graph learning are necessary to enable cognitive functionalities in digital twins, addressing existing gaps [14]. The evolution of digital twins within smart ecosystems, particularly in infrastructure and energy sectors, demonstrates their versatility across various domains [15]. Digital twins also significantly enhance automation, efficiency, and standardization in predictive maintenance practices [16].

Addressing integration challenges associated with system modeling and digital twins is vital for maximizing their potential in enhancing manufacturing processes. Ensuring these systems remain efficient, adaptive, and resilient allows manufacturers to navigate the complexities of modern industrial environments effectively. The advancement of digital twin technology, exemplified by architectures like TiLA, which employs heterogeneous modeling techniques, highlights ongoing efforts to improve accuracy and capabilities in manufacturing [9]. Moreover, creating models that evolve over time to reflect the complexity of real systems is essential for capturing the dynamic nature of manufacturing environments [10]. The necessity of leveraging case-based reasoning to automate and optimize adaptation processes further enhances manufacturing efficiency [11].

1.3 Industrial Automation and Systems Integration

Industrial automation and systems integration are critical for the successful implementation of Model-Based Systems Engineering (MBSE) in manufacturing, enabling seamless coordination and interaction of complex production systems with advanced technologies. The integration of digital twins with collaborative robots (cobots) enhances safety and efficiency, highlighting the importance of human-machine interaction in modern industrial contexts [17]. However, the lack of standardized definitions for digital twins across industries complicates their implementation and integration [12].

Integrating Internet of Things (IoT) technologies with traditional manufacturing systems poses challenges, as industrial engineers often lack familiarity with these technologies, complicating development processes [18]. The introduction of large language models (LLMs) into industrial automation significantly improves task automation and flexibility, facilitating intelligent decision-making and enhanced operational efficiency [19]. Furthermore, the Modular State-based Stackelberg Games (Mod-SbSG) framework supports cooperative decision-making among self-learning agents, essential for industrial automation [4].

Security and safety are paramount in industrial automation, as existing architectures often inadequately address these concerns [20]. The integration of learning-based AI controllers in Cyber-Physical Systems (CPS) enhances performance but introduces new safety risks, emphasizing the need for robust systems integration [21]. Additionally, the complexity of implementing autonomous communicating entities and ensuring efficient decision-making in holonic architectures presents significant challenges in industrial automation [8].

The DDS architecture exemplifies flexibility and platform independence, essential for managing complex workflows and enhancing integration capabilities in industrial automation [7]. However, the need for standardized interfaces and semantic interoperability remains a challenge, particularly in transforming non-destructive evaluation (NDE) data for use in networked production environments [22].

Incorporating surrogate models, such as Gaussian process emulators, into the digital twin framework enables more accurate modeling of system parameters over time [23]. This integration is crucial for overcoming traditional management theories' inadequacies, which often fail to capture the dynamic nature of production flows [24]. Platforms like HUBCAP and DIGITbrain emphasize the necessity for systems that support continuous adaptation and integration, addressing rapid reconfiguration in response to evolving production requirements [25].

The complexity of considering the impacts of decisions on the entire lifecycle of a system introduces significant computational demands and uncertainty, further underscoring the importance of industrial automation and systems integration [2]. Challenges in capturing physical dynamics, ensuring real-time performance, managing uncertainties, and integrating big data analytics with digital twin technologies must be addressed to fully realize MBSE's potential in manufacturing [26]. Moreover, the absence of effective methods for uncertainty propagation in CPS complicates ensuring the reliability of combined sensor measurements, critical for the accuracy and effectiveness of integrated systems [27]. Developing semantic web services that facilitate AI-based research in Industry 4.0, enabling near real-time execution without complex reasoning burdens, offers a promising avenue for overcoming these integration challenges [28].

1.4 Objectives and Structure of the Survey

This survey aims to elucidate the transformative impact of Model-Based Systems Engineering (MBSE) on manufacturing systems, particularly within the context of Industry 4.0. By systematically analyzing the integration of MBSE with digital twins, industrial automation, and systems integration, this survey provides a comprehensive understanding of the methodologies, challenges, and potential benefits associated with MBSE implementation in manufacturing environments [29]. Furthermore, it emphasizes the importance of automated reviews and version control in MBSE practices, particularly in educational contexts, to enhance the robustness and adaptability of these systems [30].

The survey's structure is meticulously designed to guide the reader through a logical progression of topics. It begins with an introduction to the fundamental concepts of MBSE and its relevance to manufacturing systems, followed by an exploration of system modeling and digital twins. Subsequent sections delve into critical aspects of industrial automation and systems integration, underscoring their significance in the successful deployment of MBSE. The survey addresses challenges and barriers to MBSE adoption, particularly in companies developing embedded software systems, while contrasting these with the driving forces propelling organizations toward MBSE implementation [31].

In the latter part of the survey, the focus shifts to examining system modeling techniques, the role of digital twins in industrial automation, and the importance of systems integration and interoperability. The conclusion discusses challenges and future directions for MBSE, digital twins, and systems integration in manufacturing, providing insights into emerging trends and potential research avenues. This structured approach fosters a cohesive narrative that conveys essential knowledge while encouraging further exploration and innovation in MBSE. By integrating advanced methodologies and practices, such as knowledge reuse and collaborative learning tools, this framework enhances understanding and addresses the complexities of modern engineering projects. It highlights the importance of smart reuse strategies that facilitate innovation, enabling engineers to develop new ideas from existing knowledge and improve engineering processes, ultimately streamlining workflows, reducing costs, and promoting a culture of continuous improvement within MBSE [30, 32, 33, 31].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Frameworks and Methodologies

Model-Based Systems Engineering (MBSE) in manufacturing relies on diverse frameworks and methodologies to enhance system design, integration, and management. The Cyber-Physical Microservices Framework (CPMS) exemplifies this by leveraging model-driven engineering to semi-automate IoT-based microservices integration, facilitating the seamless incorporation of IoT technologies into manufacturing [1]. The Activity Execution Engine (AEE) serves as a model-driven execution architecture that automates supervisory control in Flexible Manufacturing Systems (FMS), ensuring process efficiency and reliability through precise timing and behavior adherence [6].

In digital twin technology, a framework categorizing research by modeling approaches, fidelity levels, and models of computation (MoC) enhances integration for real-time insights and predictive maintenance in manufacturing systems [26]. The Architectural Design for Measurement Uncertainty Evaluation (AD-MUE) systematically evaluates measurement uncertainties in sensor networks within Cyber-Physical Systems (CPS), utilizing Digital Twins and Asset Administration Shells to improve sensor data reliability and accuracy, crucial for effective MBSE system modeling [27].

Incorporating large language models into MBSE frameworks via the LLM Multi-Agent System (LLM-MAS) fosters intelligent agents capable of data interpretation, process planning, and task execution in automated production, enhancing decision-making and operational efficiency [19]. The digital twin concept elucidates interdependencies between design and operational decisions, optimizing system performance across MBSE frameworks [2]. Additionally, Semantic Web Services for AI-Based Research (SWS-AI), comprising over 300 semantic web services, provide a declarative ontological representation of manufacturing capabilities, enhancing AI integration and real-time operations within MBSE frameworks [28].

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These integrated frameworks and methodologies bolster MBSE implementation in manufacturing, addressing system complexities and challenges. They foster advanced solutions like autonomous energy management systems for energy sustainability and promote knowledge reuse and innovation, enabling engineers to adapt to new challenges effectively. Advancements in MBSE education, including collaborative tools and automated feedback mechanisms, are essential for equipping practitioners with skills to navigate the evolving engineering landscape [34, 30, 32, 33]. By integrating cutting-edge technologies and methodologies, MBSE continues to evolve, delivering robust solutions to meet the dynamic demands of contemporary manufacturing.

2.2 Modeling Tools and Languages

Selecting appropriate modeling tools and languages is crucial in MBSE for managing manufacturing system complexities. Building Information Modeling (BIM) and Digital Twin (DT) technologies play pivotal roles, with BIM primarily used in design and construction phases, and Digital Twins in operational phases, highlighting their evolving functionalities within MBSE frameworks [35]. The landscape of modeling tools is enriched by various formalisms tailored to dynamic structures in manufacturing systems. Benchmarking these formalisms is essential for evaluating their performance and applicability, as illustrated by datasets encompassing diverse modeling approaches and their performance metrics [36].

Surrogate modeling techniques, such as Kriging and artificial neural networks (ANN), significantly reduce computational costs while maintaining modeling accuracy, especially in high-fidelity scenarios where computational resources are constrained [15]. Integrating these techniques into MBSE frameworks enhances modeling efficiency and scalability, facilitating the development of robust digital representations of manufacturing systems. The adoption of Domain-Specific Modeling Languages (DSML) allows for the creation of precise and semantically rich models tailored to specific manufacturing domains, enhancing model clarity and interoperability, and addressing the inherent complexity of manufacturing systems within MBSE [13].

The tools and modeling languages in MBSE establish a robust framework essential for comprehensive design, analysis, and optimization of manufacturing systems. This framework enables professionals across industries—including Defense, Aerospace, Automotive, and IT—to manage complex specifications throughout all development life cycle phases, from initial conceptualization to final disposal [30, 37]. By leveraging advanced modeling techniques and languages, MBSE continues to drive innovation and efficiency in the manufacturing sector, ensuring systems remain adaptable and resilient in response to evolving technological and industrial demands.

In the context of modern manufacturing practices, the adoption of Model-Based Systems Engineering (MBSE) has emerged as a pivotal approach to enhance lifecycle support and operational efficiency. As illustrated in Figure 2, the hierarchical structure of MBSE is depicted, showcasing its comprehensive framework. This figure categorizes essential components, including digital twin frameworks and real-time monitoring, which are integral to lifecycle support. Moreover, it highlights significant case studies that demonstrate the application of digital twins, predictive maintenance, and advanced technologies. The diagram effectively emphasizes MBSE's critical role in optimizing manufacturing processes, thereby improving system reliability and overall performance.

3 Model-Based Systems Engineering (MBSE) in Manufacturing

3.1 Lifecycle Support and Efficiency Enhancement

Model-Based Systems Engineering (MBSE) plays a pivotal role in the lifecycle management of manufacturing systems, enhancing operational efficiency through advanced modeling techniques and digital technologies. Central to this is the use of digital twin frameworks, which optimize design and operational decisions, thus streamlining lifecycle management and decision-making [2]. The TiLA architecture exemplifies this by integrating heterogeneous models with real-time data to create scalable digital twins, enhancing operational efficiency through immediate insights [9]. This is further augmented by case-based reasoning frameworks that enhance digital twins' adaptability to unforeseen circumstances, boosting manufacturing efficiency [11].

Operational efficiency is bolstered by algorithms that assess the reliability of rework networks, crucial for addressing product defects [38]. In semiconductor manufacturing, advanced modeling

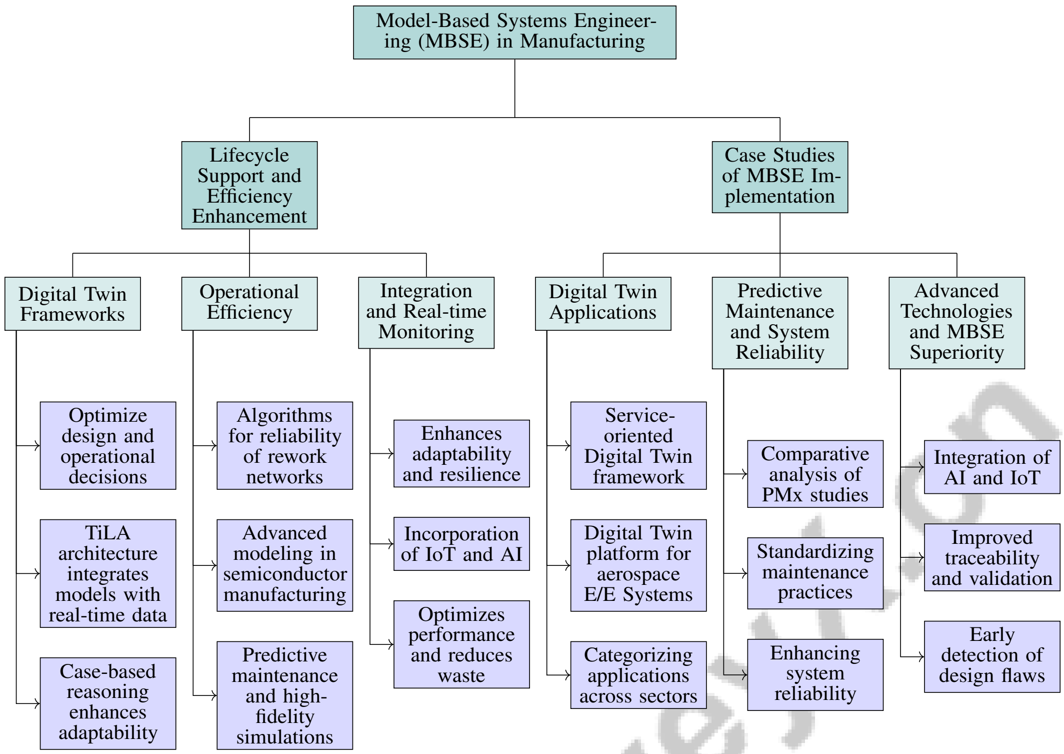

Figure 2: This figure illustrates the hierarchical structure of Model-Based Systems Engineering (MBSE) in manufacturing, focusing on lifecycle support, efficiency enhancement, and case studies of implementation. The diagram categorizes key elements such as digital twin frameworks, operational efficiency, and real-time monitoring under lifecycle support, while highlighting digital twin applications, predictive maintenance, and advanced technologies under case studies. The structure emphasizes MBSE's role in optimizing manufacturing processes and improving system reliability and performance.

approaches improve cycle time predictions, addressing challenges that impact operational efficiency [5]. Foundational models for digital twins further facilitate predictive maintenance and high-fidelity simulations, enhancing operational efficiency [26]. The Digital Twin-Oriented Complex Networked Systems (DT-CNSs) framework integrates diverse features and dynamic interactions to improve model accuracy, supporting complex systems' lifecycle [10].

The integration of digital twins and advanced methodologies within MBSE significantly enhances the management of manufacturing systems throughout their lifecycle. Real-time monitoring and analysis through dynamic digital representations ensure adaptability and resilience, effectively addressing modern industrial challenges. Insights from operational data optimize performance, reduce waste, and facilitate self-adaptive manufacturing processes. Incorporating technologies such as IoT and AI within MBSE frameworks further enhances their effectiveness in navigating contemporary engineering complexities [11, 30, 39, 33].

3.2 Case Studies of MBSE Implementation

Various case studies illustrate the implementation of Model-Based Systems Engineering (MBSE) in manufacturing, demonstrating its applications and benefits across sectors. The Service-oriented Digital Twin framework, empirically validated, significantly enhances operational efficiencies, showcasing MBSE's transformative potential in optimizing manufacturing processes through digital twin integration [40]. In aerospace, the development of a Digital Twin platform for Electrical/Electronic Systems (E/E Systems) of space launch vehicles exemplifies MBSE's capability to manage complex architectures and improve reliability and performance using the DEVOTION methodology and the Digital Twin Management Environment (DTME) [13].

The manufacturing sector benefits from categorizing digital twin applications across fields such as aerospace, healthcare, and construction, emphasizing predictive maintenance and real-time monitoring as critical stages, thus highlighting digital twins' versatility in enhancing operational performance and system resilience [12]. A case study applying the TiLA architecture to a manufacturing line demonstrates practical digital twin implementation for real-time data integration and system optimization, involving models like a two-link planar robot and inspection stations, illustrating MBSE's efficacy in seamless system integration and operational efficiency [9].

Moreover, MBSE's role in predictive maintenance is underscored by a comparative analysis of existing PMx studies, revealing variability in the application of Informational Requirements (IRs) and Functional Requirements (FRs), highlighting MBSE's importance in standardizing maintenance practices and enhancing system reliability [16]. These case studies underscore MBSE's significant impact in manufacturing, demonstrating its ability to integrate advanced technologies such as AI and IoT. MBSE enhances operational efficiency by improving energy management systems and lifecycle processes across various industrial contexts, including aerospace, automotive, and defense. Furthermore, they emphasize MBSE's superiority over traditional systems engineering by providing improved traceability, validation, and early detection of design flaws, addressing challenges related to scalability and integration across engineering disciplines [37, 34, 33].

4 System Modeling Techniques

Category	Feature	Method
System Modeling Techniques and Challenges	Model Integration	SysML[41], SysML-IRM[42], HAS[1], MBSE-TDSS[43], HDT[44]
	Hierarchical and Abstraction Techniques	Mosaic[21], HMDT[45], ADTCM[46]
	Verification and Synchronization Methods	MCTD[47], TiLA[9]
	Dynamic Network Modeling	DT-CNS[10]
Hybrid and Multi-Level Modeling Approaches	Physics-Based Modeling	OCT[48]
Challenges and Solutions in System Modeling	Reliability and Accuracy Enhancements	RAPTA-MPC[49], MDTS[50], BAT[38], DJDMPS[51]
	Virtual Modeling Techniques	SCDT[52], VMDT[53], AD-MUE[27]

Table 1: This table provides a comprehensive overview of various system modeling techniques and challenges within Model-Based Systems Engineering (MBSE). It categorizes the methods into system modeling techniques, hybrid and multi-level modeling approaches, and challenges and solutions, highlighting key features and methods employed in each category. The table serves as a resource for understanding the integration of advanced methodologies in addressing the complexities of contemporary manufacturing systems.

In Model-Based Systems Engineering (MBSE), system modeling techniques are indispensable for navigating the complexities of modern manufacturing systems. Table 1 presents a detailed summary of system modeling techniques and challenges, illustrating the application of various methodologies in Model-Based Systems Engineering (MBSE) to enhance system design and integration in complex manufacturing environments. Table 4 offers a comprehensive comparison of various system modeling techniques and challenges in MBSE, emphasizing their significance in addressing the complexities of modern manufacturing systems. This section delves into various methodologies within MBSE, focusing on their roles in system design, analysis, and integration, and addressing the challenges encountered in dynamic manufacturing environments.

4.1 System Modeling Techniques and Challenges

System modeling techniques in MBSE are crucial for aligning technological capabilities with strategic business objectives, particularly in complex sectors like automotive, where precise specification of system requirements is challenging due to intricate interactions and evolving stakeholder demands [43]. To address these challenges, the integration of meta models is vital for formalizing domain knowledge and enabling adaptable system models [1].

The integration of data-driven and physics-based models poses challenges in process plant modeling, requiring accurate real-world system representations [44]. In AI-Cyber-Physical Systems (AI-CPSs), high-dimensional state spaces and existing safety method limitations necessitate advanced techniques for reliable safety analysis [21]. Hierarchical modeling techniques support real-time simulations essential for condition monitoring and predictive maintenance [45]. Formal verification methods, like

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Method Name	Modeling Techniques	System Challenges	Verification Methods
MBSE-TDSS[43]	Hierarchical Modeling	Interoperability	Formal Verification
HAS[1]	Model-driven Engineering	Lack OF Interoperability	Formal Verification
HDT[44]	Hybrid Approach	Interoperability	Model-checking
Mosaic[21]	Markov Decision Process	Safety Guarantees	Probabilistic Model Checking
HMDT[45]	Hierarchical Modeling	Real-time Synchronization	Model-checking
MCTD[47]	Model-checking Techniques	Interoperability Real-time Synchronization	Formal Verification Methods
TiLA[9]	Heterogeneous Modelling Techniques	Real-time Synchronization	Formal Verification
ADTCM[46]	Graph-based Representation	Manual Reverse Engineering	-
DT-CNS[10]	Extendable Modeling Framework	Interoperability Real-time Synchronization	Formal Verification Model-checking
SysML[41]	Sysml-based Modeling	Interoperability, Synchronization, Integration	Formal Verification, Model-checking
SysML-IRM[42]	Sysml-based Information	Lack OF Integration	Risk Analysis

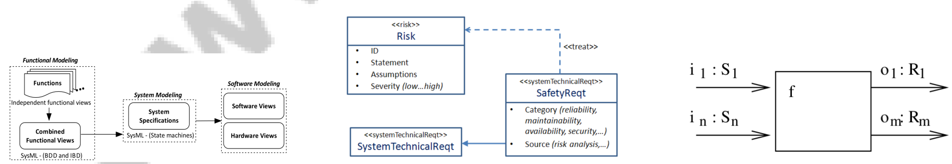
Table 2: This table provides a comprehensive comparison of various modeling methods used in Model-Based Systems Engineering (MBSE), highlighting their respective modeling techniques, system challenges, and verification methods. It serves as an essential resource for understanding how different methodologies address interoperability, synchronization, and safety in complex systems, particularly within the context of AI-Cyber-Physical Systems and manufacturing environments.

the IF model-checker, enhance model reliability by systematically verifying system design properties [47].

The TiLA framework exemplifies how diverse modeling strategies within scalable architectures improve real-time synchronization and address traditional manufacturing challenges [9]. However, manual reverse engineering for Digital Twins remains inefficient, highlighting the need for comprehensive data and methodologies [46]. Interoperability, particularly standardizing interfaces across Non-Destructive Evaluation (NDE) technologies, is a significant challenge [22]. Developing autonomous control systems that adapt to real-time changes is crucial for manufacturing system resilience [8].

Constructing dynamic networks based on node preferences addresses the modeling of complex interactions and heterogeneous features, improving model accuracy in dynamic manufacturing environments [10]. The evolution of MBSE techniques is essential for addressing modern manufacturing complexities, enhancing adaptability, efficiency, and resilience by leveraging advanced methodologies like SysML for energy management and integrating technologies such as AI and IoT [34, 37, 30, 33, 32].

Table 2 presents a detailed comparison of different system modeling methods in MBSE, illustrating their modeling techniques, system challenges, and verification methods, which are critical for addressing the complexities of modern manufacturing systems and AI-Cyber-Physical Systems.



(a) Functional and System Modeling in Software Engineering[41]

(b) Risk Management and Safety Requirements[42]

(c) A block diagram illustrating a function f that takes n inputs (i1, i2, ..., in) and outputs m outputs (o1, o2, ..., om).[54]

Figure 3: Examples of System Modeling Techniques and Challenges

Figure 3 illustrates system modeling techniques in software engineering, bridging abstract functional requirements with concrete system implementations. The first image shows the transition from functional to system modeling, integrating independent functional views into comprehensive SysML specifications. The second image explores risk management and safety requirements, emphasizing the importance of addressing potential hazards in system design. The third image simplifies functional transformation, illustrating a function's processing of multiple inputs to generate outputs, a foundational aspect of system modeling [41, 42, 54].

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4.2 Hybrid and Multi-Level Modeling Approaches

Hybrid and multi-level modeling approaches in MBSE significantly enhance the management of complex manufacturing systems. These approaches integrate diverse modeling techniques to form a comprehensive framework capturing manufacturing environments' intricate dynamics. Utilizing physics-based model libraries enables data classification and model selection for digital twin applications, improving accuracy and reliability [48].

Methods categorized by modeling aims—community discovery, link prediction, anomaly detection—demonstrate the versatility of hybrid and multi-level approaches, facilitating targeted modeling efforts and precise analysis of complex interactions [55]. These approaches enable manufacturers to tackle challenges related to system integration, predictive maintenance, and operational optimization.

Hybrid and multi-level models support real-time data integration and decision-making, essential for manufacturing system adaptability and resilience. These models employ Digital Twins and knowledge graphs for seamless data integration and simulation, enhancing planning and control in Industry 4.0 and fostering a more agile manufacturing environment [56, 40, 57, 19, 58]. Incorporating diverse data sources ensures dynamic responses to changing conditions, particularly in environments with high variability and reconfiguration needs.

Hybrid and multi-level modeling approaches advance MBSE, offering a flexible framework for managing modern industrial systems' complexities. By integrating Digital Twins, large language models, and multi-agent systems, these approaches enhance the development of resilient, efficient, and adaptive manufacturing systems, optimizing production processes and contributing to sustainable practices by reducing waste and improving responsiveness [56, 11, 59].

4.3 Challenges and Solutions in System Modeling

Method Name	Integration Challenges	Method Complexity	Adaptive Frameworks
AD-MUE[27]	Interoperability Issues	Advanced Modeling Methods	Dynamic Requirements
MDTS[50]	Data Inconsistencies	Systematic Treatment Uncertainty	Adaptive Systems
VMDT[53]	Data Accuracy Issues	Potential Complexity Involved	Adaptable Digital Twins
DJDMPS[51]	Data Inconsistencies	Benders Decomposition	Dynamic Degradation States
RAPTA-MPC[49]	Interoperability Issues	Specialized Knowledge Required	Adaptive Responses Needed
SCDT[52]	Standardized Methods Absence	-	Enhancing Framework Adaptability
BAT[38]	Interoperability Issues	Multi-state Bat	Adaptable For Various

Table 3: This table presents a comparative analysis of various methods addressing integration challenges, method complexity, and adaptive frameworks within system modeling in model-based systems engineering (MBSE). Each method is evaluated based on its ability to handle interoperability issues, data inconsistencies, and the need for specialized knowledge, providing insights into their adaptability to dynamic requirements in manufacturing systems.

System modeling in MBSE faces challenges, particularly in manufacturing, where integrating digital twins and advanced techniques is crucial. A primary challenge is the reliance on accurate initial parameter estimates for digital twin calibration; inaccuracies can compromise model reliability [27]. Behavioral inconsistencies from uncertainty sources in physical and digital twins further undermine reliability [50].

Table 3 offers a detailed comparison of different methodologies employed in system modeling, highlighting their respective integration challenges, complexity levels, and adaptive capabilities. Integrating diverse modeling approaches and ensuring data accuracy throughout the digital twin lifecycle pose significant challenges. Combining different simulation forms often leads to data inaccuracies [53]. A lack of comprehensive model adaptation approaches across different depths can cause interoperability issues [60]. Existing formalisms may not cover all necessary criteria, exacerbating modeling inconsistencies [36].

Implementing advanced methods, like Bayesian techniques for model bias identification, may be complex for practitioners without statistical knowledge, highlighting further system modeling challenges [61]. The complexity and time required for optimization, especially with larger architectures, also present significant hurdles [62].

In maintenance scheduling, the inability to account for system dynamics uncertainties can compromise reliability, emphasizing the need for adaptive scheduling frameworks [51]. Data privacy, ethical

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considerations, and interoperability between systems are pressing concerns for seamless digital twin integration [63].

Solutions include adopting model predictive control frameworks that enhance risk management and adaptability, leading to more reliable operations [49]. Standardizing activities across industries, as seen in supply chain digital twins, mitigates interoperability and data consistency challenges [52]. A method for reliability calculations in rework processes that considers deterioration effects provides a comprehensive solution, improving manufacturing system reliability [38].

To address modern manufacturing systems' challenges, comprehensive and adaptable modeling frameworks responsive to dynamic requirements are essential. Integrating approaches like model-driven system evolution, exemplified by the CRISTAL framework, supports flexible business process management and inter-application integration. Leveraging large language models within automated production systems enhances task automation and flexibility, enabling real-time process planning through microservices. These strategies promote a responsive manufacturing environment capable of evolving alongside technological advancements and market demands [19, 7]. By leveraging advanced methodologies and technologies, MBSE continues to provide robust solutions for contemporary manufacturing landscapes' intricate demands.

Feature	System Modeling Techniques and Challenges	Hybrid and Multi-Level Modeling Approaches	Challenges and Solutions in System Modeling
Integration Challenges	Meta Model Integration	Data Integration Complexity	Parameter Estimate Inaccuracies
Modeling Techniques	Hierarchical Modeling Techniques	Hybrid Modeling Approaches	Bayesian Techniques
Adaptive Capabilities	Real-time Simulations	Real-time Data Integration	Model Predictive Control

Table 4: This table provides a comparative analysis of system modeling techniques and challenges in Model-Based Systems Engineering (MBSE), highlighting integration challenges, modeling techniques, and adaptive capabilities. It examines different methodologies, including hierarchical and hybrid modeling approaches, and discusses their application in complex manufacturing environments.

5 Digital Twins in Industrial Automation

Digital twins have revolutionized industrial automation, significantly enhancing operational efficiency and redefining traditional manufacturing paradigms. As industries strive to optimize processes through cutting-edge technologies, the integration of digital twins—comprising real-time monitoring, predictive maintenance, and seamless interaction between physical and digital systems—emerges as a crucial element. The subsequent sections delve into the integration mechanisms of digital twins within manufacturing processes, highlighting their pivotal role in fostering efficiency and adaptability in the evolving industrial landscape.

5.1 Integration of Digital Twins

The integration of digital twins into manufacturing heralds a significant leap in industrial automation, offering enhanced real-time monitoring, predictive maintenance, and decision-making capabilities. Acting as virtual counterparts, digital twins provide a dynamic framework for continuous updates and optimization based on real-time data [64]. The ISAC-DT framework exemplifies this, enhancing real-time monitoring and control through dual sensing and communication functions, thereby boosting operational efficiency [65].

IoT technologies synergize with digital twins via frameworks like the Cyber-Physical Microservices Framework, supporting real-time monitoring and optimization [66]. Machine Learning models within the Digital Twin framework allow real-time updates, enhancing adaptability and responsiveness [44]. In logistics, digital twins optimize monitoring processes, as demonstrated in systems that enhance operational performance through real-time feedback control [67, 68].

Research has advanced digital twin integration for predictive maintenance and operational optimization, especially in contexts like injection molding. Model reduction and adaptive modeling are crucial for efficient real-time monitoring [45]. The FlexCell system's intelligent warehouse methodology underscores comprehensive digital twin integration in modern manufacturing, emphasizing data quality and sampling rate for reliable system representations [46, 23].

Digital twin integration enhances operational efficiency and provides a robust framework for real-time decision-making, driving innovation in manufacturing. By leveraging advanced technologies, digital twins enhance system adaptability and resilience, enabling effective responses to dynamic industry demands. These digital counterparts optimize Cyber-Physical Production Systems (CPPSs) through domain expertise and case-based reasoning, allowing real-time configuration adjustments that improve efficiency, reduce waste, and support sustainable practices in Industry 4.0. Cognitive digital twins, utilizing graph learning and AI, empower informed decision-making and operational effectiveness across the manufacturing lifecycle [69, 11, 70, 14, 64].

5.2 Applications in Predictive Maintenance and Optimization

Digital twins have transformed manufacturing by enabling real-time monitoring and proactive decision-making in predictive maintenance and optimization. This technology creates interconnected digital models representing physical systems, enhancing efficiency, automation, and accuracy in maintenance tasks. Combining machine learning and physics-based modeling within digital twin frameworks addresses traditional predictive maintenance challenges, improving operational reliability and cost-effectiveness [16, 69, 12]. Digital twins facilitate continuous system health assessments, enhancing predictive maintenance capabilities through real-time data integration and analytics, allowing early failure detection and reduced downtime.

In predictive maintenance, digital twins simulate operational scenarios to identify optimal maintenance schedules based on predictive insights, improving system reliability and extending equipment lifespan [71]. Machine learning algorithms enhance these capabilities, allowing continuous adaptation of maintenance strategies based on evolving data [44].

Digital twins significantly enhance manufacturing process optimization by simulating and analyzing complex scenarios, identifying efficient production strategies [45]. This is particularly beneficial in high-mix, low-volume settings, where rapid adaptation to changing production requirements is critical [5]. Digital twins also optimize logistics by providing real-time visibility into supply chain dynamics, facilitating resource allocation and inventory management, and ensuring responsive manufacturing processes [67]. Simulating and optimizing logistics processes in a virtual environment mitigates disruptions and enhances supply chain resilience.

Digital twin integration in predictive maintenance and optimization marks a transformative leap in manufacturing, facilitating real-time monitoring, data-driven decision-making, and enhanced system reliability. By creating interconnected digital models mirroring physical assets, digital twins optimize process design, improve quality control, and automate maintenance, leading to operational efficiency and reduced downtime. The fusion of machine learning with physics-based modeling within digital twin frameworks addresses predictive maintenance challenges, paving the way for standardized and scalable solutions in Industry 4.0 [72, 16, 69, 12]. Leveraging real-time data and analytics ensures adaptable and resilient manufacturing systems, capable of addressing contemporary industrial challenges.

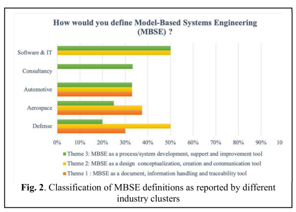
5.3 Technological Enhancements and Model Accuracy

Technological advancements have significantly improved digital twins' accuracy and capabilities in manufacturing, addressing critical gaps in practical application. A comprehensive review of DT technologies emphasizes the need for enhanced data analysis and optimization to fully leverage digital twins in industrial settings [72]. Despite simulation effectiveness, real-world application discrepancies persist, particularly in performance metrics like cycle time and localization accuracy [73], necessitating technological solutions to bridge simulated and real-world gaps.

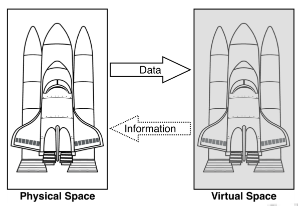
Innovations in high-fidelity modeling have enhanced digital twins' precision, enabling accurate simulations of complex processes. These advancements integrate real-time data and machine learning algorithms, empowering digital twins to adapt dynamically to operational conditions. This adaptability enhances predictive maintenance strategies, addressing challenges like limited explainability and scalability of traditional methods. Hybrid models combining machine learning with physics-based approaches overcome limitations when used independently, improving maintenance efficiency and accuracy across industries [64, 16, 12]. Advanced analytics and machine learning incorporation allow digital twins to provide accurate predictions and optimize maintenance schedules, reducing downtime and costs.

Enhanced data integration frameworks have improved digital twins' interoperability, ensuring seamless communication between diverse systems. This integration is crucial for maintaining model accuracy and reliability, enabling continuous information exchange across manufacturing components. Digital twins, integral to Industry 4.0, provide accurate system performance insights by creating interconnected digital representations of physical entities. This capability enhances process design, quality control, and predictive maintenance, facilitating informed decision-making and optimization throughout a system's lifecycle. Leveraging diverse data sources and advanced modeling techniques enables a more integrated approach to decision-making, improving manufacturing operations' efficiency and effectiveness [69, 2, 74, 70, 64].

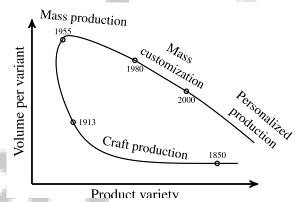
Technological advancements continue to enhance digital twins' accuracy and capabilities, ensuring effective real-world manufacturing applications. By systematically addressing limitations and harnessing advanced technologies, digital twins deliver comprehensive solutions that optimize processes, facilitate predictive maintenance, and boost operational efficiency across manufacturing lifecycle stages. This capability is essential in Industry 4.0, where digital twins replicate physical assets and enable real-time data integration and decision-making, leading to agile and resilient production systems [69, 73, 11, 14, 64].



(a) How would you define Model-Based Systems Engineering (MBSE)?[37]



(b) Data and Information in Virtual Space[64]



(c) The image depicts a graph illustrating the evolution of production methods over time.[75]

Figure 4: Examples of Technological Enhancements and Model Accuracy

As shown in Figure 4, digital twins have emerged as a transformative force in industrial automation, enhancing technological capabilities and improving model accuracy. This is illustrated through three key examples that depict the integration and evolution of digital twin technology within the industry. The first example categorizes the varied definitions of Model-Based Systems Engineering (MBSE) across sectors such as Software IT, Consultancy, Automotive, and Aerospace, showcasing MBSE's multifaceted role in process/system development and as a design and communication tool. The second example illustrates the seamless transfer of data and information between physical and virtual spaces, highlighting the digital twin's ability to replicate physical entities in a virtual environment, which is crucial for real-time monitoring and predictive analysis. Lastly, a graph depicting the evolution of production methods from mass production to personalized production underscores the digital twin's capability to adapt to changing production paradigms, enhancing flexibility and efficiency. Together, these examples underscore the pivotal role of digital twins in driving technological advancements and ensuring model accuracy in industrial automation [37, 64, 75].

5.4 Techniques for Digital Twin Calibration and Integration

Calibrating and integrating digital twins within existing manufacturing systems are critical processes that ensure the accuracy and functionality of these virtual models. Calibration involves adjusting the digital twin to accurately reflect the real-world system, essential for maintaining reliability and effectiveness in operational settings. Adaptive modeling techniques are effective for calibration, allowing digital twins to dynamically adjust to real-time data, enhancing accuracy and predictive capabilities [45].

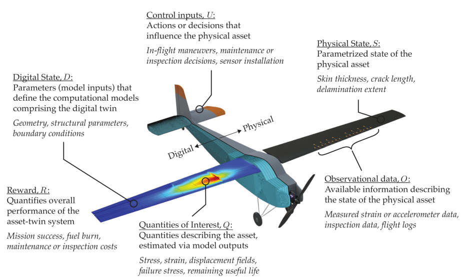
Model predictive control frameworks offer robust solutions for managing the calibration process, providing enhanced risk management and adaptability to system failures. These frameworks ensure that digital twins remain aligned with the physical systems they represent, even as operational conditions change [49]. Integrating Bayesian techniques for model bias identification can significantly improve calibration accuracy by systematically correcting biases in the digital twin model [61].

AI-generated, for reference only.

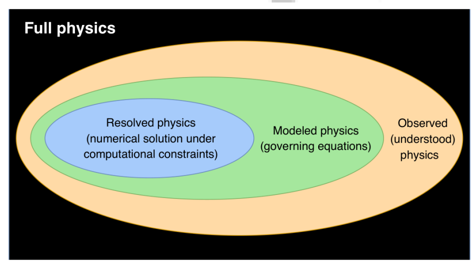
Integrating digital twins with existing systems also requires addressing interoperability and data consistency challenges. Developing standardized interfaces and semantic interoperability frameworks is crucial for ensuring seamless communication between digital twins and diverse manufacturing systems [22]. This integration is further enhanced by adopting advanced data integration frameworks, which facilitate continuous information exchange across various components of the manufacturing process, maintaining the accuracy and reliability of digital twin models.

Surrogate modeling techniques, such as Gaussian process emulators, play a significant role in calibrating digital twins by providing accurate modeling of system parameters over time [23]. These techniques are essential for overcoming traditional calibration limitations, particularly when high-fidelity modeling is required but computational resources are constrained.

The effective calibration and integration of digital twins rely on sophisticated modeling techniques and frameworks that improve accuracy and enhance interoperability across diverse applications, facilitating optimized process design, predictive maintenance, and informed decision-making in various industries [70, 76, 69, 64]. By leveraging these technologies, manufacturers can ensure that digital twins provide reliable and actionable insights, ultimately improving operational efficiency and system resilience in contemporary industrial landscapes.



(a) Digital Twin of an Aircraft[77]



(b) Full physics[63]

Figure 5: Examples of Techniques for Digital Twin Calibration and Integration

As shown in Figure 5, digital twins have become transformative tools in industrial automation, providing sophisticated means to simulate, analyze, and optimize complex systems. An illustrative example is the digital twin of an aircraft, which serves as a comprehensive digital replica, integrating its geometry, structural parameters, and boundary conditions with computational models. This digital twin mirrors the physical attributes of the aircraft and incorporates control inputs and observational data to evaluate performance and inform decision-making processes. Complementing this is the concept of "Full physics," depicted through a Venn diagram illustrating varying levels of physics understanding involved in digital twin calibration and integration. This diagram highlights the relationship between "Resolved physics," involving numerical solutions under computational constraints, "Modeled physics," representing governing equations, and "Observed (understood) physics," which refers to empirical data and insights. Together, these examples underscore the intricate techniques and methodologies employed in calibrating and integrating digital twins, emphasizing their potential to revolutionize industrial processes by enhancing accuracy, efficiency, and predictive capabilities [77, 63].

6 Systems Integration and Interoperability

Effective systems integration and interoperability are essential in Model-Based Systems Engineering (MBSE) to optimize manufacturing processes. This section delves into the importance of these elements as they enable seamless communication and collaboration among system components, thereby enhancing efficiency and adaptability in manufacturing systems amidst modern industrial challenges.

6.1 Importance of Interoperability and Integration

Interoperability and integration are fundamental to deploying MBSE in manufacturing, enabling seamless communication among diverse components. They enhance verification processes and foster cross-disciplinary collaboration, ensuring adaptability to changing industrial demands [1]. Addressing stakeholder concerns within the MBSE framework highlights the importance of managing dynamic requirement changes and ensuring system robustness [7].

The complexity of modern manufacturing requires modularity and adaptability to overcome integration challenges. Robust systems integration facilitates interaction among complex production systems, enhancing real-time control, as demonstrated by the integration of schedulability analysis into UML-RT [78]. Digital Twin technology exemplifies a methodology for enhancing system robustness and efficiency [68]. However, SMEs face challenges in adopting such technologies due to high costs, necessitating cost-effective solutions to enhance interoperability and integration.

Dynamic management of complex workflows, facilitated by DDS architecture, reduces maintenance costs and improves integration capabilities [7]. This flexibility is crucial for handling desynchronization and applying recovery strategies, ensuring manufacturing systems remain efficient and resilient.

Interoperability and integration in MBSE are crucial for enhancing operational efficiency, system reliability, and innovation, addressing dynamic industrial challenges. This approach leverages advanced technologies, including IoT and Cyber-Physical Systems, while emphasizing human knowledge and collaboration. Integrating service-oriented digital twins and cloud-based systems allows real-time data access and analysis, optimizing resource allocation and decision-making, crucial for competitiveness in Industry 4.0 [5, 18, 66, 40, 67]. Advanced integration frameworks are essential for realizing MBSE's potential in modern manufacturing.

6.2 Solutions for Seamless Integration

Achieving seamless integration in MBSE requires a multifaceted approach to tackle modern manufacturing complexities. Leveraging topological semantics and lumped parameter models enhances interoperability across systems, managing complex interactions and dependencies [78].

The Cyber-Physical Microservices Framework (CPMS) highlights dynamic service discovery mechanisms for seamless integration, supporting dynamic service assignment to maintain flexibility and adaptability [66]. By enabling on-demand service discovery and deployment, CPMS ensures efficient responses to operational requirements and technological advancements.

Integrating IoT technologies with manufacturing systems through microservices-based architectures offers a scalable, modular approach, enhancing interoperability and streamlining interactions. A model-driven approach, as in the CRISTAL system, achieves greater flexibility and adaptability in business processes, responding effectively to dynamic workflows and evolving requirements. Integrating Digital Twins and cloud-based systems facilitates real-time data access and analysis, crucial for decision-making and resource optimization in complex environments like Smart Industrial Parks [67, 20, 7].

Standardized interfaces and semantic interoperability frameworks enhance integration by promoting consistent communication protocols and data exchange formats, vital for agile manufacturing environments adapting to dynamic workflows and supporting CPS and AI. Utilizing semantic web services and modular production concepts, such as the Modular Type Package (MTP), ensures clear, machine-readable definitions of process module capabilities, optimizing integration and reconfiguration in response to evolving needs. This approach streamlines communication and supports Industry 4.0 goals, including mass customization and improved efficiency [40, 28, 79, 80, 7]. These frameworks are essential for overcoming integration challenges, enabling manufacturers to leverage advanced digital technologies fully.

Successful integration in MBSE relies on innovative strategies and frameworks enhancing interoperability, flexibility, and adaptability. By addressing contemporary manufacturing challenges, these solutions leverage human-centric approaches and advanced technologies like Digital Twins and cyber-physical systems to improve efficiency, adaptability, and resilience, ensuring systems effectively respond to evolving market demands [75, 18, 67, 40].

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6.3 Role of Standards and Frameworks

Standards and frameworks are crucial for systems integration and interoperability in MBSE, ensuring consistent communication and seamless interaction across diverse manufacturing systems. Integrating modeling languages and frameworks is essential for addressing interoperability challenges in complex environments. Tonti diagrams classify physical theories, providing a structured approach to resolving interoperability issues [78].

Developing standardized interfaces and protocols is vital for seamless integration across systems, facilitating communication and information exchange among components, significantly improving efficiency and reliability. Modular integration of process modules, known as PEAs, enhances adaptability through machine-readable capability descriptions and digital twin technologies. A human-centric approach emphasizing ubiquitous knowledge access empowers employees to utilize real-time data, optimizing performance and enabling rapid adaptability to changing environments [75, 80, 40]. Standards facilitate the integration of advanced digital technologies, enabling manufacturers to leverage digital twins, IoT, and other solutions fully.

Comprehensive frameworks support dynamic service assignment and discovery, crucial for maintaining flexibility and adaptability in system design and operation. These frameworks offer a modular approach to system integration, managing complex interactions and dependencies through rapid reconfiguration and intelligent control. The Skills Composition Framework enhances modularity and reconfiguration in reconfigurable manufacturing systems via distributed behavior trees, while integrating large language model agents with digital twins improves agility and adaptability in smart factory environments [56, 81].

Integrating standards and frameworks in MBSE is essential for seamless interoperability and integration of complex systems and technologies, enhancing traceability, validation, and early detection of design flaws, improving project outcomes across industries such as aerospace, automotive, and defense [30, 37, 33, 31]. By addressing modern manufacturing complexities, these standards and frameworks enable manufacturers to enhance efficiency, improve reliability, and foster innovation amidst evolving industrial challenges.

6.4 Frameworks and Standards for Enhanced Integration

Frameworks and standards are instrumental in enhancing integration within manufacturing systems, providing structured methodologies and protocols for seamless interaction and interoperability among diverse components. The Cyber-Physical Microservices Framework (CPMS) exemplifies a robust approach to integrating IoT technologies, employing a model-driven methodology supporting dynamic service discovery and assignment, ensuring flexibility and adaptability [66].

Integrating topological semantics and lumped parameter models offers significant advantages in managing multi-domain system complexities. These models provide a framework for understanding and resolving interoperability challenges, enhancing seamless integration of diverse components [78]. By facilitating effective handling of interactions and dependencies, these frameworks ensure efficient responses to technological advancements and industrial demands.

Standards are crucial for consistent communication protocols and data exchange formats across systems. Developing standardized interfaces is essential for overcoming challenges in integrating heterogeneous components and technologies, enabling manufacturers to leverage digital twins and IoT. These standards enhance interoperability within systems while boosting efficiency and reliability. Facilitating seamless integration of autonomous modules and enabling real-time data access through Digital Twins ensures resilience and adaptability to evolving demands. Emphasizing a human-centric approach and effective utilization of knowledge-driven solutions contributes to improved performance and operational excellence in Smart Factories, fostering innovation and economic growth across sectors [80, 67, 40].

Implementing frameworks and standards is vital for enhancing integration within manufacturing systems. Structured methodologies and protocols improve efficiency and resilience, promoting innovation through modularity and adaptability. For instance, the emerging MTP standard facilitates integration of autonomous modules, allowing easy modification of production systems. Insights from living systems inform the design of flexible task-performing systems, capable of adapting to changing environments. In business workflows, a model-driven approach, such as the CRISTAL

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system, supports dynamic reconfiguration and integration, ensuring applications remain agile and responsive to industrial challenges [75, 80, 7].

7 Challenges and Future Directions

7.1 Future Directions and Emerging Trends

The evolution of Model-Based Systems Engineering (MBSE) in manufacturing is poised to be driven by emerging trends and research aimed at overcoming current challenges and enhancing system capabilities. Key areas of focus include refining meta models and integrating advanced technologies to meet modern manufacturing demands, such as improving model hierarchies and incorporating complex multiphysics interactions to enhance system adaptability and robustness [45].

Research should prioritize the integration of identified capabilities, the development of uncertainty quantification methods, and the formulation of state reward functions for multi-objective optimization. These initiatives are crucial for enhancing MBSE's applicability in manufacturing [2]. Extending algorithms to incorporate fuzzy logic for uncertainty and multi-objective optimization beyond reliability can provide a comprehensive framework for decision-making in complex environments [38].

Developing dynamic holonic architectures that adapt to environmental changes is another promising trend. Cloud-based technologies integrated into these architectures will enable flexible and scalable manufacturing systems responsive to dynamic industrial demands [8]. Moreover, enhancing safety analysis frameworks for AI-Cyber-Physical Systems (AI-CPSs) is essential for addressing challenges such as fault localization, debugging, and repair techniques [21].

In workflow management, future research will focus on mathematical modeling of workflow processes and the creation of automated connector specifications to enhance systems like Agilium [7]. This will improve manufacturing process flexibility and efficiency, allowing systems to adapt to evolving requirements. Standardized protocols for Non-Destructive Evaluation (NDE) data integration and the application of digital twins are crucial for training NDE professionals on Industry 4.0 concepts [22].

Future efforts should also aim at optimizing execution efficiency and expanding methodologies for complex Flexible Manufacturing Systems (FMS) scenarios, reflecting emerging trends in the field [6]. Enhancements in workflow flexibility, potentially utilizing Process-Oriented Case-Based Reasoning (POCBR) and automated planning techniques, will further bolster the adaptability and resilience of manufacturing systems [28].

Additionally, enhancing the TiLA architecture with the FMI 3.0 standard and exploring more expressive temporal logics for improved monitoring and model synthesis will be crucial [9]. Quantifying variability sources, such as arrivals and processing times, and investigating their interrelationships will be key to improving model accuracy [5].

In digital twin applications, future research should focus on developing formal semantics for mixed-fidelity modeling, enhancing integration techniques for heterogeneous models, and addressing security and time-critical requirements [26]. Simplifying modeling languages for domain experts and improving the integration of complex similarity analyses within manufacturing contexts will also be vital [11].

Finally, refining the modeling framework, exploring additional interaction rules, and validating the framework with real-world data will enhance the applicability of digital twin-oriented complex networked systems [10]. These research directions underscore the continuous evolution of MBSE in manufacturing, ensuring systems remain efficient, reliable, and capable of adapting to the dynamic demands of contemporary industrial landscapes.

7.2 Future Research Directions for MBSE and Digital Twins

Advancing Model-Based Systems Engineering (MBSE) and digital twin technologies requires addressing critical research areas to enhance their application in manufacturing systems. A significant focus is the integration of decision support systems tailored for complex composite alternatives, as current studies often overlook this integration, limiting the full potential of MBSE and digital twins [82]. Developing robust decision support frameworks is crucial for improving decision-making processes and operational efficiency.

Exploring self-supervised learning paradigms within digital twin applications presents a promising research avenue. There are significant gaps in utilizing high-dimensional Industrial Internet of Things (IIoT) data for self-supervised learning, which can enhance the predictive capabilities and adaptability of digital twins [83]. Leveraging advanced learning methodologies can lead to greater accuracy and responsiveness, facilitating more effective monitoring and optimization of manufacturing processes.

Enhancing interoperability and integration of digital twins with existing systems is another critical research direction. Developing standardized protocols and frameworks for seamless communication and data exchange is essential for ensuring digital twin reliability and efficiency. This is particularly important given the complexity of digital twins as adaptive models of physical systems, requiring heterogeneous cross-domain models for their design, development, and maintenance. Uniform methodologies and tools can mitigate challenges related to data consistency, model calibration, and real-time updates, crucial for maintaining accuracy and functionality in dynamic environments [70, 63, 64].

Advancing digital twin capabilities through mixed-fidelity modeling and enhanced simulation techniques can provide more detailed and accurate representations of manufacturing systems. Research should prioritize developing formal semantics for mixed-fidelity modeling and exploring innovative methodologies for integrating heterogeneous models. This focus is essential to enhance the precision and applicability of digital twin technologies, which serve as dynamic representations of physical systems across various domains for applications such as predictive maintenance, design validation, and process optimization. By formalizing the digital twin concept and employing model-driven engineering practices, researchers can address the lack of uniformity in understanding and implementing digital twins, ultimately leading to more effective and agile software development processes in intelligent manufacturing and other industries [39, 69, 84, 76, 64].

These research directions highlight the need for ongoing innovation in MBSE and digital twin technologies. By addressing critical gaps in current methodologies and integrating innovative approaches such as Service-oriented Digital Twins and cloud-based cyber-physical systems, researchers can enhance the role of human expertise in manufacturing. This will ensure these technologies remain at the forefront of manufacturing innovation, significantly improving efficiency, reliability, and adaptability across diverse industrial environments. Accurate modeling techniques to manage variability in complex systems can lead to better forecasting of bottlenecks and cycle times, ultimately driving productivity and operational excellence in Smart Factories and industrial parks [5, 67, 40].

7.3 Potential Impact on Future Manufacturing Systems

Advancements in Model-Based Systems Engineering (MBSE) and digital twin technologies are expected to significantly impact future manufacturing systems, offering transformative possibilities for enhancing operational efficiency, resilience, and decision-making capabilities. The integration of surrogate models can improve the efficiency of energy system modeling, providing accurate predictions crucial for optimizing manufacturing processes [15]. This enhancement in modeling efficiency is vital for developing robust digital twins capable of real-time adaptation and optimization.

Incorporating large language models (LLMs) into multi-agent manufacturing systems emphasizes the potential impact of MBSE advancements. By improving task allocation efficiency, operational adaptability, and agent communication, LLMs can enhance system coordination and performance, ensuring responsiveness to dynamic industrial demands [59]. Integrating advanced technologies into MBSE frameworks is essential for maintaining competitiveness in rapidly evolving manufacturing landscapes.

Research on variability-induced events in manufacturing systems has highlighted the limitations of traditional queuing models, indicating the need for advancements in modeling methodologies. A deeper understanding of tool behaviors and dependencies is necessary for accurately predicting system performance, crucial for developing more resilient and adaptable manufacturing systems [5]. Addressing these modeling challenges will lead to greater precision and reliability, ultimately enhancing operational efficiency and system resilience.

The potential impact of advancements in MBSE and digital twin technologies on future manufacturing systems is substantial. By leveraging innovative methodologies and integrating cutting-edge technologies such as Cyber-Physical Systems, Internet of Things (IoT), and Digital Twins, advancements in manufacturing can significantly enhance operational efficiency, bolster system resilience, and improve decision-making capabilities. This transformation is driven by a human-centric approach that emphasizes ubiquitous knowledge access for employees, enabling intuitive information leverage for machine setup and maintenance. The establishment of Smart Industrial Parks and the adoption of microservice architectures facilitate real-time data analysis and resource optimization, crucial for adapting to market demands and achieving mass customization. These developments are pivotal in reshaping the future of manufacturing within a rapidly evolving industrial landscape, ensuring competitiveness and fostering economic growth [18, 66, 40, 67, 85].

8 Conclusion

This survey has explored the significant impact of Model-Based Systems Engineering (MBSE) on manufacturing systems, particularly under the Industry 4.0 paradigm. MBSE's integration of advanced modeling frameworks, such as SysML, provides robust solutions to the complexities of modern industrial environments, enhancing operational efficiency and decision-making processes. The deployment of Digital Twins, supported by techniques like cross-phase transfer learning, has proven effective in optimizing intelligent manufacturing processes by improving both time efficiency and system performance.

The survey highlights the importance of a comprehensive approach to safety management, facilitated by SysML information models, which strengthens the management of safety requirements and supports the design of safer complex systems. Establishing standardized formats for product information exchange is identified as essential for fostering collaboration and improving efficiency within manufacturing systems. Additionally, the calibration of Digital Twins is shown to offer superior fidelity and predictive accuracy, outperforming traditional methods in terms of sample efficiency and computational scalability.

The integration of large language models into digital twin systems has been identified as a key factor in enhancing the intelligence and adaptability of industrial automation, leading to increased productivity and reduced operational costs. The survey also identifies decision support platforms as versatile tools for modular system design and evaluation, with potential for further enhancement through the incorporation of additional combinatorial models.

In examining the roles of MBSE, Digital Twins, and systems integration, the survey underscores their critical contribution to digital transformation across various sectors, including manufacturing and construction. The implementation of executable Digital Twins is highlighted for its ability to improve lifecycle management and operational efficiency, thereby enhancing asset management and production processes. Furthermore, the role of digital twins in advancing the efficiency, safety, and adaptability of human-robot collaborative systems is emphasized, marking a significant step forward in the evolution of industrial automation.

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