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Procedia CIRP 136 (2025) 99–104

www.elsevier.com/locate/procedia

35th CIRP Design 2025

A Complexity-Based Framework to Design Resilient Cyber-Physical Production Systems

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Abstract

In today's competitive market with inevitable uncertainties arising from different sources, designing resilient cyber-physical production systems (CPPS) is vital. Meanwhile, dynamic-oriented and unpredictable events intensify the time-dependent complexity of systems. A complexity-based approach relying on understanding and managing the inherent uncertainties could alleviate the systems' complexity toward enhancing the resilience of systems. In this respect, this paper proposes a comprehensive framework to design resilient CPPS from a holistic perspective, considering the increasing complexity over time. The results present how adopting an appropriate approach through the proposed framework can facilitate time-dependent complexity management in CPPS and accelerate achieving resilient solutions.

Keywords: Complex Systems Engineering; Resilience; Cyber-Physical Production Systems; Uncertainty-based Design; Industry 5.0

1. Introduction

The evolution of manufacturing systems toward Industry 5.0 not only highlights its three core elements, namely human-centricity, sustainability, and resilience, but also emphasizes the shift from traditional product-based models to decentralized, autonomous, and service-oriented systems [1]. In addition, modern manufacturing systems are increasingly complex, with unpredictable interactions, non-linear behaviors and environmental uncertainties requiring systemic solutions to address raised complexity levels [2,3].

Although moving toward Industry 4.0 has brought a focus on interoperability and integration, allowing diverse systems and devices to work together in manufacturing ecosystems that function as adaptable and cohesive networks [4], underestimating the sources of uncertainties in modeling and evaluations can lead to dynamic malfunctions in practice expanding over time and bringing irreparable costs [5]. In this context, Cyber-Physical Production Systems (CPPS) as a key technology enabling efficiency, flexibility and service-driven features in modern manufacturing, have become essential for managing their dynamic changes [1,6].

CPPS are advanced complex systems made up of autonomous and cooperative elements that connect digital and physical components, supporting smart and interconnected production processes [7,8]. Furthermore, CPPS leverage data-driven technologies and smart services, such as predictive maintenance, real-time monitoring, and adaptive decision-making, to enhance manufacturing resilience, sustainability and efficiency [9]. X. Wu et al. [4] point out that CPPS go beyond isolated systems operating as a system-of-systems (SoS) problem with complex interactions.

10.1016/j.procir.2025.08.019

Despite CPPS offering significant benefits in adaptability, scalability and efficiency, high interconnectivity and the uncertainties faced in dynamic environments can create unpredictable behaviors, potentially resulting in instability over time [3,4]. Therefore, considering the dynamic complexity of CPPS and based on the work of Suh [10] and ElMaraghy et al. [2], it can be pointed out that such systems are characterized by time-dependent combinatorial complexity.

Key contributors to CPPS's complexity include real-time deviations, variable material flows, module reliability and the potential for system failures [2]. To address these challenges, researchers apply resilience and Complexity Engineering (CE) approaches. Resilience enables systems to absorb disruptions, recover and adapt to maintain functionality [11], while CE provides strategies for managing intricate interactions, adaptability, self-organization and emergent behavior [12]. Exemplary CE-oriented approaches for developing resilient CPPS range from bio-inspired and collective intelligence models to decentralized control [13-15], context-aware frameworks [6,16], real-time adaptability [17] and Digital Twin technologies [8,18]. Cyber-resilience is further enhanced through adaptive filtering and layered defenses [19,20], while ontology-based repositories advance interoperability, helping maintain stable operations under stress [21].

Despite the aforementioned research, there has been less focus on tackling the time-dependent complexity of CPPS and the unpredictability of future changes that might disrupt the systems. Additionally, design and optimization methods for managing uncertainties arising within CPPS and from their operational environments have been underexplored. This paper aims to propose a systematic approach that integrates the Axiomatic Design (AD) Complexity framework [10] with the Uncertainty-based Multidisciplinary Design Optimization framework [22]. The proposed approach in this study is designed to address time-dependent complexity and uncertainty in CPPS, achieving resilience by balancing complexity and uncertainty propagation over time. The paper is structured as follows: first, the AD Complexity framework is introduced in the context of CE. A review follows, summarizing resilience-oriented CPPS design strategies from a CE perspective. The proposed complexity-based framework is then presented. The paper concludes with a summary of contributions, key challenges, and future research directions.

2. Complex Systems Engineering

Since CPPS grow more complex due to heterogeneity and emergent properties, the demand for systems that operate under unexpected conditions has intensified [3]. Resilience is crucial for maintaining stability, while CE offers a structured approach to managing complexity and enhancing CPPS resilience within broader SoS [12]. This section introduces key CE concepts and Suh's Complexity Theory grounded in AD, referred to as the AD complexity framework.

2.1. Complexity Engineering Overview

Complexity engineering, an applied branch of complexity science, focuses on adaptive, self-organizing, and emergent behaviors within complex systems [12]. A key concept here is Complex Adaptive Systems (CAS), which naturally evolve into coherent structures that can adapt and organize autonomously, without centralized control [23]. This adaptability, characterized by anticipation, resilience, and robustness, enables CPPS to function effectively in dynamic environments. CAS principles like self-organization are crucial, allowing CPPS to adjust autonomously to change, which in turn fosters resilience [24]. Hence, CE facilitates the design and management of CPPS by addressing the inherent unpredictability and interdependency features.

Additionally, Complex Systems Engineering (CSE) incorporates principles from complexity science to manage highly interconnected and adaptable systems with emergent behaviors in the engineering field [12]. CSE strategies include complexity avoidance, reduction and control [25], while the main modeling approaches in CSE are described in [12]. ElMaraghy et al. [2] underscored the relevance of complexity theories in engineering, particularly through Suh's axiomatic design complexity theory [10,26], which has proven effective in system design applications, including manufacturing. Suh's theory, introduced in the following subsection, is regarded as a powerful framework within CSE.

2.2. Suh's Complexity Theory and Axiomatic Design

Suh's complexity theory provides a framework for addressing complexity in engineering, defining complexity as a measure of uncertainty in meeting design goals and emphasizing its measurement in the functional rather than the physical domain [10]. Suh's complexity theory rooted in AD, provides a systematic approach to designing complex systems, grounded in two fundamental axioms: the Independence and the Information Axioms [26]. These axioms guide the design process by helping engineers evaluate choices, identify dependencies, and ensure robustness [26].

AD begins by defining independent functional requirements (FRs) based on customer needs (CNs) and deriving physical solution (PS) alternatives, selecting the PSs that meet these FRs best [10,26]. According to Suh [10], complexity emerges from uncertainty in satisfying FRs within specific tolerances. When an alternative PS is chosen to meet an FR, the system's performance is characterized by a probability density function that defines the system range. The goal is to align this system range with the design range, a region known as the common range. Thus, the probability of achieving a given FR is determined by the size of this common range. Complexity, in Suh's framework, is quantified as information content, which is minimized when the probability of satisfying FRs is maximized, ideally reaching zero in optimal designs [10]. The information content (I) for a functional requirement FR_i with a design solution PS_i can be expressed as:

$$I_i = log_2 1/P_i = -log_2 P_i \tag{1}$$

In Equation (1), P_i represents the probability of achieving FR_i, with larger probabilities resulting in lower information content [26]. According to the aforementioned, complexity is a function of the relationship between the design range and the system range, which is affected by the relationships among the

FRs [10]. Therefore, Suh [10] defined two different types of complexity: time-independent and time-dependent (see Fig. 1). Time-independent complexity assesses a system's inherent capability to meet its FRs regardless of temporal changes. It includes real complexity, where system range and design range alignment are evaluated, and imaginary complexity, which arises from unknowns in the system design. On the other hand, time-dependent complexity reflects unpredictability over time, where evolving conditions may cause a system's performance to drift outside its intended range [10].

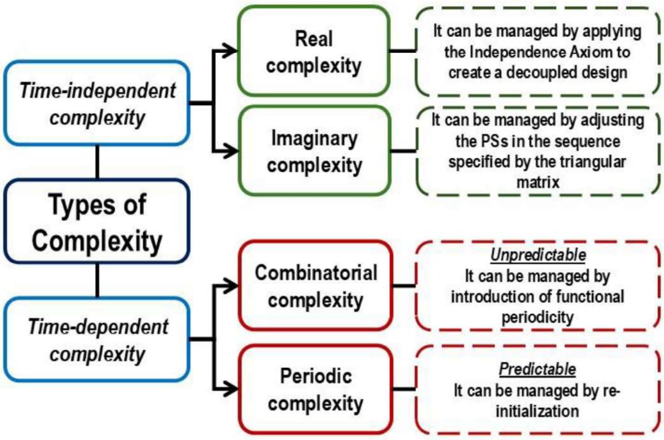

Fig. 1. Types of complexity based on Suh' Complexity Theory [10]

Suh distinguishes two types of time-dependent complexity [10]: periodic complexity and combinatorial complexity. Periodic complexity exists only for a finite period due to a limited number of possible combinations, while combinatorial complexity increases over time as new combinations of the system's FRs emerge, which poses a greater threat due to its chaotic potential. In resilience-oriented CPPS, time-dependent complexity arises as system ranges shift over time due to interconnectivity, dynamic conditions and uncertainty. Suh recommends managing time-dependent complexity by converting combinatorial complexity into periodic complexity through functional periodicity, making it more predictable and manageable [10,27,28]. It is a method derived directly from Suh's theory for reducing system complexity.

3. Towards Complexity Engineering-based Resilience-oriented CPPS

This research addresses resilience in CPPS as a complex problem due to the dynamic and uncertain nature of manufacturing systems. Resilience is defined as a system's ability to withstand, recover, and adapt to disturbances while maintaining stability and functionality [11]. It is considered a time-dependent function in engineering systems, acknowledging that recovery occurs gradually [29]. Treating CPPS's resilience as a time-dependent problem, it can be evaluated on how it responds to disruptions over time, accounting for complexity factors such as interconnectivity, non-linear interactions, and inherent uncertainties. The following subsection explores studies focused on resilience-oriented CPPS development through a CE approach, aiming to enhance systems' ability to adapt and recover in complex and evolving environments.

Research into resilient CPPS has increasingly focused on CE methods to help systems manage uncertainty in manufacturing. For instance, Estrada-Jimenez et al. [3] discussed how complexity and self-organization principles can address CPPS challenges like high interconnectivity, decentralized structure, and autonomy. Bagozi et al. [16] introduced a service-oriented and context-aware framework to enhance resilience in CPPS, targeting disruptions and recovery. Similarly, Engelsberger and Greiner [17] presented a method for dynamically reconfiguring CPPS resources via a Fog/Edge and Cloud-based approach, enhancing adaptability by distributing services across nodes in a decentralized manner.

Further resilience approaches are explored by Wunderlich et al. [6], who used dynamic context modeling and adaptive process management to address unexpected disruptions in CPPS. W. Wu et al. [30] proposed a fractal and multi-agent system-based model for flexible and decentralized production, emphasizing collaboration, self-organization, and intelligent decision-making. Other frameworks include Digital Twins (DT) for real-time monitoring and predictive maintenance in rechargeable battery production [8]. Aruväli et al. [19] have proposed a structured resilience-focused approach to address cybersecurity in CPPS using AD decomposing FRs into PSs centered on cybersecurity. Qin and Sun [20] introduced a method to enhance CPPS's robustness against data attacks and nonlinear disturbances. Bitsch et al. [21] developed an ontology-based tool consolidating CPPS domain knowledge to improve responsiveness, flexibility, and interoperability.

Bio-inspired resilience is highlighted by [13-15]. BIOSOARM by Dias-Ferreira et al. [13] uses self-organizing principles to enable CPPS adaptability, with components acting autonomously within a virtual environment, allowing the system to respond flexibly to disruptions. Leitão et al. [14] further emphasized collective intelligence, leveraging distributed interactions among autonomous entities to enhance modularity and adaptability. Similarly, Siafara et al. [15] proposed SAMBA, a cognitive framework that improves resilience and self-awareness in CPPS, supporting autonomy and dynamic self-diagnosis in automated environments.

To sum up, by adopting diverse strategies ranging from self-organization and bio-inspiration to cybersecurity and collective intelligence, the reviewed works suggest that a multifaceted approach is essential for building resilient CPPS capable of thriving in dynamic and uncertain manufacturing environments.

4. Development of the Complexity-based Approach for Designing Resilience-oriented CPPS

The complexity of CPPS is increasing at such a pace that traditional reductionist design methods struggle to foster the necessary resilience and adaptability. As a result, complexity-based methodologies rooted in CSE have emerged to improve the robustness of CPPS. However, research on resilience-oriented CPPS within the scope of CE indicates a need for a more comprehensive framework, especially in handling time-dependent complexities, dynamic interdependencies, and uncertainty management throughout the design process.

4.1. Axiomatic Design Complexity and Uncertainty-Based Multidisciplinary Design Optimization

This study considers resilience-oriented CPPS as systems with time-dependent combinatorial complexity. According to Suh [10], such complexity can cause system failure over time due to physical limitations or excessive FR combinations leading to chaos. To mitigate this, Suh suggests converting combinatorial complexity into periodic complexity by periodically reinitializing FRs to maintain stability. This periodicity is functional rather than strictly temporal, addressing the system's recurring needs.

Achieving functional periodicity begins by decoupling the system, following Suh's Independence Axiom, to ensure that FRs can be independently satisfied. This requires identifying cyclically repeating FRs, particularly those prone to combinatorial complexity, and reinitializing them at the start of each functional period to prevent chaos [10]. Furthermore, given the inherent uncertainties in CPPS, arising both from the system itself and external dynamic conditions, it is essential to address these uncertainties from the outset of the design process. Uncertainty-Based Multidisciplinary Design Optimization (UMDO) provides a holistic approach tailored for complex engineering design processes that aim to handle uncertainties within complex systems, resulting in designs that are not only optimized but also robust and reliable under a range of conditions [5]. The main steps in UMDO are [31]: (I) Uncertain System Modeling, which involves developing a mathematical representation of the system, defining design variables, objectives, constraints, and the design space. This phase also includes uncertainty modeling, where uncertainties are identified, categorized, and quantified. (II) UMDO Procedure, which focuses on structuring and executing optimization under uncertainty. It involves optimization and uncertainty analysis, exploring the design space while accounting for unpredictability, which is computationally demanding for complex systems. Uncertainty propagation and analysis assess the impact of uncertainties on system outputs to ensure reliability and robustness

To manage CPPS complexity and uncertainties, UMDO and AD can be integrated into the platform of Model-based Systems Engineering (MBSE) tools [32], creating a robust approach for resilience-oriented CPPS. MBSE offers a structured framework for managing the entire system lifecycle, while UMDO ensures resilient and reliable solutions under uncertainty by considering interdisciplinary interactions and system constraints [33]. Together, MBSE and UMDO enable a data-driven, adaptive approach aligned with Suh's Complexity Theory, equipping engineers to design resilient CPPS that withstand modern manufacturing challenges.

4.2. Complexity-based Approach to Design Resilience-oriented CPPS

This study proposes a complexity-based design framework for resilience-oriented CPPS, built upon the AD complexity framework and UMDO within an MBSE context. The proposed approach emphasizes managing time-dependent complexities through uncertainty modeling and systematic optimization to enhance CPPS's resilience.

The approach begins with implementing AD via system design decomposition [34], as shown in step one of Fig. 2. In this initial phase, AD will be utilized to decompose CPPS into their constituent parts, enhancing the understanding of interactions and facilitating informed design. The proposed approach extends system decomposition by integrating MBSE and decision-centric design using UMDO, creating a "digital thread" that spans the lifecycle of the manufacturing system, culminating in a conceptual resilience-oriented CPPS design. Figure 2 outlines this approach, which consists of four key steps to develop an iterative and adaptive methodology for enhancing CPPS resilience: (1) AD Complexity Framework, (2) Uncertain System Modeling, (3) Uncertainty-Based Multidisciplinary Analysis, and (4) UMDO. A detailed breakdown of each step is provided below.

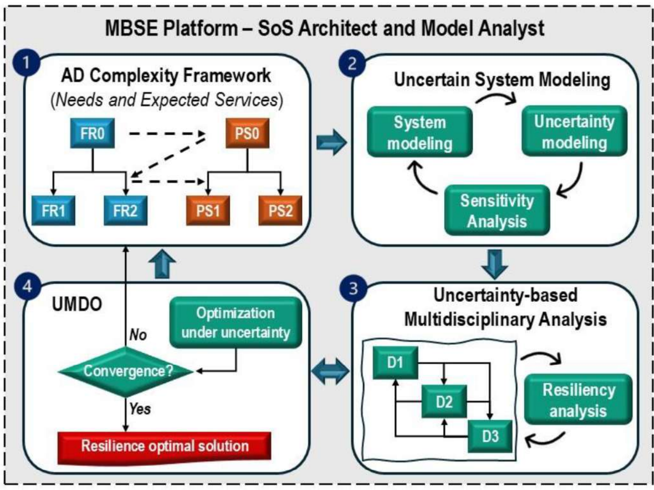

Fig. 2. Complexity-based approach to design resilience-oriented CPPS

Step 1. AD Complexity Framework: Suh's AD Complexity Framework is applied to address both time-independent and time-dependent complexities in system design. Initially, the needs and expected services for a resilience-oriented CPPS are identified to apply the AD systematic approach described in section 2.2. This process applies the Independence Axiom to manage time-independent complexity, creating a decoupled design that reduces the bias and variability within the system. Nonetheless, some residual uncertainty may exist if the system range differs from the design range, necessitating further adjustments to meet Suh's criteria. To address this, imaginary complexity is managed by configuring design parameters to be aligned with the triangular matrix model, ensuring each design parameter interacts predictably.

To further enhance resilience, the approach seeks to transform time-dependent combinatorial complexity into periodic complexity. By reinitializing FRs at the start of each operational cycle, this step minimizes the risk of chaotic behavior over time, making the CPPS design more predictable and manageable. The proposed approach follows the detailed steps on how to manage real and combinatorial complexity, as elaborated in [10]. Despite applying the above strategies to manage the complexity of resilience-oriented CPPS, the system is still exposed to various uncertainties throughout its lifecycle. Addressing such uncertainties requires a resilient design that is less sensitive to potential variations, achieved by applying the UMDO framework, covering steps two to four in Fig. 2.

Step 2: Uncertain System Modeling: In the Uncertain System Modeling step, design variables, objectives, constraints and uncertainty sources are identified, and their evaluation method is planned. Furthermore, modeling uncertainties allows designers to use sensitivity analyses, identify factors with minor impacts, and exclude them from the uncertainty analysis process, simplifying the uncertainty analysis.

The probability theory and possibility theory relying on fuzzy logic can be used to model various types of uncertainties and address the nonlinear interdependencies within CPPS [22]. These theories are well-suited for CPPS environments due to their flexibility in dealing with complex multi-layered interactions with discrete and continuous parameters. Sampling-based sensitivity analysis is recommended to incrementally gauge the impact of input variations on system behavior, effectively managing both epistemic and aleatory uncertainties [35]. Overall, the Uncertain System Modeling step is an iterative process involving three interconnected parts (System Modeling, Uncertainty Modeling, and Sensitivity Analysis) to refine and manage uncertainty in the disciplinary models.

Step 3: Uncertainty-Based Multidisciplinary Analysis (UMDA): UMDA organizes uncertainty-based analysis, incorporating multidisciplinary system analysis and performance evaluation. Here, uncertainty analysis is a key task, which quantifies the impact of input uncertainties and their propagation through computational simulations on system outputs. In resilient CPPS design, decomposition-based uncertainty analysis techniques are useful [31], as they divide complex systems into discipline-specific areas (e.g. D1, …, D3 as shown in Fig. 2), enabling concurrent computations and greater efficiency. This approach manages the computational demands of uncertainty propagation across multiple and interdependent subsystems, balancing feasibility and accuracy for large-scale resilience-focused systems like CPPS.

The Concurrent Subsystem Uncertainty Analysis (CSSUA) method is one of the decomposition-based techniques that enables efficient uncertainty propagation in coupled systems [22]. A refinement of CSSUA, the Modified CSSUA method further improves computational efficiency by: computing only mean values of coupled state variables; reducing system-level optimization variables by 50%; and using the Sensitivity-Based Uncertainty Analysis Method for standard deviation estimation [31]. Moreover, an Implicit Uncertainty Propagation can be utilized within a collaborative framework, enabling the estimation of each subsystem's uncertainty effects without explicit system-level consistency constraints [22].

Step 4: UMDO procedure: Following UMDA, Robust Design Optimization (RDO) is applied to optimize performance while reducing sensitivity to variations through optimization under uncertainty. In the proposed approach, RDO aims to create stable, high-performing CPPS designs that can meet operational requirements under a wide range of uncertain conditions. For CPPS, where adaptability and robustness are essential, RDO enhances resilience by enabling systems to maintain functionality across fluctuating conditions, directly supporting CPPS's resilience and adaptability.

The multi-objective nature of RDO requires balancing trade-offs between the mean and variance of objectives. Common methods can be considered in the proposed framework, including the weighted sum approach, preference-based physical programming, compromise programming, normal-boundary intersection, and evolutionary optimization methods [35]. Evolutionary algorithms, particularly genetic algorithms, are widely used due to their gradient-free nature and their effectiveness in handling complex, high-dimensional optimization problems. Additionally, non-probabilistic RDO approaches, such as cloud theory and info-gap decision theory, are also considered to handle imprecise probabilities, expanding the scope of uncertainty representation [22].

The final task is the convergence check. This step evaluates whether the design of the whole CPPS with a set of solutions resulting from the decomposition can fulfill the resistance constraints in the presence of uncertainties. Otherwise, a new set of alternative solutions by revisiting the decomposition is chosen and AD complexity and uncertainty sources will be reviewed accordingly, and UMDO will be done again to find a new resilient design point. However, it involves a significant computational burden, particularly in systems with coupled uncertainties, which typically require adopting double-loop frameworks [31]. The outer loop executes an optimization algorithm to identify the best design, while the inner loop performs uncertainty analysis, evaluating the robustness of the design through intensive sampling-based simulations. This feedback loop ensures continuous alignment with resilience goals. Upon achieving convergence, the approach yields a set of optimal solutions, a CPPS design robustly prepared to handle uncertainties and dynamic conditions, ensuring resilient performance when facing different sources of disruptions.

5. Conclusion and Outlook

This study presents a complexity-based approach for designing resilience-oriented CPPS grounded in AD Complexity and UMDO, integrated within MBSE tools. The proposed framework enables CPPS to maintain functional independence, optimize performance and enhance resilience in highly dynamic and uncertain manufacturing environments. This study contributes to the field by offering a comprehensive methodology that addresses the inherent time-dependent complexity and uncertainties that characterize CPPS. The proposed framework aims to enhance CPPS's resilience, enabling systems to withstand and adapt to disruptions over their lifecycle. While this approach supports system adaptability and robustness, challenges remain in managing combinatorial complexity, accurately modeling cross-layer uncertainties without high computational costs, and coordinating multidisciplinary domains for cohesive system behavior. Future work will focus on validating the proposed approach through a case study in a controlled lab environment, aiming to provide a robust foundation for managing time-dependent complexity and uncertainty in a resilient CPPS demonstrator.

Acknowledgements

This study was developed in the framework of Doctoral studies coordinated by the Free University of Bolzano, in cooperation with Fraunhofer Italia Research, as part of Cycle 39° (DM 117-118) funded by PNRR (National Resilience and Recovery Plan) of the Government of Italy.

References

[1] J. Leng *et al.*, 'Towards resilience in Industry 5.0: A decentralized autonomous manufacturing paradigm', *Journal of Manufacturing Systems*, vol. 71, pp. 95–114, Dec. 2023, doi: 10.1016/j.jmsy.2023.08.023.

[2] W. ElMaraghy, H. ElMaraghy, T. Tomiyama, and L. Monostori, 'Complexity in engineering design and manufacturing', *CIRP Annals*, vol. 61, no. 2, pp. 793–814, Jan. 2012, doi: 10.1016/j.cirp.2012.05.001.

[3] L. A. Estrada-Jimenez, T. Pulikottil, R. S. Peres, S. Nikghadam-Hojjati, and J. Barata, 'Complexity theory and self-organization in Cyber-Physical Production Systems', *Procedia CIRP*, vol. 104, pp. 1831–1836, Jan. 2021, doi: 10.1016/j.procir.2021.11.309.

[4] X. Wu, V. Goepp, and A. Siadat, 'Cyber Physical Production Systems: A Review of Design and Implementation Approaches', in *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Dec. 2019, pp. 1588–1592. doi: 10.1109/IEEM44572.2019.8978654.

[5] B. Ebrahimi and A. A. Bataleblu, 'Intelligent reliability-based design optimization: Past and future research trends', in *Developments in Reliability Engineering*, M. Ram, Ed., in Advances in Reliability Science. , Elsevier, 2024, pp. 787–826. doi: 10.1016/B978-0-443-13242-1.00026-6.

[6] T. Wunderlich, J. Hansert, S. Koch, R. Heinrich, T. Schlegel, and S. Ihlenfeldt, 'Increasing Resilience of Production Systems by Dynamic Context Modelling and Process Adaption', *Procedia CIRP*, vol. 118, pp. 282–287, Jan. 2023, doi: 10.1016/j.procir.2023.06.049.

[7] L. Monostori, 'Cyber-physical Production Systems: Roots, Expectations and R&D Challenges', *Procedia CIRP*, vol. 17, pp. 9–13, Jan. 2014, doi: 10.1016/j.procir.2014.03.115.

[8] K.-T. Park, Y. H. Park, M.-W. Park, and S. D. Noh, 'Architectural framework of digital twin-based cyber-physical production system for resilient rechargeable battery production', *Journal of Comp. Design and Eng.*, vol. 10, no. 2, pp. 809–829, Apr. 2023, doi: 10.1093/jcde/qwad024.

[9] S. Wiesner and K.-D. Thoben, 'Cyber-Physical Product-Service Systems'. In: *Multi-Disciplinary Engineering for Cyber-Physical Production Systems: Data Models and Software Solutions for Handling Complex Engineering Projects*, S. Biffl, A. Lüder, and D. Gerhard, Eds., Cham: Springer International Publishing, 2017, pp. 63–88. doi: 10.1007/978-3-319-56345-9_3.

[10] N. Suh, *Complexity - Theory and Applications*. New York: Oxford University Press, 2005.

[11] S. Hosseini, K. Barker, and J. E. Ramirez-Marquez, 'A review of definitions and measures of system resilience', *Reliability Engineering & System Safety*, vol. 145, pp. 47–61, Jan. 2016, doi: 10.1016/j.ress.2015.08.006.

[12] P. Parrend and P. Collet, 'A Review on Complex System Engineering', *J Syst Sci Complex*, vol. 33, no. 6, pp. 1755–1784, Dec. 2020, doi: 10.1007/s11424-020-8275-0.

[13] J. Dias-Ferreira, L. Ribeiro, H. Akillioglu, P. Neves, and M. Onori, 'BIOSOARM: a bio-inspired self-organising architecture for manufacturing cyber-physical shopfloors', *Journal of Intellig. Manuf.*, vol. 29, no. 7, pp. 1659–1682, 2018, doi: 10.1007/s10845-016-1258-2.

[14] P. Leitão, J. Queiroz, and L. Sakurada, 'Collective Intelligence in Self-Organized Industrial Cyber-Physical Systems', *Electronics*, vol. 11, no. 19, Art. no. 19, Jan. 2022, doi: 10.3390/electronics11193213.

[15] L. C. Siafara, H. Kholerdi, A. Bratukhin, N. Taherinejad, and A. Jantsch, 'SAMBA – an architecture for adaptive cognitive control of distributed Cyber-Physical Production Systems based on its self-awareness', *Elektrotechnik und Informationstechnik*, vol. 135, no. 3, pp. 270–277, 2018, doi: 10.1007/s00502-018-0614-7.

[16] A. Bagozi, D. Bianchini, and V. De Antonellis, 'Designing Context-Based Services for Resilient Cyber Physical Production Systems'. In: *Web Information Systems Engineering – WISE 2020*, Z. Huang, W. Beek, H. Wang, R. Zhou, and Y. Zhang, Eds., Cham: Springer International Publishing, 2020, pp. 474–488. doi: 10.1007/978-3-030-62005-9_34.

[17] M. Engelsberger and T. Greiner, 'Dynamic reconfiguration of service-oriented resources in cyber–physical production systems by a process-independent approach with multiple criteria and multiple resource management operations', *Future Gener Comput Syst*, vol. 88, pp. 424–441, 2018, doi: 10.1016/j.future.2018.06.002.

[18] A. A. Bataleblu, E. F. Tinsel, B. Schneider, E. Rauch, A. Lechler, and O. Riedel, 'AI-MBSE-Assisted Requirements Writing and Management – Towards a Knowledge-Based Framework'. In: *DS 134: Proceedings of the 26th International DSM Conference (DSM 2024), Stuttgart, Germany*, 2024, pp. 050–058. doi: 10.35199/dsm2024.06.

[19] T. Aruväli, M. De Marchi, E. Rauch, and D. Matt, 'Design Decomposition for Cyber Resiliency in Cyber-Physical Production Systems'. In: *Proceedings of the 15th International Conference on Axiomatic Design 2023*, E. Puik, D. S. Cochran, J. T. Foley, and P. Foith-Förster, Eds., in LNNS. Cham: Springer Nature Switzerland, 2024, pp. 3–14. doi: 10.1007/978-3-031-49920-3_1.

[20] Y. Qin and Z. Sun, 'Asynchronous event-triggered adaptive robust switching filtering for nonlinear industrial cyber physical systems under data injection attacks', *Int J Robust Nonlinear Control*, vol. 34, no. 5, pp. 3142–3166, 2024, doi: 10.1002/rnc.7129.

[21] G. Bitsch, P. Senjic, and J. Askin, 'Dynamic adaption in cyber-physical production systems based on ontologies', *Procedia Computer Science*, vol. 200, pp. 577–584, Jan. 2022, doi: 10.1016/j.procs.2022.01.255.

[22] A. A. Bataleblu, 'Computational Intelligence and Its Applications in Uncertainty-Based Design Optimization'. In: *Bridge Optimization - Inspection and Condition Monitoring*, IntechOpen, 2019. doi: 10.5772/intechopen.81689.

[23] J. H. Holland, *Hidden Order: How Adaptation Builds Complexity.* Reading, MA, USA: Addison-Wesley, 1995.

[24] C. Gershenson, 'Guiding the Self-Organization of Cyber-Physical Systems', *Front. Robot. AI*, vol. 7, 2020, doi: 10.3389/frobt.2020.00041.

[25] G. Herrera Vidal and J. R. Coronado Hernández, 'Complexity in manufacturing systems: a literature review', *Prod. Eng. Res. Devel.*, vol. 15, no. 3, pp. 321–333, Jun. 2021, doi: 10.1007/s11740-020-01013-3.

[26] N. Suh, *Axiomatic Design: Advances and Applications*, Oxford University Press. New York, 2001.

[27] E. Rauch and D. T. Matt, 'Artificial Intelligence in Design: A Look into the Future of Axiomatic Design'. In: *Design Engineering and Science*, N. P. Suh, M. Cavique, and J. T. Foley, Eds., Cham: Springer International Publishing, 2021, pp. 585–603. doi: 10.1007/978-3-030-49232-8_21.

[28] E. Rauch, P. Dallasega, and D. T. Matt, 'Complexity reduction in engineer-to-order industry through real-time capable production planning and control', *Prod. Eng. Res. Devel.*, vol. 12, no. 3–4, pp. 341–352, Jun. 2018, doi: 10.1007/s11740-018-0809-0.

[29] D. Henry and J. Ramirez-Marquez, 'Generic metrics and quantitative approaches for system resilience as a function of time', *Reliability Engineering & System Safety*, vol. 99, pp. 114–122, Mar. 2012, doi: 10.1016/j.ress.2011.09.002.

[30] W. Wu, J. Lu, and H. Zhang, 'A fractal-theory-based multi-agent model of the cyber physical production system for customized products', *J Manuf Syst*, vol. 67, pp. 143–154, 2023, doi: 10.1016/j.jmsy.2023.01.008.

[31] W. Yao, X. Chen, W. Luo, M. van Tooren, and J. Guo, 'Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles', *Progress in Aerospace Sciences*, vol. 47, no. 6, pp. 450–479, Aug. 2011, doi: 10.1016/j.paerosci.2011.05.001.

[32] A. A. Bataleblu, E. Rauch, and D. S. Cochran, 'Model-Based Systems Engineering in Smart Manufacturing - Future Trends Toward Sustainability'. In: *Proceedings of the 15th International Conference on Axiomatic Design 2023*, E. Puik, D. S. Cochran, J. T. Foley, and P. Foith-Förster, Eds., Cham: Springer Nature Switzerland, 2024, pp. 298–311. doi: 10.1007/978-3-031-49920-3_20.

[33] A. A. Bataleblu, E. Rauch, and D. S. Cochran, 'Resilient Sustainability Assessment Framework from a Transdisciplinary System-of-Systems Perspective', *Sustainability*, vol. 16, no. 21, Art. no. 21, Jan. 2024, doi: 10.3390/su16219400.

[34] A. A. Bataleblu, E. Rauch, and D. S. Cochran, 'Sustainable Manufacturing Design Decomposition Based on Axiomatic Design Theory'. In: *Proceedings of the 5th International Conference on Quality Innovation and Sustainability (ICQIS 2024)*, Lisbon, 2024, pp. 16–19. https://repositorio.ipl.pt/bitstream/10400.21/17736/1/ICQIS2024

[35] J. Roshanian, A. A. Bataleblu, and M. Ebrahimi, 'A novel evolution control strategy for surrogate-assisted design optimization', *Struct Multidisc Optim*, vol. 58, no. 3, pp. 1255–1273, Sep. 2018, doi: 10.1007/s00158-018-1969-4.