

IMITSION MODELLASHTIRISH MAMATOVA Z.X., MIRZAYEV A.M.

FarDU dotsenti, mamatova.zilolakhon@gmail.com

FarDU talabasi mirzayevasadbek7177@gmail.com

Abstract: Simulation modeling is a powerful methodology for analyzing complex systems and predicting their behavior without direct real-world experimentation. This article delves into the fundamental principles and diverse applications of simulation modeling across various scientific, engineering, and economic domains. We explore the critical stages of model conceptualization, development, validation, and verification, emphasizing best practices for ensuring accuracy and reliability. Furthermore, the paper discusses the significant benefits of employing simulation for informed decision-making, process optimization, and comprehensive risk assessment in dynamic environments. Ultimately, this work aims to provide a concise yet comprehensive overview of simulation modeling's indispensable role in modern research and industrial practice.

Keywords: Simulation Modeling, System Analysis, Predictive Analytics, Model Validation, Optimization, Decision Support, Complex Systems, Risk Assessment

Introduction

The increasing complexity of modern systems across engineering, business, healthcare, and social sciences often renders purely analytical or empirical approaches insufficient for comprehensive understanding, prediction, and optimization. Decision-makers and researchers are frequently confronted with dynamic, stochastic, and highly interactive environments where direct experimentation is impractical, unethical, or prohibitively expensive. In this context, simulation modeling, or "imitatsion modellashtrish," has emerged as an indispensable methodological paradigm. It provides a powerful computational framework for replicating the behavior of real-world or hypothetical systems over time, allowing for the exploration of various scenarios, the identification of emergent properties, and the evaluation of alternative strategies without disturbing the actual system [1]. This capability is particularly vital in an era characterized by rapid technological advancement and an imperative for robust, data-driven decision-making, where the ability to foresee outcomes and mitigate risks is paramount. The inherent flexibility of simulation allows for the abstraction of complex phenomena into manageable models, facilitating a deeper engagement with the underlying mechanisms that drive system behavior.

While the conceptual underpinnings of simulation can be traced back to early statistical experiments and war gaming, its practical application and theoretical sophistication have undergone a profound evolution, particularly with the advent of high-performance computing, advanced algorithms, and the proliferation of accessible data [2]. From its early uses in operations research during World War II to its current pervasive role in fields as diverse as supply chain management, urban planning, epidemiology, financial risk assessment, and climate science, simulation modeling has consistently proven its value as a versatile tool for insight generation. Its significance lies not merely in its ability to mimic reality, but in its capacity to facilitate a deeper understanding of system dynamics, uncover hidden relationships, and quantify the impact of interventions under controlled conditions. Contemporary research continues to push the boundaries of what is possible, integrating simulation with artificial intelligence, machine learning, big data analytics, and virtual reality to create increasingly realistic, adaptive, and interactive models that address previously intractable problems [3]. This ongoing evolution underscores simulation's critical role in navigating the uncertainties and complexities of the 21st century.

This article aims to provide a comprehensive and critical examination of simulation modeling, navigating its foundational concepts, diverse methodologies, and practical implications. We begin by elucidating the core principles of simulation modeling, tracing its historical trajectory, and

underscoring its enduring significance as a scientific and engineering discipline. Subsequently, we delve into a detailed typology of simulation models, offering a systematic classification that illuminates their varied structures, underlying assumptions, and appropriate applications. The intricate stages of the simulation study lifecycle, from initial problem formulation and data collection to model verification, validation, experimentation, and the ultimate deployment of findings for decision support, are then meticulously explored. Furthermore, the article will showcase the expansive utility of simulation through diverse industry case studies, highlighting its transformative impact across various sectors and its capacity to drive innovation and efficiency. A critical analysis of the inherent benefits, limitations, and practical challenges associated with simulation modeling will provide a balanced perspective on its capabilities and constraints, acknowledging the complexities involved in model development and interpretation. Finally, we will investigate the enabling technologies, including state-of-the-art simulation software, tools, and advanced methodologies such as agent-based modeling and discrete-event simulation, before concluding with an outlook on emerging trends and future research directions that are poised to shape the next generation of simulation science and its interdisciplinary applications [4].

Literature Review

The scholarly discourse surrounding simulation modeling has intensified significantly in recent years, reflecting its growing methodological sophistication and pervasive application across an ever-broader spectrum of disciplines. While the foundational principles of replicating system behavior over time remain constant, contemporary literature emphasizes the nuanced theoretical underpinnings and practical advancements that distinguish modern simulation science. Researchers consistently highlight simulation's unique capacity to address problems characterized by high dimensionality, non-linearity, stochasticity, and emergent properties, where analytical solutions are often intractable or overly simplistic [5]. This perspective is particularly salient in fields like supply chain resilience, urban mobility planning, and public health policy, where interconnectedness and dynamic feedback loops necessitate a holistic, time-dependent analysis that only simulation can effectively provide [6]. The epistemological role of simulation has also received renewed attention, with scholars debating its function not merely as a predictive tool, but as an experimental laboratory for theory building, hypothesis testing, and deep systemic understanding, thereby extending its utility beyond mere problem-solving to knowledge generation itself [7].

A significant body of recent literature has focused on refining the conceptual and theoretical frameworks of simulation modeling. Beyond the basic definition, contemporary scholarship delves into the philosophical implications of creating digital twins and virtual representations, exploring questions of fidelity, abstraction, and the boundaries between model and reality [8]. For instance, the distinction between "what-if" analysis and "how-to" design, facilitated by simulation, is increasingly articulated, positioning simulation as a proactive design tool rather than solely a reactive analytical instrument [9]. Furthermore, the evolution of simulation paradigms, notably Discrete-Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM), continues to be a vibrant area of research. DES, traditionally strong in operational processes, has seen advancements in its application to complex service systems and manufacturing networks, incorporating sophisticated scheduling algorithms and resource allocation strategies to optimize performance under uncertainty [10]. Recent work in DES often integrates real-time data streams for dynamic model updates, moving towards adaptive simulation environments that mirror operational realities more closely [11].

System Dynamics, with its emphasis on feedback loops and delays, continues to be a powerful approach for understanding macro-level system behavior and long-term trends, particularly in socio-economic and environmental contexts. Contemporary SD research frequently explores its integration with other methodologies to capture both aggregate dynamics and individual-level heterogeneity. For example, hybrid models combining SD with ABM are increasingly prevalent, allowing for the exploration of how micro-level agent interactions give rise to macro-level system behaviors, and vice versa, offering a more comprehensive understanding of complex adaptive systems [12]. This methodological convergence addresses the limitations of purely top-down or bottom-up approaches, providing richer insights into phenomena like disease spread, market dynamics, and social unrest [13]. The theoretical underpinnings of ABM, in particular, have undergone substantial development, moving beyond simple rule-based agents to incorporate cognitive architectures, learning capabilities, and sophisticated interaction protocols, enabling the simulation of increasingly realistic human and organizational behaviors [14]. The rise of computational social science has significantly propelled ABM research, demonstrating its unique ability to model decentralized decision-making, emergent phenomena, and the impact of individual heterogeneity on collective outcomes [15].

The convergence of simulation modeling with advanced computational technologies represents one of the most transformative trends in recent scholarship. Artificial Intelligence (AI) and Machine Learning (ML) are increasingly integrated into various stages of the simulation lifecycle, from model construction and parameter estimation to output analysis and optimization [16]. For instance, ML algorithms are employed to learn complex system behaviors from data, which can then be used to build more accurate and parsimonious simulation models, or to create surrogate models that accelerate simulation runs [17]. Deep learning techniques are being utilized for automated calibration of complex simulation models, reducing the manual effort and expertise traditionally required [18]. Conversely, simulation is also serving as a crucial training ground for AI agents, particularly in reinforcement learning, where virtual environments provide safe and scalable platforms for agents to learn optimal policies without real-world risks [19]. This symbiotic relationship between AI/ML and simulation is creating a new generation of "intelligent simulations" that are more adaptive, autonomous, and capable of handling unprecedented levels of complexity and data [20].

Furthermore, the proliferation of Big Data analytics has profoundly impacted simulation modeling. Large datasets, often derived from sensors, social media, or transactional records, provide unprecedented opportunities for model calibration, validation, and initialization, enhancing the empirical grounding of simulation studies [21]. Techniques for data-driven simulation, where models are continuously updated and refined based on real-time data streams, are becoming more sophisticated, enabling predictive capabilities that were previously unattainable [22]. High-Performance Computing (HPC) and cloud computing infrastructures have also revolutionized the feasibility of running large-scale, computationally intensive simulations, allowing for the exploration of vast parameter spaces and the execution of ensemble simulations for robust uncertainty quantification [23]. The ability to distribute simulation tasks across numerous processors or cloud instances has made it possible to model systems with millions of interacting agents or to simulate complex physical processes with high spatial and temporal resolution, pushing the boundaries of what is practically achievable [24].

A critical area of ongoing research in simulation science concerns Verification, Validation, and Uncertainty Quantification (VVUQ). As models become more complex and their outputs

increasingly influence high-stakes decisions, ensuring their credibility and trustworthiness is paramount. Recent literature emphasizes the need for rigorous VVUQ frameworks that go beyond traditional statistical comparisons, particularly for models that incorporate AI components or are driven by large, potentially noisy, datasets [25]. Verification, which ensures the model is implemented correctly according to its conceptual design, benefits from advanced software engineering practices and automated testing tools [26]. Validation, the process of ensuring the model accurately represents the real system for its intended purpose, is increasingly challenging for complex adaptive systems where direct empirical data may be scarce or system behavior is emergent. Scholars advocate for multi-faceted validation approaches, including expert judgment, historical data comparison, sensitivity analysis, and cross-model comparison, to build confidence in model predictions [27]. Uncertainty Quantification (UQ) has gained significant traction, moving beyond simple sensitivity analysis to comprehensive frameworks that characterize and propagate uncertainties arising from input data, model parameters, and structural assumptions, providing decision-makers with a clearer understanding of the confidence intervals associated with simulation outputs [28]. The integration of Bayesian methods and advanced statistical techniques for UQ is a particularly active research domain, offering more robust ways to incorporate prior knowledge and update beliefs as new data become available [29].

The application of simulation modeling for enhanced decision support and policy making continues to be a central theme in contemporary literature. Simulation provides an invaluable platform for scenario planning, allowing decision-makers to explore the potential consequences of various interventions or external shocks in a risk-free virtual environment [30]. This is particularly crucial in areas like climate change adaptation, disaster response planning, and economic policy formulation, where the long-term and systemic impacts of decisions are difficult to predict through intuition alone [31]. Optimization via simulation, where simulation models are coupled with optimization algorithms to find optimal system configurations or policies, has seen significant advancements, especially with the development of more efficient metaheuristics and gradient-free optimization techniques suitable for stochastic simulation outputs [32]. Furthermore, the role of simulation in supporting participatory decision-making processes is gaining recognition. Interactive simulation models and serious games are being developed to engage stakeholders, facilitate collaborative learning, and build consensus around complex policy issues, fostering a deeper understanding of system dynamics among diverse groups [33]. This shift highlights simulation's potential not just as an analytical tool, but as a communication and learning instrument that bridges the gap between technical analysis and practical implementation [34].

Despite its immense utility and ongoing advancements, the literature also critically examines the inherent limitations and practical challenges associated with simulation modeling. One persistent challenge is the computational cost associated with running large-scale, high-fidelity simulations, particularly for models involving millions of agents or fine-grained spatial-temporal resolution [35]. While HPC and cloud computing mitigate some of these issues, the demand for ever more detailed and expansive models continues to push computational boundaries. Data availability and quality remain significant hurdles; complex models often require extensive and accurate input data for calibration and validation, which can be difficult or expensive to obtain, especially for novel systems or future scenarios [36]. The "garbage in, garbage out" principle remains highly relevant, underscoring the importance of robust data collection and preprocessing pipelines [37]. Model complexity itself can be a double-edged sword; while it allows for greater realism, it can also lead to

issues of interpretability and explainability, making it challenging for non-experts to understand how model outputs are generated and to trust the results [38]. This is particularly pertinent for AI-integrated simulations, where the internal workings of ML components can be opaque, raising concerns about "black box" models [39].

Ethical considerations are also emerging as a critical area of discussion in the simulation literature, especially as models are applied to sensitive social and human systems. Concerns include the potential for bias in model design, parameterization, or data inputs to perpetuate or amplify existing societal inequalities [40]. For example, simulations used in urban planning or resource allocation could inadvertently disadvantage certain demographic groups if not carefully constructed and validated against diverse data [41]. The responsible use of simulation, transparency in model assumptions, and the need for diverse perspectives in model development teams are increasingly emphasized to mitigate these risks [42]. Furthermore, the potential for misuse of simulation results, particularly in policy debates, necessitates clear communication of model uncertainties and limitations to prevent overconfidence in predictions [43].

Looking ahead, contemporary research identifies several promising future directions for simulation modeling. The development of more sophisticated multi-scale and multi-paradigm simulation frameworks is a key area, aiming to seamlessly integrate different modeling approaches (e.g., ABM for micro-level, SD for macro-level, DES for operational processes) within a single coherent framework to capture system behavior across various scales and levels of abstraction [44]. The integration of virtual reality (VR) and augmented reality (AR) with simulation is also gaining traction, offering immersive environments for training, design, and collaborative decision-making, enhancing the intuitive understanding of complex simulation outputs [45]. Real-time simulation, driven by continuous data streams and capable of providing immediate feedback for operational control or adaptive decision-making, represents another frontier, particularly in smart cities, autonomous systems, and dynamic supply chains [46]. Finally, the push towards more explainable and interpretable AI in simulation, coupled with robust ethical guidelines for model development and deployment, will be crucial for fostering trust and ensuring the responsible application of this powerful methodological paradigm in addressing the complex challenges of the 21st century [47]. The ongoing evolution of simulation modeling, therefore, is not merely a technical endeavor but a multidisciplinary pursuit that continually redefines our capacity to understand, predict, and shape complex realities.

Research Methodology

The research methodology employed for this comprehensive academic article on "imitatsion modellashitirish" (simulation modeling) is rooted in a systematic, critical, and integrative literature review approach. This methodology was chosen to provide a holistic understanding of simulation modeling, encompassing its foundational concepts, diverse methodologies, practical applications, and emerging trends, while also critically evaluating its benefits, limitations, and challenges. Given the interdisciplinary nature and rapid evolution of simulation science, a purely quantitative meta-analysis would be insufficient to capture the nuanced theoretical developments and practical innovations. Instead, this study adopts a qualitative, interpretivist paradigm, synthesizing a vast body of scholarly work to construct a coherent narrative and offer a forward-looking perspective on the field. The objective was not merely to summarize existing knowledge but to critically analyze, synthesize, and identify key themes, convergences, divergences, and future research directions within the contemporary landscape of simulation modeling. This approach aligns with recent calls for more

integrative reviews that bridge disciplinary divides and provide actionable insights for researchers and practitioners alike [1].

The literature search and selection strategy was designed to ensure both breadth and depth, capturing seminal works alongside cutting-edge research published predominantly from 2020 onwards, reflecting the dynamic advancements in the field. A multi-database search was conducted across prominent academic repositories, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and PubMed, to cover the diverse disciplinary applications of simulation modeling, from engineering and computer science to healthcare and social sciences. Initial broad search terms included "simulation modeling," "discrete event simulation," "agent-based modeling," "system dynamics," "hybrid simulation," "digital twins," "AI in simulation," "machine learning for simulation," "simulation optimization," "simulation verification and validation," "simulation ethics," and "future of simulation." These primary keywords were combined with Boolean operators (AND, OR) and refined through iterative searches to capture relevant literature effectively. For instance, combinations such as "simulation modeling AND applications," "agent-based modeling AND social systems," or "AI AND simulation AND healthcare" were utilized to narrow down results for specific thematic areas. The search was primarily limited to peer-reviewed journal articles, conference proceedings, and reputable book chapters published in English, ensuring the academic rigor and quality of the included sources. The timeframe emphasis on 2020 onwards was crucial for reflecting the most recent advancements, theoretical refinements, and technological integrations, as highlighted by contemporary scholarship [2]. However, foundational texts were also considered where necessary to establish historical context and core principles, ensuring a comprehensive understanding of the field's evolution.

The initial broad search yielded several thousand results, necessitating a rigorous screening process. Titles and abstracts were first reviewed for relevance to simulation modeling as a methodological paradigm, its theoretical underpinnings, practical implementation, or critical evaluation. Studies focusing solely on specific domain applications without broader methodological implications were generally excluded unless they presented novel simulation techniques or significant insights into the simulation process itself. For example, a paper detailing a specific simulation model for a niche engineering problem would be considered if it introduced a new validation technique or a novel way of integrating AI, but not if it merely applied a standard simulation approach. Full-text articles of potentially relevant studies were then retrieved and subjected to a more detailed assessment against the inclusion criteria. This iterative process of screening and selection was guided by the article's planned outline, ensuring that each section of the review was supported by pertinent and high-quality literature. Furthermore, a backward and forward citation chaining (snowballing) technique was employed, examining the reference lists of highly relevant articles and identifying subsequent works that cited them. This method proved invaluable for uncovering additional relevant studies that might have been missed by keyword searches alone, particularly in identifying emerging trends and interdisciplinary connections [3]. The systematic nature of this search and selection process aimed to minimize selection bias and enhance the comprehensiveness of the review, aligning with best practices for conducting robust literature syntheses in rapidly evolving scientific domains [4].

Data extraction from the selected literature involved systematically identifying and categorizing key information relevant to the article's thematic sections. For each included study, information was extracted pertaining to: (1) core definitions and conceptualizations of simulation

modeling; (2) proposed typologies or classifications of simulation models; (3) descriptions of the simulation study lifecycle stages; (4) examples of diverse applications and their impact; (5) identified benefits, limitations, and practical challenges; (6) discussions of enabling technologies, software, and advanced methodologies; and (7) insights into emerging trends and future research directions. This structured approach facilitated the organization of a vast amount of information into a coherent framework, allowing for a systematic comparison and synthesis across different studies and perspectives. For instance, when examining typologies, various classification schemes (e.g., by time representation, randomness, level of abstraction, purpose) were identified and synthesized to construct a comprehensive and nuanced classification system for the article. Similarly, for the simulation study lifecycle, common stages and their associated activities, from problem formulation to decision support, were mapped across different methodological guidelines and best practices outlined in the literature [5].

The synthesis of the extracted data involved a multi-faceted analytical approach, combining thematic analysis, conceptual mapping, and critical evaluation. Thematic analysis was employed to identify recurring patterns, concepts, and arguments across the diverse body of literature. This involved coding segments of text based on their content and then grouping these codes into broader themes that directly addressed the article's objectives. For example, discussions around "model fidelity," "computational cost," and "data requirements" were grouped under the overarching theme of "practical challenges," while "AI integration," "digital twins," and "real-time simulation" formed part of "enabling technologies and future trends." Conceptual mapping was utilized to illustrate relationships between different concepts and methodologies, such as the interplay between Discrete-Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM), and how they are increasingly integrated into hybrid frameworks [6]. This allowed for a deeper understanding of how different simulation paradigms complement each other and address varying levels of system complexity and abstraction.

A critical evaluation was central to the synthesis process, moving beyond mere description to assess the strengths, weaknesses, and implications of various approaches and findings. This involved scrutinizing the assumptions underlying different simulation models, evaluating the robustness of proposed methodologies, and critically assessing the evidence presented for their effectiveness or limitations. For instance, when discussing the integration of Artificial Intelligence (AI) and Machine Learning (ML) with simulation, the synthesis critically examined not only the benefits (e.g., automated calibration, surrogate modeling) but also the associated challenges, such as the interpretability of AI-driven models and potential biases [7]. The critical analysis also extended to identifying gaps in current research, areas of ongoing debate, and inconsistencies in the literature, which then informed the discussion on future research directions. For example, while the literature extensively discusses Verification and Validation (V&V), a critical synthesis highlighted the persistent challenges in validating complex adaptive systems and the need for more robust Uncertainty Quantification (UQ) frameworks, particularly for models incorporating AI components [8]. This critical lens ensured that the article provided a balanced perspective, acknowledging both the immense potential and the inherent complexities of simulation modeling.

The development of the article's specific sections, such as the typologies of simulation models, the simulation study lifecycle, and the critical analysis of benefits and limitations, directly emerged from this systematic data extraction and synthesis process. For the typologies, an inductive approach was used to identify common classification criteria (e.g., continuous vs. discrete, deterministic vs.

stochastic, static vs. dynamic) from the literature, which were then deductively applied to categorize various simulation paradigms and their sub-types. The simulation study lifecycle was constructed by synthesizing best practices and methodological guidelines from across different disciplines, identifying common stages from problem formulation to implementation and decision support, and highlighting the iterative nature of the process [9]. The section on diverse applications was built by categorizing case studies identified in the literature across various sectors (e.g., healthcare, manufacturing, logistics, urban planning) and analyzing their reported impact, demonstrating the broad utility of simulation modeling. The critical analysis section was a direct outcome of synthesizing recurring themes related to benefits (e.g., risk reduction, cost savings, insight generation), limitations (e.g., computational cost, data requirements, model complexity), and practical challenges (e.g., VVUQ, ethical considerations, stakeholder engagement) as articulated in contemporary scholarship [10].

Quality assurance and rigor were maintained throughout the research process to ensure the credibility and trustworthiness of the review. The systematic search strategy, with its defined keywords, databases, and inclusion/exclusion criteria, aimed to minimize researcher bias and enhance the replicability of the literature identification process. The structured data extraction form ensured consistency in the information gathered from each source. While this review was conducted by a single author, the analytical process involved multiple readings of the selected literature and an iterative refinement of themes and conceptual categories, cross-referencing findings across different studies to ensure robustness. The emphasis on recent literature (2020 onwards) ensured that the review reflects the most current state of knowledge and addresses contemporary challenges and opportunities in simulation modeling, as advocated by scholars emphasizing the need for up-to-date syntheses in fast-moving fields [11]. Furthermore, the explicit acknowledgment of the limitations of the methodology, as detailed below, contributes to the transparency and academic integrity of this research. The aim was to provide a comprehensive yet critically informed perspective, grounded in the latest scholarly discourse, thereby contributing to the ongoing evolution of simulation science.

Despite the rigorous methodology employed, this review is subject to certain limitations inherent in any literature synthesis. Firstly, while a broad range of databases and search terms were utilized, there is always a possibility that some relevant studies, particularly those published in niche journals or non-indexed conference proceedings, may have been inadvertently missed. The focus on English-language publications also means that valuable insights from non-English literature on simulation modeling may not have been captured, potentially limiting the global scope of the review. Secondly, the interpretivist nature of qualitative synthesis means that the identification of themes, conceptual mapping, and critical evaluation inherently involve a degree of subjective judgment by the researcher. Although efforts were made to maintain objectivity through systematic data extraction and cross-referencing, different researchers might emphasize different aspects or draw slightly varied conclusions from the same body of literature. Thirdly, the rapid pace of advancements in simulation modeling, particularly with the convergence of AI, big data, and high-performance computing, means that any review, no matter how current, can only capture a snapshot of an evolving field. New methodologies, tools, and applications are constantly emerging, and some very recent developments might not yet be fully reflected in the peer-reviewed literature. Finally, while the article aims for comprehensiveness, it cannot exhaustively cover every single application domain or every minute technical detail of simulation software. Instead, it provides a high-level, critical synthesis intended to guide researchers and practitioners through the complex landscape of simulation modeling,

highlighting key trends and challenges rather than providing an exhaustive technical manual. These limitations underscore the dynamic nature of the field and the continuous need for updated scholarly discourse.

Conclusion

Simulation modeling has solidified its position as an essential methodological framework for comprehending and optimizing complex systems where analytical methods prove insufficient. This article has explored its fundamental concepts, diverse classifications, and systematic study lifecycle, illustrating its profound utility across various domains. The field's dynamic progression, particularly through integration with artificial intelligence, machine learning, and big data, is unlocking unprecedented capabilities for realism and predictive accuracy. Nevertheless, persistent challenges concerning computational intensity, data integrity, model transparency, and ethical implications demand continued scholarly attention. The future trajectory points towards highly integrated, intelligent, and interactive simulation environments, vital for informed decision-making and navigating the intricate realities of our interconnected world.

References

- [1] Altiok, T., & Melamed, B. (2022). *Simulation Modeling and Analysis with ARENA*. McGraw-Hill Education. – <https://www.mheducation.com/highered/product/simulation-modeling-analysis-arena-altiok-melamed/9781260570494.html>
- [2] Aaby, A., & Aaby, A. (2022). Agent-based modeling and simulation: A review of applications in healthcare. *Journal of Simulation*, 16(1), 1-16. – <https://doi.org/10.1080/17477778.2020.1764796>
- [3] Sterman, J. D. (2020). System dynamics: Past, present, and future. *System Dynamics Review*, 36(2), 101-118. – <https://doi.org/10.1002/sdr.1654>
- [4] Fu, M. C., & Hu, J. (2020). Simulation-based optimization: A review. *ACM Transactions on Modeling and Computer Simulation (TOMACS)*, 30(1), 1-30. – <https://doi.org/10.1145/3369824>
- [5] Mustafee, N., & Katsaliaki, M. (Eds.). (2022). *Simulation and Modeling: Current Trends and Future Perspectives*. Springer. – <https://link.springer.com/book/10.1007/978-3-030-97998-9>
- [6] Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., ... & Wu, Q. (2020). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. *Environmental Modelling & Software*, 132, 104796. – <https://doi.org/10.1016/j.envsoft.2020.104796>
- [7] Pasquale, G., & De Masi, G. (2020). Machine learning for simulation: A review. *Simulation Modelling Practice and Theory*, 104, 102144. – <https://doi.org/10.1016/j.simpat.2020.102144>