Modeling: The Heart and Soul of Engineering Smart Ecosystems

Antonio Bucchiarone[*], Benoit Combemale[†], Alfonso Pierantonio[*], Nelly Bencomo[‡],
Mark van den Brand[§], Jean-Michel Bruel[¶], Antonio Cicchetti[‖], Juri Di Rocco[*], Leen Lambers[**],
Judith Michael[††,‡‡], Bernhard Rumpe[††], Mikael Sjödin[‖], Gabriele Taentzer[x], Matthias Tichy[xi],
Hans Vangheluwe[xii], Manuel Wimmer[xiii], Steffen Zschaler[xiv]

[*] *Università degli Studi dell'Aquila*, Email: {antonio.bucchiarone, alfonso.pierantonio, juri.dirocco}@univaq.it
[†] *University of Rennes, IRISA, Inria*, Email: benoit.combemale@irisa.fr
[‡] *Durham University*, Email: nelly.bencomo@durham.ac.uk
[§] *Eindhoven University of Technology*, Email: m.g.j.v.d.brand@tue.nl
[¶] *University of Toulouse / CNRS-IRIT*, Email: jmb@irit.fr
[‖] *Mälardalen University*, Email: {antonio.cicchetti, mikael.sjodin}@mdu.se
[**] *BTU Cottbus - Senftenberg*, Email: leen.lambers@b-tu.de
[††] *RWTH Aachen University*, Email: {michael, rumpe}@se-rwth.de
[‡‡] *University of Regensburg*, Email: judith.michael@ur.de
[x] *Philipps-Universität Marburg*, Email: taentzer@mathematik.uni-marburg.de
[xi] *Ulm University*, Email: matthias.tichy@uni-ulm.de
[xii] *University of Antwerp and Flanders Make*, Email: hans.vangheluwe@uantwerpen.be
[xiii] *Johannes Kepler University Linz*, Email: manuel.wimmer@jku.at
[xiv] *King's College London*, Email: szschaler@acm.org

***Abstract*—The pervasive digitalization of our world has ushered in a new era marked by increased complexity and diversity in the development, optimization, and maintenance of modern software-intensive systems. These systems, often characterized by intricate socio-technical components and AI integration, pose challenges for conventional systems engineering approaches and require an alliance of different disciplines. In this vision paper, we argue that they demand a paradigm shift towards integrative modeling across systems engineering, software engineering, data science, and simulation engineering. We highlight the key challenges faced in the development of modern complex systems that need to be addressed by this paradigm shift. We argue that achieving this shift requires new research, tools, and education.**

***Index Terms*—MDE, MBSE, Simulation, Data Science, AI.**

I. Introduction

As digitalization continues to shape our world, the development, optimization, and maintenance of modern systems have become increasingly complex. Today, systems engineers face unprecedented challenges stemming from the heterogeneity of technologies, the diversity of stakeholders, and the dynamic nature of application domains [1], [2]. The rise of cyber-physical systems and interconnected infrastructures, collectively referred to as smart ecosystems, such as smart cities [3], [4], exemplifies this complexity. These systems of systems operate within socio-technical contexts [5] and frequently require the integration of Artificial Intelligence (AI) components.

Despite the growing demand for integrated, intelligent, and adaptive systems, many organizations struggle to effectively engineer them. This is in part due to the historical separation between key communities involved in system development: systems engineers, software developers, data scientists, AI researchers, and simulation experts often operate in silos, limiting opportunities for collaboration and knowledge exchange.

In parallel, multiple subfields of computer science have advanced distinct modeling theories tailored to their specific objectives [6]. The Modeling and Simulation (M&S) community has developed techniques for deductive reasoning over analytical representations of real-world phenomena, supported by domains such as high-performance computing, discrete-event simulation (e.g., DEVS [7]), agent-based models, and numerical methods. These approaches enable the cost-effective testing of complex scenarios in a virtual space.

Complementing this, Model-Based Systems Engineering (MBSE) addresses system complexity through structured representations of user needs and system architectures. However, simulating system behaviors or verifying properties often requires manual transitions to separate technological spaces.

Meanwhile, Data Science (DS) and AI have risen in response to systems that evolve rapidly in dynamic, uncertain environments [8]. These fields use inductive reasoning methods to uncover insights and adjust to changing demands by continuously integrating new data.

Finally, the Model-Driven Engineering (MDE) community has introduced formal foundations in meta-modeling and model transformation [9], [10]. MDE emphasizes the creation of precise abstractions and domain-specific modeling languages, significantly enhancing the tooling for MBSE. However, its integration with M&S and DS/AI remains limited, with existing synergies underexplored or manually managed.

This paper argues for an integrative paradigm shift, a unified modeling theory that bridges these diverse communities and leverages their respective strengths. We begin by identifying key modeling enablers across M&S, MBSE, DS/AI, and MDE. We then demonstrate how an integrated approach can enhance the development of complex systems in socio-technical settings. Finally, we propose directions for a cohesive framework that fosters collaboration and innovation at the intersection of modeling, data, and intelligent systems.

II. Looking Ahead in Systems Engineering

In the dynamic realm of a smart city (cf. Figure 1), characterized by constant evolution and complexity, the call for a paradigm shift in mobility management is urgent. This requires a holistic strategy that uses modeling techniques and brings together experts in MBSE, M&S, DS&AI, and MDE. Each model is tailored to one facet of the city, using different notations and paradigms. As one facet evolves, others must be adapted for the efficiency of urban infrastructure. The shift to a multi-view specification is crucial due to the complexity of urban mobility. Traditional methods are faltering and require a transformation to meet the evolving needs of citizens effectively. As shown in Figure 1, the use of MBSE for infrastructure modeling, M&S for scenario simulation, DS&AI for data integration and predictive analysis, and MDE for translation, leads to shared system representations, allowing robust decisions. This approach enables personalized recommendations, real-time optimizations, and improves the resilience of the city, fostering a safer, more adaptive, and sustainable future in the midst of constant change.

The use of model-based methods for capturing systems engineering artifacts has grown among systems engineering groups, although the acceptance of these techniques is not uniform across all sectors or even within specific organizations.

As an example, custom simulations are developed for every project rather than using standardized and configurable simulations, and there is a lack of model sharing, especially between critical activities such as system architecture and design validation. In the context of the City Twin scenario, the use of various ontologically linked (virtual) models [11], is considered to perform specific tasks (i.e., traffic or emergency management). These interconnected models will be continuously updated to provide an immersive virtual reality environment for design, exploration, and optimization. This virtual collaboration space, which will be supported by Modeling-as-a-Service [12] and hosted on the cloud, will enable large-scale simulation by leveraging high-performance computing infrastructures.

A range of integrated models and simulation frameworks are available to facilitate collaboration between businesses and government. Inspired by INCOSE Systems Engineering Vision 2035 [13], we highlight the *key challenges* (KC) that research must address to realize this future (Figure 2, top).

KC1: Systematically characterize and connect heterogeneous and complex data: As more data become available, sophisticated models must become more elaborated to allow for more precise and accurate analysis and predictions. Critical decisions and design choices are based on the accuracy of the models and data. This requires support for (i) highly connected data, complemented by AI/ML-based or ontology mapping services, (ii) automated (virtual) model creation, (iii) model correlation, verification and validation, and (iv) effective balancing of competing priorities, taking into account factors such as cost, performance, scalability, and ethical considerations, to ensure optimal decision-making and design choices.

KC2: Create an efficient model-as-a-service and collaborative environment for Systems Engineering: Providing easy access to city models on top of platforms that provide a range of analytical tools and modeling environments can help users collaboratively improve system performance, reduce development time and cost, and increase efficiency in a variety of industries. Modeling environments should provide zoom-in/zoom-out access to models and data, facilitate dependency analysis of models, and support efficient model evolution [14]. These aspects help reduce or minimize accidental complexity, allowing users to focus on the essential aspects of their models and streamline the modeling process. It is crucial for next-generation modeling environments to employ semantically rich modeling standards for descriptive, prescriptive, and predictive models [15], ensure efficient traceability, and provide separation of views to enhance the effectiveness and usability of the modeling process.

KC3: Improve the fidelity and accuracy of data and models: Virtualization of complex ecosystems, such as the City Twin, is crucial for creating multi-layered simulation models. This approach allows for real-time simulation across various scales and fidelity, from detailed simulations of individual vehicles to broader analyses of multi-agent traffic systems, city infrastructure fleets, and even regional or cross-country scenarios. The integration of diverse urban elements within the modeling environment enhances simulator capabilities, enabling seamless processing and analysis of both real-time and historical data. Such comprehensive integration addresses challenges like data complexity and system scalability, empowering users to effectively use the models for gaining insights, making informed decisions, and optimizing responses in a variety of emergent situations.

KC4: Separate concerns: Each virtual model within the City Twin serves as a digital representation of a specific facet, encompassing distinct components and potential external interactions with other facets. This digital representation is used to simulate the comprehensive behavior of the entire complex system within a virtual environment for designing, testing, and validating. This simulation allows for the analysis and optimization of the system performance, fidelity, reliability, and safety. To accomplish this, data must be extracted from multiple sources, analyzed, and integrated into a cohesive representation of the complex system.

Smart City Ecosystem

In a smart city, Sarah, a dedicated city planner, and John, the head of the city's transportation authority, found themselves facing a challenge as a massive snowstorm approached. To navigate this complex landscape, they relied on an innovative solution known as the **City Twin – a digital replica of their urban environment**. The City Twin served as a tool, allowing them to manage urban mobility efficiently and respond to the challenges posed by the impending snowstorm.

With **MBSE**, Sarah had crafted detailed _models of the city's infrastructure_, including *road networks, public transportation systems, and emergency response facilities*. These models provide insights into the capacity of different roads, the locations of bus stops, and the availability of emergency response resources. Additionally, she used a _traffic flow model_ to *predict traffic congestion based on current conditions and the expected snowfall rate*. John used the **M&S** component to *simulate various snow-storm scenarios* within the City Twin.

Through this simulation, he could anticipate potential challenges, such as the *impact of heavy snow on road conditions, the potential for traffic congestion, and the effects of snow accumulation on public transportation schedules*. John employed a _weather impact model_, which *integrated real-time weather data* with the city's infrastructure models to assess the effects of snowfall on road friction and traffic flow.

As the snowstorm progressed, *real-time data* from weather sensors, traffic cameras, and public transportation systems were continuously processed by **DS&AI** algorithms. These algorithms provided minute-by-minute insights into *weather conditions, road blockages, and public transport delays*. For example, real-time data from traffic cameras indicated which roads were congested due to snow buildup, and weather sensor data helped predict the snowfall rate. DS&AI also utilized a *predictive model*, which used *historical weather data and current conditions* to *forecast the severity and duration of the snowstorm*, allowing for more precise decision-making.

MDE played a crucial role by *transforming the models* created by MBSE, the simulations from M&S, and the real-time data from DS&AI *into actionable plans*. It ensured *consistency* and *coherence* among the different models, creating a *shared representation* of the system. E.g., MDE helped *align the simulated scenarios with the real-time data*, enabling a seamless transition from predictive models to real-world decision-making. This harmonization was essential for making robust and reliable decisions, such as optimizing bus routes based on current traffic conditions and weather predictions.

As the snowstorm intensified, Sarah and John received alerts and recommendations from the City Twin. These actionable insights enabled them to take specific measures, such as *rerouting buses to avoid congested roads, deploying snowplows strategically to clear critical routes, and notifying citizens about alternative transportation options*. These actions ensured the safety and well-being of the city's residents and demonstrated the power of integrated modeling techniques in managing complex urban challenges.

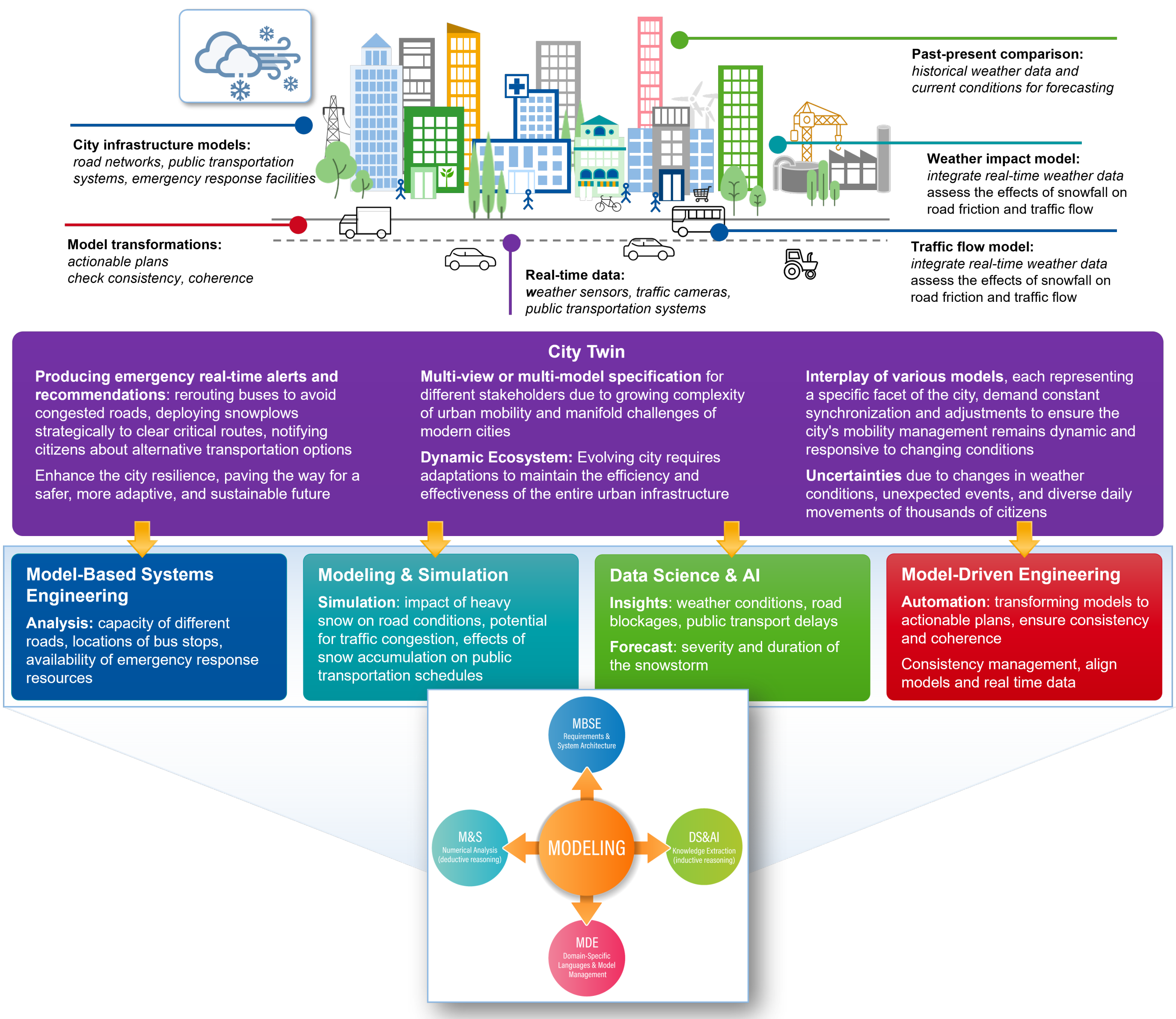

Fig. 1. The Smart City Ecosystem, its models and data needs for emergency real-time alerts and recommendations

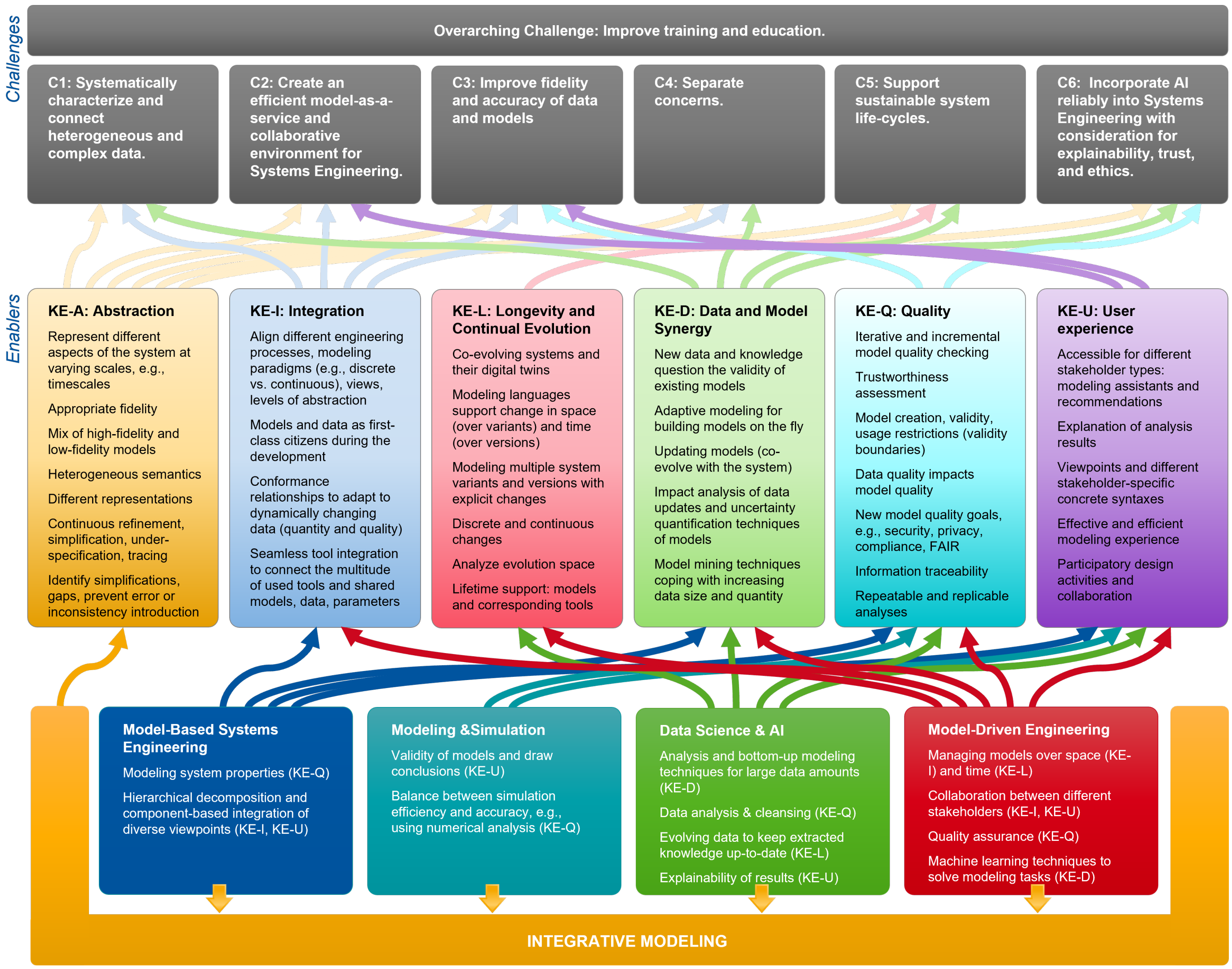

Fig. 2. Integrative (Modeling) Paradigm Shift: Challenges and Enablers for a Multi-Disciplinary Realization of Complex Systems.

KC5: Support sustainable system lifecycles: Using the City Twin to simulate different scenarios allows designers and engineers to make decisions that align more closely with societal needs and goals, such as reducing CO2 emissions. While individual system lifecycles must still meet stakeholder demands, time constraints, and budget limitations, they also contribute to a larger, coordinated response to strategic business objectives and societal challenges. These lifecycles need to be synchronized with global industry trends, economic conditions, and societal movements, which influence system requirements and expectations. Complex systems must be designed to be variable, adaptable, and configurable to ensure their long-term value and relevance. This approach tackles challenges related to strategic alignment, adaptability, and sustainability in system design.

KC6: Incorporate AI reliably into Systems Engineering with consideration for explainability, trust, and ethics: It is a growing challenge for systems engineering to meet stakeholder demands while ensuring that unintended outcomes are avoided. This will require taking advantage of continuously expanding technological innovations to create products and services that are intelligent, self-organizing, sustainable, resource-efficient, reliable, and safe. For example, incorporating AI/ML in a City Twin can enhance its ability to accurately simulate system behavior, optimize the design of various components, and enable real-time monitoring and control of the running system. However, the integration of advanced technologies into systems engineering can pose complex challenges related to explainability and trust that need to be addressed to ensure that these systems are designed and developed responsibly and ethically. At the same time, we need to ensure that the systems use AI in a responsible and trustworthy manner at runtime.

Overarching Challenge: Improve training and education: Success in developing complex ecosystems relies on skilled engineers and their evolving capabilities. A diverse workforce equipped with advanced tools is crucial for innovation and competitiveness. Interdisciplinary collaboration is vital for City Twin projects, requiring expertise in engineering, data science, and domain knowledge. Ensuring data quality and integrity is essential for effective model representation. A strong foundation in model validation and verification techniques is necessary to assess reliability. Addressing these aspects in training empowers individuals to realize the potential of modeling and contribute to robust system development. Therefore, investing in the education, effectiveness, and ongoing competency development of engineers is critical.

III. Key Modeling Enablers

To address the challenges of engineering complex systems, several *key enablers* (KE) for modeling emerge, covering six aspects: Abstraction, Integration, Data and Model Synergy, Longevity and Continuous Evolution, Quality, and User Experience (see Figure 2, middle). These aspects provide a framework for understanding the benefits of modeling in the engineering of future complex systems. The challenges listed in parentheses next to each enabler title highlight the specific issues that each enabler helps to address, underlining their role in achieving effective solutions for complex system challenges.

KE-A: Abstraction (KC1 - KC6): Modeling complex systems requires different abstraction levels to effectively represent different aspects [16], [17]. For instance, consider the City Twin scenario: to address urban mobility during a snowstorm, abstraction allows for modeling the macro-level city dynamics alongside the micro-level vehicle interactions. To reshape mobility strategies in real-time, the levels of abstraction must be scalable, flexible, secure, and interoperable while maintaining consistency and traceability.

KE-I: Integration (KC1 - KC4): Complex systems demand seamless integration of diverse components and data sources. In the urban mobility scenario, integrating weather data, traffic patterns, and public transportation schedules enables predictive analysis and adaptive decision-making. Beyond existing techniques for model composition [18] and co-simulation [19], composable digital twins of city segments facilitate interoperability [20], allowing for holistic system analysis and effective mobility management. The data required for the system to work (both historical [11], [21] and current runtime [22]) shall be considered as first-class citizens during the development, analogous to models. Consequently, conformance relationships should be flexible to adapt to dynamically changing data, both in terms of quantity and quality.

KE-L: Longevity and Continuous Evolution (KC5): Systems such as City Twins exist for decades and require continuous evolution [23]. Modeling languages must explicitly support change over time and across system variants. In urban mobility, evolving models account for changes in transportation infrastructure, population dynamics, and climate patterns. This continuous evolution ensures the relevance and accuracy of models for informed decision-making.

KE-D: Data and Model Synergy (KC1, KC4 - KC6): Data-driven approaches are vital for complex systems. In the City Twin scenario of Figure 1, data from sensors, social media, and historical records synergize with models to optimize mobility strategies during a snowstorm. Adaptive modeling techniques [24] ensure that models evolve with dynamic data, maintaining system integrity and effectiveness. Considering uncertainty in data models ensures the integrity throughout the lifecycle of complex systems, promoting the efficient and effective use of data.

KE-Q: Quality (KC3, KC6): Ensuring model quality is crucial for reliable decision-making in complex systems such as City Twins. Quality assessment includes trustworthiness, adherence to standards, and consideration of data quality principles such as FAIR [25]. In urban mobility, model quality guarantees accurate predictions and efficient resource allocation during snowstorms, thereby increasing overall system resilience. Quality properties such as traceability of information, e.g., in predictive analysis, require connecting models, the data used, and the analysis results. This information is also required if analyses are to be repeatable or reproducible over time.

KE-U: User Experience (KC2, KC3): User experience plays a pivotal role in leveraging modeling for complex systems. In the City Twin scenario, modeling tools need to cater to different stakeholders by providing intuitive interfaces and explainable analysis results. Usability enhancements such as modeling assistants and interactive what-if modeling streamline decision-making processes, fostering collaboration and innovation in urban mobility management. Accordingly, the modeling tools need to be accessible to these different types of stakeholders (e.g., by including modeling assistants and recommender mechanisms [26]) and we need explainable analysis results. In addition, modeling tools need to support different viewpoints and user interfaces, possibly with different stakeholder-specific concrete syntaxes.

IV. Integrative Paradigm Shift

Most of the aforementioned key modeling enablers already exist, but they are currently fragmented across different communities and engineering subfields that operate in isolation from each other. In particular, some enablers have been developed and explored in **MBSE** while others have been explored and developed in **MDE**, **M&S**, and **DS&AI**. In the following, we briefly discuss these domains and their respective use of models (Figure 2, bottom).

A. Model-Based Systems Engineering

The key driver for Systems Engineering [27] is the overall process of managing the complex interactions between stakeholders and different engineering domains involved in developing complex systems. As such, models, associated analysis and techniques are a cornerstone in the design, implementation and management of complex systems. As a result, in MBSE, the emphasis is on system properties (KE-Q) and on hierarchical decomposition and component-based integration of different viewpoints [28] (KE-I, KE-U). This is achieved through domain-specific models, which can be thought of as ”gray boxes”, with a focus on integrating the entire system. A future trend in systems engineering is the intensive use of data leading to data-driven systems engineering (KE-D).

Models in MBSE allow for a more systematic representation of information compared to documents, such as spreadsheets. They also provide an abstraction of the architecture of a system, even before its concrete realization within the different disciplines, as well as the expected properties and how they are validated. Models in MBSE consist of "views" representing different, domain-specific perspectives on the system or its parts. This is the basis for coordination and collaboration within interdisciplinary engineering processes.

B. Modeling & Simulation

The key driver in M&S is the validity of models and the ability to draw conclusions (KE-U) through (interactive) execution that can reliably predict real-world behavior. As a result, there is a strong focus on concepts such as fidelity, scale, uncertainty, and integration across different levels of abstraction. Another significant consideration is the balance between simulation efficiency and accuracy. Numerical analysis plays a vital role in achieving this balance (KE-Q).

In M&S, an artifact serves as a "model" of a system within a specific experimental context to achieve goals such as system understanding or optimization of properties. Simulation/virtual experimentation replaces real-world experimentation due to cost, practicality, or ethical concerns, requiring that the results of virtual experiments closely match the results of real-world experiments. Different validity types correspond to different distance metrics. Simulation models are expressed in various modeling languages, each with precise semantics encoded in simulation engines [29]. These engines generate behavioral traces that enable the analysis of properties of interest.

C. Data Science and Artificial Intelligence

The key driver in DS&AI is the management of large amounts of weakly structured data and the extraction of knowledge from it through a wide range of analysis and bottom-up modeling techniques [30] (KE-D). In preparation for knowledge extraction, data analysis and cleaning techniques are used (KE-Q). An ongoing challenge is dealing with evolving data to keep the extracted knowledge current (KE-L). Moreover, a current trend in this discipline is explainability [31] (KE-U) to enable appropriate use of the extraction results.

In DS&AI, the term "model" refers to models within analysis components, such as machine learning, and differs from the notion of "model" in other domains. Analysis transforms data into information and knowledge [32], closer to the idea of a "model" in systems engineering, serving as abstractions/summaries of data, as discussed in enablers.

D. Model-Driven Engineering

MDE focuses on models as artefacts and considers how to manage them over space (KE-I) and time (KE-L) (in particular, variability, co-evolution and versioning). MDE also enables collaborations between different stakeholders (KE-I, KE-U), includes consistency, and captures domain-specific knowledge in languages and modeling notations. The MDE community, thus, provides advanced key enablers for the development of modeling languages and tools, and for the management of models. Quality assurance in MDE includes various methods and techniques such as model smells and refactoring, model verification, and model consistency and synchronization through model transformations (KE-Q). A current trend in MDE is the use of machine learning techniques to solve modeling tasks such as model mining, modeling-by-example, model transformation, etc. (KE-D).

MDE is all about "models", but it focuses less on what the models are and more on how they work as artefacts within the development lifecycle. Thus, the focus is on how to create modeling languages (including their syntax and semantics) and models, what are the core notions of consistency, and how to construct transformation and analysis tools that integrate well with other model management activities. MDE uses the most general definition of the term "model" [33], which is defined as something that abstracts from a particular (software) system or domain, capturing relevant aspects for at least one purpose with respect to the original.

E. Towards an Integrative Paradigm

As it is evident from the domains introduced above, they all rely heavily on models (KE-A), which provides a unique and unifying opportunity to bridge the gaps between them.

To fully exploit the power of the models in different domains, an integrative paradigm shift in the engineering of complex systems is needed. The shift should include a holistic approach to the use of modeling techniques that enable developers from MBSE, MDE, M&S, and DS&AI. Integrating these modeling techniques [34]–[36] would allow engineers to create more comprehensive and accurate models of systems that reflect the complexity and dynamicity of the real world.

The City Twin scenario exemplifies the extensive use of models in laying the groundwork for complex ecosystems, as depicted in Figure 1. City Twins, virtual replicas of urban environments, rely heavily on sophisticated modeling techniques. Through these techniques, engineers capture and simulate complex system behavior, interactions, and performance to facilitate understanding, analysis, optimization, and decision-making throughout the system's lifecycle. The integration of different modeling techniques enables the creation of comprehensive and accurate models that are essential for the successful implementation of City Twin across the different public and private stakeholders involved.

MBSE helps capture system requirements, architecture, and behavior, while MDE can enable automatic generation of code from models. DS&AI can provide insight into system performance and user behavior and enhance the system's ability to learn and adapt to changing conditions. Simulation can help validate and test the performance of the system in different scenarios. An integrative approach that incorporates these different modeling goals would let software developers to create more robust, reliable, and intelligent systems that continuously meet the needs of users and stakeholders.

A holistic paradigm shift that explores a cohesive conceptual framework is essential. This shift will require and foster collaborative research to create innovative methods, facilitating the development of advanced tools for future MBSE complex systems. Considering these domains together requires a novel educational strategy: *future engineers will need to navigate the intersections of these domains*, necessitating a unified approach in curricula and training methods.

V. Conclusion

Integrating AI/ML components into highly complex systems has pushed traditional engineering approaches to their limits. We need a paradigm shift in the integrative use of models and modeling across systems engineering, software engineering, data science, and simulation. Future software and systems engineering requires an integrative modeling paradigm for MBSE, M&S, DS&AI, and MDE. This requires multidisciplinary collaboration to address the complexity and heterogeneity of complex systems, as well as new research, tools, and education in modeling.

References

[1] Helena Holmström Olsson and Jan Bosch. Going digital: Disruption and transformation in software-intensive embedded systems ecosystems. *Journal of Software: Evolution and Process*, 32(6):e2249, 2020.

[2] Jason Bickford, Douglas L. Van Bossuyt, Paul Beery, and Anthony Pollman. Operationalizing digital twins through model-based systems engineering methods. *Systems Engineering*, 23(6):724–750, 2020.

[3] Neda Mohammadi and John E. Taylor. Smart city digital twins. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1–5, 2017.

[4] Sue Weekes. The rise of digital twins in smart cities. *Smart Cities World*, 2019.

[5] Federico Bonetti, Antonio Bucchiarone, Judith Michael, Antonio Cicchetti, Annapaola Marconi, and Bernhard Rumpe. Digital Twins of Socio-Technical Ecosystems to Drive Societal Change. In *MODELS Companion '24: Int. Conf. on Model Driven Engineering Languages and Systems*, pages 275–286. ACM, 2024.

[6] Judith Michael, Dominik Bork, Manuel Wimmer, and Heinrich C. Mayr. Quo Vadis Modeling? Findings of a Community Survey, an Ad-hoc Bibliometric Analysis, and Expert Interviews on Data, Process, and Software Modeling. *Journal Software and Systems Modeling (SoSyM)*, 23(1):7–28, Feb 2024.

[7] A.I. Concepcion and B.P. Zeigler. Devs formalism: a framework for hierarchical model development. *IEEE Transactions on Software Engineering*, 14(2):228–241, 1988.

[8] Francisco J. Montáns, Francisco Chinesta, Rafael Gómez-Bombarelli, and J. Nathan Kutz. Data-driven modeling and learning in science and engineering. *Comptes Rendus Mécanique*, 347(11):845–855, 2019. Data-Based Engineering Science and Technology.

[9] Stefan Götz, Matthias Tichy, and Raffaela Groner. Claimed advantages and disadvantages of (dedicated) model transformation languages: a systematic literature review. *Software and Systems Modeling*, 20(2):469–503, 2021.

[10] Jean-Michel Bruel, Benoit Combemale, Esther Guerra, Jean-Marc Jézéquel, Jörg Kienzle, Juan de Lara, Gunter Mussbacher, Eugene Syriani, and Hans Vangheluwe. Comparing and classifying model transformation reuse approaches across metamodels. *Software and Systems Modeling*, 19(2):441–465, 2020.

[11] Jörg Christian Kirchhof, Judith Michael, Bernhard Rumpe, Simon Varga, and Andreas Wortmann. Model-driven digital twin construction: Synthesizing the integration of cyber-physical systems with their information systems. In *23rd ACM/IEEE Int. Conf. on Model Driven Engineering Languages and Systems*, MODELS '20, page 90–101. ACM, 2020.

[12] Olaf David, Wes J. Lloyd, Ken Rojas, Mazdak Arabi, Frank Geter, James C. Ascough, Timothy R. Green, George H. Leavesley, and Jack R. Carlson. Model-As-A-Service (MaaS) Using the Cloud Services Innovation Platform (CSIP). 2014.

[13] Systems engineering vision 2035, 2021. https://www.incose.org/publications/se-vision-2035.

[14] Silvia Abrahão, Francis Bourdeleau, Betty Cheng, Sahar Kokaly, Richard Paige, Harald Stöerrle, and Jon Whittle. User experience for model-driven engineering: Challenges and future directions. In *2017 ACM/IEEE 20th International Conference on Model Driven Engineering Languages and Systems (MODELS)*, pages 229–236, 2017.

[15] Benoît Combemale, Jörg Kienzle, Gunter Mussbacher, Hyacinth Ali, Daniel Amyot, Mojtaba Bagherzadeh, Edouard Batot, Nelly Bencomo, Benjamin Benni, Jean-Michel Bruel, Jordi Cabot, Betty H. C. Cheng, Philippe Collet, Gregor Engels, Robert Heinrich, Jean-Marc Jézéquel, Anne Koziolek, Sébastien Mosser, Ralf H. Reussner, Houari A. Sahraoui, Rijul Saini, June Sallou, Serge Stinckwich, Eugene Syriani, and Manuel Wimmer. A hitchhiker's guide to model-driven engineering for data-centric systems. *IEEE Softw.*, 38(4):71–84, 2021.

[16] Ankica Barisic, Ivan Ruchkin, Dusan Savic, Mustafa Abshir Mohamed, Rima Al Ali, Letitia W. Li, Hana Mkaouar, Raheleh Eslampanah, Moharram Challenger, Dominique Blouin, Oksana Nikiforova, and Antonio Cicchetti. Multi-paradigm modeling for cyber-physical systems: A systematic mapping review. *J. Syst. Softw.*, 183:111081, 2022.

[17] Nelly Bencomo, Jordi Cabot, Marsha Chechik, Betty H. C. Cheng, Benoit Combemale, Andrzej Wasowski, and Steffen Zschaler. Abstraction engineering, 2024.

[18] Jörg Kienzle, Gunter Mussbacher, Benoît Combemale, and Julien Deantoni. A unifying framework for homogeneous model composition. *Softw. Syst. Model.*, 18(5):3005–3023, 2019.

[19] Cláudio Gomes, Casper Thule, David Broman, Peter Gorm Larsen, and Hans Vangheluwe. Co-simulation: a survey. *ACM Computing Surveys (CSUR)*, 51(3):1–33, 2018.

[20] Benoit Combemale, Jörg Kienzle, Gunter Mussbacher, Pascal Archambault, Jean-Michel Bruel, Lola Burgueño, Betty H.C. Cheng, Loek Cleophas, Gregor Engels, Damien Foures, Stefan Klikovits, Vinay Kulkarni, Judith Michael, Sebastien Mosser, Houari Sahraoui, Eugene Syriani, and Andreas Wortmann. On the Challenges of Integrating Digital Twins. In *Int. Conf. on Engineering Digital Twins (EDTconf'25)*. IEEE, October 2025.

[21] Antonio García-Domínguez, Nelly Bencomo, Juan Marcelo Parra Ullauri, and Luis Hernán García Paucar. Querying and annotating model histories with time-aware patterns. In *22nd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems, MODELS 2019*, pages 194–204. IEEE, 2019.

[22] Gordon Blair, Nelly Bencomo, and Robert B. France. Models@run.time. *Computer*, 42(10):22–27, 2009.

[23] Tarek Alskaif, Önder Babur, Francis Bordeleau, Loek Cleophas, Benoit Combemale, Joachim Denil, Ø ystein Haugen, Judith Michael, Phu Nguyen, Tiberiu Seceleanu, Mark van den Brand, and Hans Vangheluwe. Evolution at the Core of Digital Twin Engineering. In *Int. Conf. on Engineering Digital Twins (EDTconf'25)*. IEEE, October 2025.

[24] Pierre F.J. Lermusiaux. Adaptive modeling, adaptive data assimilation and adaptive sampling. *Physica D: Nonlinear Phenomena*, 230(1):172–196, 2007. Data Assimilation.

[25] Mark D Wilkinson, Michel Dumontier, IJsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axton, Arie Baak, Niklas Blomberg, Jan-Willem Boiten, Luiz Bonino da Silva Santos, Philip E Bourne, et al. The fair guiding principles for scientific data management and stewardship. *Scientific data*, 3, 2016.

[26] Gunter Mussbacher, Benoît Combemale, Jörg Kienzle, Silvia Abrahão, Hyacinth Ali, Nelly Bencomo, Márton Búr, Loli Burgueño, Gregor Engels, Pierre Jeanjean, Jean-Marc Jézéquel, Thomas Kühn, Sébastien Mosser, Houari A. Sahraoui, Eugene Syriani, Dániel Varró, and Martin Weyssow. Opportunities in intelligent modeling assistance. *Softw. Syst. Model.*, 19(5):1045–1053, 2020.

[27] SEBoK: System Modeling Concepts, 2024. https://sebokwiki.org/wiki/System_Modeling_Concepts.

[28] Manfred Broy, Wolfgang Böhm, and Bernhard Rumpe. *Advanced Systems Engineering*, pages 353–364. Springer International Publishing, Cham, 2021.

[29] Moussa Amrani, Dominique Blouin, Robert Heinrich, Arend Rensink, Hans Vangheluwe, and Andreas Wortmann. Multi-paradigm modelling for cyber–physical systems: a descriptive framework. *Software and Systems Modeling*, 20(3):611–639, 2021.

[30] Wil M. P. van der Aalst. *Process Mining - Data Science in Action, Second Edition*. Springer, 2016.

[31] Rudresh Dwivedi, Devam Dave, Het Naik, Smiti Singhal, Rana Omer, Pankesh Patel, Bin Qian, Zhenyu Wen, Tejal Shah, Graham Morgan,

and Rajiv Ranjan. Explainable AI (XAI): Core Ideas, Techniques, and Solutions. *ACM Comput. Surv.*, 55(9), January 2023.

[32] Jennifer Rowley. The wisdom hierarchy: representations of the DIKW hierarchy. *Journal of Information Science*, 33(2):163–180, 2007.

[33] Herbert Stachowiak. *Allgemeine Modelltheorie*. Springer Verlag, Wien New York, 1973.

[34] Simon Rädler, Luca Berardinelli, Karolin Winter, Abbas Rahimi, and Stefanie Rinderle-Ma. Bridging MDE and AI: a systematic review of domain-specific languages and model-driven practices in AI software systems engineering. *Software and Systems Modeling*, 24(2):445–469, 2025.

[35] Araz Jabbari and Michael Rosemann. Modeling 4.0: Conceptual modeling in a digital era. *Commun. Assoc. Inf. Syst.*, 53:42, 2023.

[36] Judith Michael, Loek Cleophas, Steffen Zschaler, Tony Clark, Benoit Combemale, Thomas Godfrey, Djamel Eddine Khelladi, Vinay Kulkarni, Daniel Lehner, Bernhard Rumpe, Manuel Wimmer, Andreas Wortmann, Shaukat Ali, Balbir Barn, Ion Barosan, Nelly Bencomo, Francis Bordeleau, Georg Grossmann, Gabor Karsai, Oliver Kopp, Bernhard Mitschang, Paula Muñoz Ariza, Alfonso Pierantonio, Fiona A. C. Polack, Matthias Riebisch, Holger Schlingloff, Markus Stumptner, Antonio Vallecillo, Mark van den Brand, and Hans Vangheluwe. Model-Driven Engineering for Digital Twins: Opportunities and Challenges. *INCOSE Systems Engineering*, 2025.