AI-Integrated Framework for Enhancing High Level Architecture Design Across System Lifecycle Stages

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Abstract: AI technology is increasingly being introduced into the automotive industry to support the product design process and address the challenges arising from growing product complexity. Systems Engineering is an interdisciplinary approach and methodology aimed at designing, developing, and managing complex systems throughout entire system lifecycle. The development of Model-Based Systems Engineering (MBSE) significantly enhances complexity management and requirement traceability in conceptual design phases. In the design and analysis phases, the use of Multidisciplinary Design Analysis and Optimization (MDAO) effectively addresses challenges in multidisciplinary problems, identifies optimal solutions, and supports decision-making. Digital Twin (DT) technology is extensively studied and applied to monitor, analyse, and predict operational system behaviour. Integrating AI into system design, along with its combination with MBSE, MDAO, and DT technologies, not only addresses design challenges but also creates new opportunities to advance systems engineering. This paper focuses on how high-level architecture design supports different stages of system lifecycle. The study explores the roles AI can play in the process, as well as its integration with related technologies, and proposes an AI-integrated framework to ensure digital continuity throughout system lifecycle stages.

1 INTRODUCTION

With the increase in automotive functionalities and components, systems have become more complex, and advanced features such as autonomous driving systems and intelligent connectivity further complicate development challenges. To address these challenges, modern technologies such as Artificial Intelligence (AI), Model-Based Systems Engineering (MBSE), Multidisciplinary Design Analysis and Optimization (MDAO), and Digital Twin (DT) have been introduced. Their integration enhances efficiency and optimizes decision-making across all lifecycle stages, from design to operation.

Systems Engineering (SE) is a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods (INCOSE, 2023). Starting with requirements analysis, it covers conceptual design, system integration, verification and validation, and eventually operation and disposal. The primary objective is to manage complexity, ensuring that all functionalities and requirements are aligned, ultimately delivering a product that meets stakeholders' expectations.

MBSE is a model-centric approach to performing systems engineering (Douglass et al., 2022). MBSE

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helps organize requirements and rapidly create and evaluate various architectural solutions. For instance, MBSE is applied in autonomous vehicles to ensure the integration of functionalities across software, hardware, and communication systems (Raza et al., 2024), drive co-simulation of different disciplinary analysis models (Zhao et al., 2024), and optimize the thermal management system of vehicles by analyzing energy flow and heat dissipation efficiency in advance (Habermehl et al., 2022).

MDAO is a methodology used during the design phase to foster collaboration across various disciplines such as aerodynamics, structural mechanics and cost optimization, and identify optimal system designs (Simpson et al., 2011). MDAO addresses challenges in managing interactions among disciplines while ensuring optimized results across different design objectives. (Moerland et al., 2020) applied MDAO in the next generation of aircraft to provide significant reductions in aircraft development costs and time to market. Through MDAO analysis, the design optimization of fuel consumption, take-off weight, and rotor dynamics parameters was completed, achieving an integrated process of system design and optimization (Qi et al., 2024).

DT refers to a virtual representation of a physical entity that is interconnected with its real-world counterpart through continuous and bidirectional data exchange in real time (Singh et al., 2021). DT can monitor vehicle conditions in real time and predict potential issues, and can optimize logistics vehicle routes and maintenance plans in fleet management (Alexandru et al., 2022). DT is also is beneficial to enhance the traditional product design and development processes (Tao et al., 2018).

AI simulates human intelligence through technologies such as Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) (Aurélien, 2019). Its primary methods include supervised learning, unsupervised learning, and Reinforcement Learning (RL). AI enhances system design efficiency, such as through automated requirement analysis and model generation (Zhao et al., 2021), and supports design decision-making via optimization algorithms (Mirjalili et al., 2020).

This concept of AI4MBSE refers to leveraging AI to enhance MBSE. AI4MBSE focuses on improving tasks like requirements engineering, model generation, and decision-making by using ML and NLP. Examples include automated traceability of requirements and intelligent model recommendations to streamline systems engineering workflows. AI helps handle complexity and reduce errors in MBSE processes, especially in domains like transportation and aerospace (Li et al., 2022). Automates repetitive and error-prone MBSE tasks, such as requirements extraction and traceability (Ghanawi et al., 2024). Enhances decision-making through AI-driven model analysis (Raz et al., 2021). Improves MBSE modeling capabilities based on domain knowledge (Zhang et al., 2024).

This concept of MBSE4AI applies MBSE principles to design and develop AI systems themselves. It ensures that AI solutions are integrated systematically, considering requirements, constraints, and validation across the system lifecycle. MBSE4AI emphasizes structuring AI system designs to ensure safety, reliability, and interoperability in complex environments (Anton et al., 2023). Systematically integrates AI solutions into larger systems while managing risks and ensuring transparency, and enables continious validation and verification of AI components against system requirements (Torkjazi and Raz, 2024).

AI is used to enhance the efficiency and accuracy of MDAO workflows. Accelerating optimization algorithms by using AI models to reduce computation time. Assisting in exploring diverse design spaces through AI-guided sampling and evaluation methods (Karali et al., 2024). This approach addresses challenges like high computational costs and the difficulty of identifying optimal solutions in complex systems.

AI supports DT by improving real-time data analysis, anomaly detection, and predictive maintenance. It enhances simulation accuracy by using AI models to fill gaps in physical modeling or to simulate scenarios that are computationally intensive with traditional methods (Rasheed et al., 2020). In operation, AI enables better system monitoring and decision-making, such as in fields like manufacturing, healthcare, and transportation.

This research aims to explore the roles of AI in early stages of the system lifecycle based on their diverse capabilities. It focuses on leveraging AI to enhance MBSE capabilities, such as in requirements modeling and architecture modeling. Additionally, it seeks to improve the efficiency of MDAO processes using AI while accelerating design space exploration. Furthermore, the study investigates the application of AI to enhance the accuracy of DT models, as well as their updating and generation capabilities. Ultimately, this work aims to support digital continuity throughout the system lifecycle using AI technologies.

This research investigates the integration of AI into system design processes, emphasizing its role in enhancing system design and aligning with specific capabilities needs. By integrating AI into MBSE the study aims to improve modeling efficiency, maintain model consistency, and provide heuristic alternatives for decision-making. In the context of MDAO, AI is leveraged to enhance computational efficiency, reduce computational burdens, and enable multifidelity analysis for more effective design optimization. For DT applications, AI contributes to the generation of predictive models, enabling accurate system monitoring, forecasting, and optimization. Finally, an AI-integrated framework is proposed to facilitate interaction across lifecycle stages, ensuring cohesive system development and lifecycle management.

This research addresses several problems regarding the integration of AI into system design processes. First, it should explore the current capabilities of AI and its developmental trends, investigating the roles AI can play in system design and the improvements it can bring to the process. In the field of MBSE, the study should examine pressing challenges that AI could address, identifying gaps in its current applications and unresolved issues. For MDAO, it investigates existing directions of AI application and explores potential areas for further enhancement. Within the DT technology, the research should explore into AI’s current applications and evaluates how AI can introduce new capabilities and improve performance. Finally, it needs to consider the interrelationships between different stages of the system lifecycle, analyzing how AI can enhance iteration across these stages to ensure a more efficient and integrated system design process.

This paper focuses on how AI technology can support system design processes by enhancing various aspects of the system lifecycle. These include supporting MBSE models during the conceptual design phase, MDAO models during the design and analysis phase, and DT models during the operational phase. By leveraging AI to ensure digital continuity across design activities, this research aims to improve the efficiency and quality of product development. The integration of AI with MBSE, MDAO, and DT technologies has been widely studied and applied across various fields. While these applications share the use of AI, the field of AI encompasses a diverse array of methods and models, resulting in diverse solutions for each research focus or application case. This paper investigates how AI can support a cross-lifecycle design framework for system development, exploring the roles AI can play within this framework and the potential outcomes that can be achieved. However, the application of MBSE to AI systems for specific design problems and case studies is beyond the scope of this paper.

This paper discusses the roles that AI technology can play in system design processes, highlighting the improvements it can bring to areas such as MBSE, MDAO, and DT applications. Based on the current state of AI technology, it further elaborates on how high-dimensional system architectures can be applied effectively across different stages of the system lifecycle.

This paper defines the application of AI in system design and explores how AI can be applied to different aspects of the system lifecycle. It addresses AI's roles in various stages, such as the MBSE model in the conceptual phase, the MDAO model in the design phase, and the DT model in the operational phase. The paper provides a definition of AI's role in these stages and presents an extendable AI supported framework that supports the interaction and integration of these three domains across the lifecycle. This framework ensures digital continuity in system design solutions throughout different stages of the lifecycle.

2 STATE OF THE ART

2.1 Artificial Intelligence

AI technology is increasingly being introduced into the automotive industry to support the product design process and address the challenges posed by growing product complexity. Machine Learning (ML) is a subset of AI, where machines learn from data to perform pattern recognition, prediction, and decision-making without explicit programming. ML provides solutions for many complex fields and drives the application of AI.

One of the most popular ML algorithms today is Deep Learning (DL), where the ML model consists of an Artificial Neural Network (ANN) (Ian et al., 2017). These ANNs are widely used for tasks such as image recognition, natural language processing, and predictive analytics.

Reinforcement Learning (RL) is a semi-supervised learning model in which an agent continuously makes decisions and adjusts its actions through trial and error based on the environment's responses. The agent is the core component of the RL model, and it determines which actions to take based on a policy function (Sutton and Barto, 2018). Most RL algorithms can use an ANN, a method known as Deep Reinforcement Learning (DRL).

The goal of Transfer Learning (TL) is to leverage the knowledge of a pre-trained model to solve new but similar problems. This method can adapt the retrained model to a new problem by adding layers to the ANN (Wang and Chen, 2023). This approach significantly reduces the training time. TL is also a highly effective technique when there is limited data.

Progressive Learning (PL) is a form of TL. ML models in TL are gradually retrained to solve increasingly complex tasks. PL can significantly reduce training time and, consequently, decrease the required computational resources (Fayek et al., 2020).

The concept of advisor agents is a relatively new field, and new methodologies are still being explored. Advisor agents are trained agents that can support the training of a new primary agent. While agents and multi-agent systems have a long history as a major approach in distributed AI, the advisor agent framework represents a more recent advancement, offering a highly flexible architecture. The number of advisor agents and their interactions with the primary agent can be determined by the engineer (Zhang et al. 2021).

Surrogate models are widely used in optimization and engineering design, aiming to accelerate the computational process by replacing high computational cost models with simpler or less computationally expensive ones (Hao et al., 2022). Surrogate models can also be created using supervised ML algorithms. These ML models attempt to identify certain trends in large amounts of training data. When the trends generated by the underlying high-fidelity simulations are too complex, ML algorithms based on ANN can be selected.

2.2 AI and MBSE

International Council on Systems Engineering (INCOSE) has initiated two key initiatives, AI4MBSE and MBSE4AI, that explore the integration of AI with MBSE. AI4MBSE focuses on leveraging AI technologies to enhance MBSE processes, improving aspects such as system modelling, requirements analysis, and design optimization. This initiative aims to make MBSE more efficient and adaptive through the application of AI. On the other hand, MBSE4AI examines how MBSE methodologies can be used to support and improve AI systems, especially in terms of model validation, integration, and lifecycle management. Together, these initiatives aim to bridge the gap between AI and MBSE, creating a synergy that can optimize system engineering processes and enable smarter, more robust system designs.

2.2.1 MBSE4AI

Future system operations increasingly require the integration and interoperability of multiple intelligent systems driven by AI, which has become a core element of the system, spanning the entire system lifecycle. (Raz et al., 2021) discussed the challenges faced by AI-driven aerospace systems in systems engineering activities. To develop and implement AI to meet the conceptual design needs of aerospace systems, AI will be designed as one of the primary functional elements. To train and develop AI models, the system design process may undergo corresponding modifications, such as the AI pipeline (Blasch and Pokines, 2019). In this process, they propose Systems Engineering as Data Curator for AI to address challenges such as the availability of data, the type of data, and the role of SE. Data architecture is added to the MBSE model to establish relationships with operational concepts, functional architecture, physical architecture, and so on, to ensure that MBSE supports the overall R&D process of integrating AI systems.

AI systems also have varying degrees of intelligence. (Torkjazi and Raz, 2024) based on the steps of the Object-Oriented Systems Engineering Method (OOSEM), utilized the Unified Architecture Framework (UAF) to model autonomy integration. They modelled autonomous systems through SE technical processes. To reflect the differences in autonomy between systems, they added accuracy Technical Performance Measures (TPMs) to the AI/ML components to assess different system solutions.

A MBSE-Enhanced Long Short-Term Memory (LSTM) Framework has been provided for Satellite System Reliability and Failure Prediction, which offers a case study on how MBSE can support the design of AI-integrated systems (Alandihallaj et al., 2024). The framework describes the predictive system architecture using LSTM networks, an AI technique, through the MBSE model. The integration of AI with MBSE, as demonstrated in this study, shows significant potential in enhancing the reliability and longevity of satellite systems.

2.2.2 AI4MBSE

MBSE can be applied to support AI-integrated systems, and conversely, AI can also enhance and support the MBSE processes and activities. (Chami et al., 2022) focus on the challenges faced by MBSE at different stages of its application and analyse the capabilities AI can offer and how these can be allocated to address the corresponding MBSE challenges. The paper provides an outlook on how AI can support MBSE, relevant research has already been conducted in different fields for specific research questions.

The first capability of AI applied to MBSE is ensuring data extraction for MBSE. MBSE models can establish traceability management between requirements and system design solutions. With the application of NLP-based models, research and applications for converting natural language into machine-readable language are becoming increasingly diverse.

Standard documents, as an important source of requirements in various fields, serve as one of the key references for requirement engineers in requirement extraction. (Ghanawi et al., 2024) contribute to the integration of AI with MBSE, focusing solely on the extraction and transformation of medical standards information from documents into SysML norm models. They employed an open-source multimodal classifier model and a proprietary Large Language Model (LLM) to achieve this goal. Although the title retrieval performed well in terms of recall across different approaches, the precision was generally low. Future improvements to the proprietary AI model are needed to achieve better results, but this may increase the training and subsequent usage costs.

(Chen et al., 2022) proposed an NLP-based framework for information extraction under the general condition that can automatically detect the actors and their responsible actions. To validate the performance of the developed model, the study compared the NLP-generated report with the manually created SysML model. The results showed that the precision and recall rates for extracting roles and responsibilities were 0.86 and 0.66, respectively, indicating that this text-to-model framework has the potential to accurately convert general policy documents into SysML.

(Chami et al., 2019) also utilized NLP techniques to train a Named Entity Recognition (NER) model. However, their objective extended beyond just extracting requirements, stakeholder roles, and responsibilities. Their scope included identifying system actors, use cases, associations, and blocks, aiming to use AI technologies to generate parts of SysML models from text. This approach allows the model to be trained through label annotation, enabling semi-structured text to be converted into SysML model entities with minimal training effort.

In addition to research on the automated supplementation and transformation of requirement models in MBSE using AI, another emerging trend is leveraging AI technology to enable the automatic generation of system design solutions or provide design references. Prior to the application of AI technology, rule-based generative design methods and tools already existed in various disciplines. These design tools often address specific disciplinary problems, enabling rapid design space exploration and generating many solutions that meet specified requirements.

With the application of AI and ML technologies, data-driven generative techniques have also advanced. (Zhang et al. 2021) proposed an MBSE modeling process recommendation method based on domain knowledge and SysML models by using a Global Vectors for Word Representation (GLOVE) model pre-trained on both domain-specific and general knowledge, combined with the concept of a recommendation system. This method not only considers the influence of general and domain-specific knowledge on the modeling process but also utilizes SysML models as training data to provide recommendations for subsequent modeling. These recommendations are generated based on textual training and proposed as suggested solutions derived from the knowledge. The information structure that a SysML model can encompass is closely related to the data structure of the knowledge base.

For MBSE models, in addition to the logical architecture used to describe the composition of the system, the system architecture also includes other types of information such as system requirements and interfaces. To cover all the information in a SysML model, it is necessary to continuously refine the data structure of the knowledge base, which will also impose higher demands on the methods and costs of data training.

The emergence of LLM, such as OpenAI's GPT series, has brought significant opportunities for transformation across multiple domains, driving industry professionals to explore their potential applications. (Johns et al., 2024) integrated OpenAI's GPT-4 Turbo with CATIA Magic for MBSE, creating the AI Systems Modeling Enhancer (AI-SME) to generate MBSE models. Compared to the time required for human modeling, AI-SME offers significant advantages. The results demonstrate that the requirements, structural, and interface definitions created by AI-SME maintain coherence and consistency, but they are not complete. AI-SME can serve as a modeling assistant to automate primary tasks and improve the efficiency of prototype architectural development.

AI algorithms can also solve specific design problems. (Rudolph, 2024) introduced AI methods using three artificial intelligence search algorithms

(PMSO, SA, and A*) to automate packing, piping, and routing for arbitrarily complex 3D CAD geometries. Packing, piping, and routing problems are considered NP-complete problems. Models in these specific disciplines often have higher confidence but also require greater computational power. In the field of MBSE, multidisciplinary problems are often encountered, and solving these problems typically requires integration, verification, and validation. Solving NP problems in individual disciplines is a prerequisite for ensuring the efficiency of integration and verification.

2.3 AI and MDAO

Multidisciplinary Design Analysis and Optimization (MDAO) is a methodology used for designing complex engineering systems. During this process, there is a need to integrate multidisciplinary analysis models, which include many design variables, objective functions, and state variables arising from coupling relationships. These models exhibit high complexity in both structure and processes. (Karali et al., 2024) proposed an AI-driven multidisciplinary conceptual design framework for UAVs to ensure the MDAO process. They employed AI-based surrogate models, using Latin Hypercube Sampling (LHS) to optimize the design space exploration process, NN (neural networks) for black-box model training, and genetic algorithms to search for optimal solutions along the Pareto front. By introducing and implementing this intelligent conceptual design algorithm, numerical data can be incorporated into the early stages of the design process, significantly reducing reliance on manual intervention.

In addition to optimizing the MDAO process through AI, AI technologies are also applied to address specific challenges arising from multidisciplinary interactions, improving the efficiency of MDAO analysis while ensuring the accuracy of results. For example, (Wang et al., 2023) leveraged AI technologies to tackle challenges associated with Uncertainty-based Multidisciplinary Design Optimization (UMDO). In this process, data is first processed using unsupervised learning for clustering analysis and dimensionality reduction. Subsequently, supervised learning is employed to train disciplinary models using pre-prepared datasets to reduce computational costs. Finally, evolutionary algorithms such as genetic algorithms are used to search for optimal solutions.

In addition to optimizing the MDAO process and improving solution efficiency, the integration of AI technologies also provides new methods for surrogate model generation. (Sisk et al., 2023) utilized generative adversarial networks (GANs) to establish a training framework for model generation, addressing the challenges of urban air mobility (UAM). This training framework is like the XDSM structure commonly used in MDAO. By training flight trajectories through a twin generator and combining the generated model data with Deep Neural Network (DNN) methods, surrogate models are trained. These generated surrogate models can then be re-applied in the MDAO process.

2.4 AI and DT

DT refers to the virtual representation of a physical system that is connected in real-time to enable monitoring, prediction, and optimization. The development of AI technologies has significantly contributed to the application of DT by providing data-driven solutions. The process of constructing a DT is highly complex, and it varies depending on the application purpose and the selected technologies. (Orlova, 2022) conducted a comprehensive analysis of the design methods for DT of organizational and technical systems, defining the various stages of DT development as well as the relevant technologies that can be applied during the Design and Engineering phase. However, for complex organizational and technical systems operating under conditions of uncertainty, there is currently no comprehensive and universal methodological approach to address these challenges.

Although current trends suggest that DT will be entirely controlled by AI, as with the integration of AI and MBSE, DT and AI influence each other mutually. (Bariah et al., 2024) explored the interrelationship between AI and DT in practical applications. On one hand, TL in AI can be used to address network updates in distributed DT, thereby reducing the training time required for model updates. On the other hand, leveraging communication technologies, DT can provide experience-driven learning methods and integrate model-based learning approaches, such as DT-enabled RL methods, to enhance reasoning capabilities in AI algorithms. This approach achieves a complementary combination of data-driven and model-driven methods, leveraging the advantages of both.

(Groshev et al., 2021) applied DT to Cyber-Physical Systems (CPS) by defining AI agents and provided the allocation relationships between applications, AI technologies, and physical devices. The AI agents were used for functional and infrastructure applications, with detailed definitions of their usable input data and expected output data. The research results demonstrated that DT applications employing AI agents can effectively predict system dynamics. AI agents offer significant opportunities to enhance the reliability, robustness, and performance of DT.

As an application model during the system operation phase, the DT model has stricter requirements for computation time and, like simulation analysis models, faces NP problems. (Karali et al., 2023) developed a data generation algorithm, which includes high-fidelity models based on Computational Fluid Dynamics (CFD) methods and low-fidelity models based on computational aerodynamics methods. Then, using multi-fidelity data, they generated a new surrogate model based on TL. Thanks to this approach, the developed AI model can use data from lower-fidelity models to more accurately predict missing flow conditions in the high-fidelity data.

2.5 AI and Digital Continuity

Digital Continuity refers to the ability to ensure that all digital information remains consistent, accessible, understandable, and usable throughout the entire product lifecycle or business process (Ren et al., 2020). We mentioned the support of AI for MBSE, MDAO, and DT, which are situated at different stages of the system lifecycle. Various fields have also analysed the advantages and challenges brought by the integration of these processes. The integration of design activities at different stages of the system lifecycle has also introduced the issue of digital continuity.

2.5.1 Interaction Across Lifecycle Stages

MBSE is an effective approach for demonstrating multidisciplinary coupling relationships needed to meet specific requirements. By integrating MBSE with MDAO, it is possible to improve system architecting, streamline the development of agile MDAO design systems, to trace analysis results back to the corresponding requirements, revealing implicit relationships between different requirements that arise from the solution domain. (Fouda et al., 2024) proposed a novel MBSE-driven MDAO process design and implementation method to address the wing shape optimization problem. By establishing a metamodel of the MDAO process within the MBSE model environment, data consistency is ensured. The MDAO process is described using MBSE, which in turn drives multidisciplinary simulations. The integration of MBSE and MDAO provides significant flexibility in adapting to changing requirements, while also improving the traceability of design decisions throughout the product development lifecycle.

(Wu et al., 2022) proposed a new multidisciplinary collaborative design method supported by DT. To describe complex products in a virtual environment, they further developed a systematized multidisciplinary collaborative design framework based on DT, integrating multidisciplinary collaboration into three stages: conceptual design, detailed design, and virtual validation. By utilizing DT for parallel design across different disciplines within the virtual environment, this approach can reduce anomalies caused by multidisciplinary integration. Although this multidisciplinary integrated design method does not directly employ AI technologies, it reveals that the same disciplinary problems can be described using both model-driven and data-driven methods, such as DT models. This provides the potential for iterative optimization between detailed design models and DT models, as well as a foundation for integrating AI technologies.

The integration of MBSE and DTs has also seen significant development in various fields. For example, (Lopez and Akundi, 2022) have explored the use of MBSE in the development process of DT. (Bordeleau et al., 2020) research demonstrates that MBSE can manage heterogeneous models from different disciplines. MBSE models include the relationships between system components, enabling the driving of other design processes and providing a foundation for multidisciplinary simulation. However, challenges exist regarding the accuracy and sources of analysis models driven by MBSE, which DT can address. (Purohit and Madni., 2022) developed a DT prototype and obtained experimental results, collecting data from physical systems in the real world to update the DT model, enhancing operational analysis and modelling. DT models are also seen as an important application in supporting V&V processes. By incorporating DT into MBSE models, significantly reduced the time required for early-stage V&V (Bouhali et al., 2024). (Madni et al., 2019) have also considered DT technology as an integral part of MBSE methodology and experimentation testbeds.

2.5.2 Ai Integration

According to current research, systematic methods to ensure digital continuity throughout the system's lifecycle are still under exploration. The introduction of AI technologies has also brought new capabilities to address this issue.

(Erikstad) explored whether LLM, particularly multi-agent LLM, can be combined with MBSE principles to address the high development costs and potential errors of optimization and simulation models. The system to be optimized is captured as classes and instances to serve as the syntax for the narrative-to-model mapping, while the MBSE models and views become the grammar. In the article, ChatGPT is used to directly create different AI agents, each of which can be considered as directly replacing the corresponding designer roles. The deliverables produced by these agents interact based on business processes and roles, thus achieving a complete design process. According to the research findings, the team of agents can complete the work and collaboratively develop solutions through autonomous coordination of processes. However, further in-depth research is needed to determine to what extent the capabilities and specialization of each agent should be enhanced.

(Scott et al., 2016) proposed another use of agents, where a typed database is used as a knowledge representation to create agents that utilize AI techniques. These agents can check the quality of information and provide feedback, integrated within the tools of the lifecycle chain. This improves process quality and helps with design activities.

2.6 Discussion

This paper aims at supporting activities across different lifecycle stages of a system engineering using AI technology, such as the digital continuity between MBSE, MDAO, and DT. The application of AI across various topics effectively demonstrates the fundamental capabilities of AI and the challenges faced within each topic, while also providing a foundation for the digital continuity of activities at different lifecycle stages. By integrating AI to ensure digital continuity, it further advances the role of MBSE throughout the system's lifecycle.

3 PROPOSED FRAMEWORKS

3.1 Roles of AI

For each system life cycle process, an Input-Process-Output (IPO) diagram can illustrate the typical inputs, process activities, and typical outputs, as shown in Figure 1. Additionally, each activity includes controls and enablers. We aim to use this format to classify and define the capabilities AI can provide during the system design process, allowing us to better position AI within the entire life cycle.

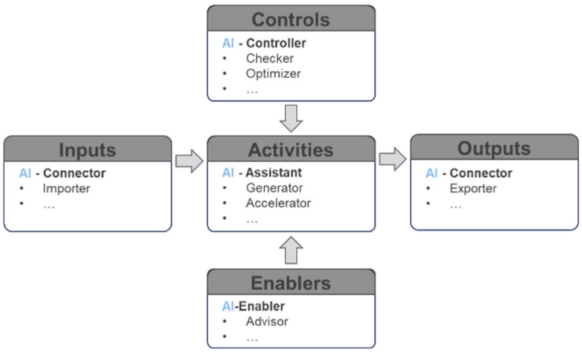

Figure 1: Roles of AI in IPO diagram.

The AI-Connector functions at the input and output ends of each process activity, ensuring data continuity and simplifying data extraction processes through AI algorithms, such as natural language extraction and output. This category includes two roles: importer and exporter. These two roles may overlap from the perspective of different processes, as the exporter of the previous process can also serve as the importer for the next process.

- Importer: Serves as the input for data, ensuring that the current activity has all the necessary inputs to initiate.
- Exporter: Serves as the output for data, ensuring the continuity and consistency of output data.

The AI-Assistant operates within each design process and aims to assist staff in design activities using AI technology, enhancing work efficiency and quality. This category includes two roles: generator and accelerator.

- Generator: Directly generates part of the design solution by providing multiple alternative or optimal solutions based on given inputs and the current context.
- Accelerator: Improves the efficiency and quality of solution generation.

The AI-Controller is used to inspect and optimize design activities to ensure the quality of the design process. It can extract existing design standards to verify design content and optimize results or provide optimization suggestions. This optimization can target individual design activities or support the optimization of multiple design activities. This category includes two roles: checker and optimizer.

- Checker: Inspects the content of design activities.
- Optimizer: Optimizes single or multiple design activities.

The AI-Enabler incorporates one or more methods to ensure the execution of design tasks, providing references for the design process. For AI-Enabler, this can be implemented through advisor agents.

3.2 AI in MBSE

In the MBSE process, we can utilize NLP models to establish the importer and exporter roles in the requirements management process. NLP models can extract relevant requirements from stakeholder needs and narratives, transforming them into requirements models. In this process, NLP or LLM can also serve as generators, assisting in the creation of requirements models. By training on standards and norms related to requirements definition, a checker can be established to automatically verify the syntax, semantic, and conflicts within the model.

Table 1: AI roles in MBSE.

Roles	Capabilities	Potential method
RM importer	Extract form needs	NLP, ML, DL
RM exporter	Transform requirements into MBSE model	NLP, KE
MBSE exporter	Transform from MBSE to MDAO	ML, NLP
Generator	Generate requirement model from text	NLP, DL, KE
	Generate behaviour from narrative	NLP, ML
	Generate model structure	RL, KE
Advisor	Provide references and alternatives	DL
Checker	Syntax and semantic review	NLP

After obtaining itemized requirements, ML models or NLP models can be used to automatically transform requirements into SysML use cases. Furthermore, using Knowledge Engineering (KE) and RL methods, existing requirements and solution data can be trained to automatically construct system architectures from requirements, functioning as a generator. During this process, checkers implemented using NLP methods for SysML syntax and grammar remain applicable.

Once the tasks within MBSE are completed, ML can be employed to transform specific MBSE information, such as the MDAO structure described by a parametric diagram, into the corresponding downstream design environment. To enable the smooth progression of the design process, an advisor can be implemented by adding LLM-based agents. Advisors share similar capabilities with generators, but specialized LLM training is more challenging, albeit more powerful. If the models generated by specialized LLM achieve a certain level of certification accuracy, these agents can also be applied as generators.

3.3 AI in MDAO

Table 2: AI roles in MDAO.

Roles	Capabilities	Potential method
Importer	Convert DSM	ML
Exporter	Transfer results	ML
	Transform SM	ML, RL
Accelera-tor	Enhance optimizer algorithm	RL, DL
Generator	Generate SM for analyzer	ML, RL, DL
Advisor	Provide references and solutions	DL

In the MDAO process, the importer can transform input content into the format required by the MDAO workflow, such as converting the Design Structure Matrix (DSM) defined in the MBSE model into a data structure usable within the optimization environment, while ensuring information completeness. During the simulation process, the accelerator enhances efficiency by replacing traditional optimization algorithms with RL, thereby speeding up analysis and optimization. The generator can leverage model order reduction methods, also referred to as a trainer, to train surrogate models using ML, reducing the computational cost of discipline-specific analysis models. At the end of the MDAO process, the exporter can transfer the resulting data back to the MBSE environment to verify whether the requirements have been met. It can also transform the generated surrogate models into the DT environment to support system operation. Similarly, the MDAO process can incorporate agents as advisors to provide recommendations for solving multidisciplinary problems.

3.4 AI in DT

In the context of DT, DT models are planned and developed during the design phase. As shown in table 3, they can also be formed during the operational phase in a data-driven manner to address emerging issues. An importer functions as a tool to transform models defined during the design phase into operational formats within the DT space. A generator in this process can also act as a model trainer, continuously iterating and updating the DT model using operational data through methods such as RL or TL. High-fidelity DT models can replace traditional discipline-specific analysis models and participate in MDAO simulation and analysis processes.

Table 3: AI roles in DT.

Roles	Capabilities	Potential method
Importer	Transform models in DT environment	ML
Exporter	Output DT models	ML
Generator	Train and upgrade DT	RL, TL

3.5 AI in Digital Continuity

This study aims to leverage AI technologies to support digital continuity, facilitating the integration of MBSE, MDAO, and DT. Beyond the roles that AI can play in enhancing process efficiency and quality within these workflows, this framework also emphasizes the contribution of AI in ensuring digital continuity throughout the system's lifecycle, the AI integrated framework is defined as shown in Figure 2.

From a methodological perspective, MBSE effectively describes the interactions between various components of the system, providing essential inputs for MDAO simulation structures. By ensuring digital continuity between MBSE and MDAO through AI, the establishment of MDAO simulation workflows can be made more efficient. During the MDAO process, AI can be used to generate lightweight, high-fidelity surrogate models, reducing the computational cost associated with integrated simulations. Furthermore, AI algorithms can accelerate the exploration of the design space, enabling the identification of optimal solutions in a shorter timeframe.

In the integration of MDAO and DTs, AI plays a critical role. Some DT applications during the operational phase are planned and developed during the design phase. By utilizing AI training techniques, surrogate models generated through MDAO can be applied to certain DT applications. Through ML methods such as TL, DT models can be continuously updated and optimized using the vast amounts of data generated during operation.

Models that represent the same object, such as surrogate models generated from simulation data and those developed from operational data, can contribute to beneficial iterations in system design. By leveraging operational data validated during runtime to refine the analyzers in MDAO simulations, the confidence in the models can be enhanced while maintaining computational efficiency. This also provides a new pathway for the reuse of historical data and digital artifacts to meet new business objectives during the system design process.

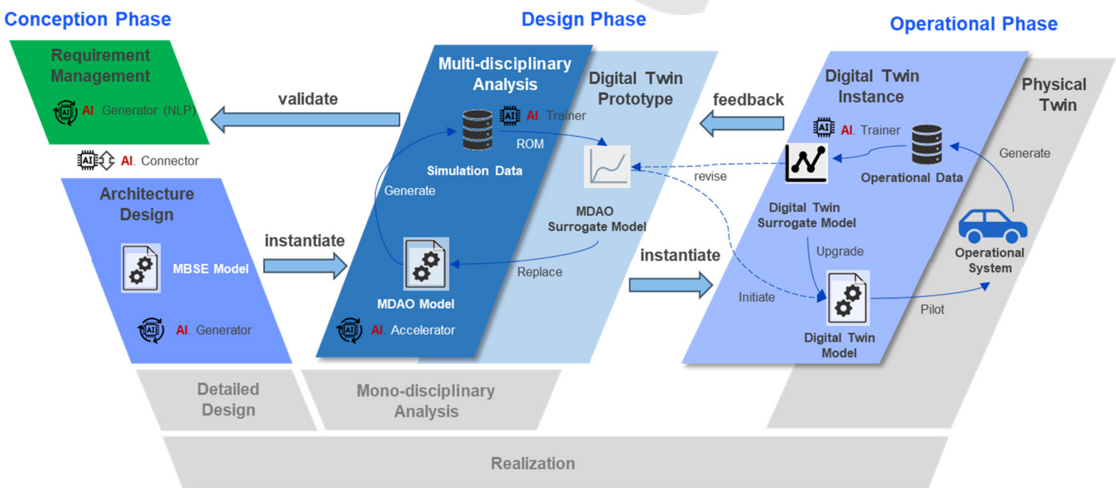

Figure 2: AI-Integrated Framework to support Digital Continuity.

4 CONCLUSIONS

Based on current development trends and the capabilities offered by AI, we proposed an AI-integrated digital continuity framework. This framework connects MBSE, MDAO, and DT, enabling the utilization of high-dimensional architectural design information across different stages of the system lifecycle, and establishes data feedback loops for subsequent processes in the traditional system lifecycle, such as detailed design and system operational data, offering new options to support early-stage design verification and validation.

Within this framework, we defined the roles that AI can play and the capabilities it provides. The AI-integrated digital continuity framework supports object-oriented design methods, offering a holistic methodology for the evolution and optimization of systems at different design stages.

In future work, we will apply AI algorithms to enhance the efficiency of each process while focusing on the practical value brought by this cross-lifecycle iterative design process in improving system design quality and efficiency, as well as uncovering opportunities for new solutions.

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