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Artificial Intelligence and Digital Engineering as Enablers for System Engineering in the Energy Sector

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Abstract

Systems engineering is of utmost importance for the success of high-cost, high-complexity megaprojects, which are common in the energy sector. However, the traditional document-centric systems engineering approach tends to be labor-intensive and time-consuming, which has inhibited its full adoption despite proven metrics on its return on investment. With the modern approach of digital engineering and advancements in artificial intelligence (AI) technologies, the barriers to systems engineering adoption can finally be broken. This paper goes through the systems engineering V-model for lifecycle management and assesses the current state of implementation of digital engineering (especially, model-based systems engineering, digital twins, and digital threads) and AI for each step. It was observed that a combination of digital engineering and AI is being used across different industries to accelerate and optimize systems engineering processes such as concept development, requirements management, architecture definition, system development, verification and validation, operations, and maintenance. Specifically in the energy sector, AI-augmented digital engineering has shown initial potential in accelerated development and deployment, performance optimization, anomaly detection, predictive maintenance, and configuration management. However, challenges remain in the safe and reliable integration of digital engineering and AI into an end-to-end system lifecycle management ecosystem. Addressing these challenges and continuously developing impactful tools will enable fast, efficient, and high-frequency deployment of power generation capabilities to keep up with the world's energy demands and build energy security.

Keywords

Systems engineering, digital engineering, artificial intelligence (AI), model-based systems engineering, digital twin, digital thread.

Introduction

In today's dynamic technological landscape, engineered systems are becoming increasingly complex and autonomous. The proliferated use of "intelligent" and interconnected machines, coupled with rapid in-novation across industries, has necessitated thoughtful design and adaptable operations. Now more than ever, systems engineering (SEBoK Editorial Board, 2024) is crucial for the end-to-end lifecycle management of engineered systems. Systems engineering is inherently transdisciplinary, as it seeks to integrate the disparate processes across the system lifecycle into a cohesive whole. The systems engineering process spans conceptualization through disposal. It includes tasks such as defining requirements, creating the system architecture, implementing deployment plans, verifying system performance, and tracking cost, schedule, and risks across the lifecycle. While integration has always been at the core of systems engineering, its implementation has traditionally relied on a high volume of documents of several different types. As a result, systems engineering has often been characterized as time-consuming and labor-intensive (Beasley, 2017), leading to reluctance in adopting it to the fullest extent despite proven metrics on its return on investment. However, with the modern approach of digital engineering and advancements in artificial intelligence (AI) technologies, the barriers to systems engineering adoption can finally be broken. This paper conducts a narrative state-of-the-art survey on how digital engineering and AI are facilitating systems engineering and explores opportunities for their combined application to the energy sector.

The Systems Engineering V-Model

The systems engineering process is often described using the "V-model," originally proposed by Forsberg & Mooz (1992). This representation illustrates not only the sequentially connected steps but also the traceability across the process. The left arm of the V represents the design phase, the base of the V represents implementation, and the right arm represents testing and evaluation, which includes verification ("building it right") and validation ("building the right thing"). Verification and validation (V&V) are traced to the design phase. The system is verified against the requirements to ensure all the design criteria are met and then validated against the conceptual design to ensure that it behaves as expected and performs all its functions correctly. Despite its two-dimensional depiction, the V-model was envisioned to be three-dimensional. According to Forsberg & Mooz, the third dimension is perpendicular to the plane of the paper and represents multiple Configuration Items (CIs) at each step of the system lifecycle. Figure 1 shows the Systems Engineering V-model (adapted from Federal Highway Administration, 2007).

Digital Engineering

Digital Engineering (DE) is an approach that uses digital models and data to represent all aspects of the system and serve as authoritative sources of truth throughout its lifecycle (Baldwin et al., 2018; Suprun & Elsawah, 2024). A core principle of digital engineering is the continuous integration of data across the system, thereby facilitating collaboration in multidisciplinary project teams. While there are various schools of thought on how to delineate the scope of digital engineering, the field may be perceived as the sum of the following three elements, as shown in Figure 2.

1. **Modeling and simulation:** Computer models form a foundational pillar of digital engineering. These models emulate and simulate various aspects of the system. For example, computer-aided design (CAD), Building Information Modeling (BIM), and other forms of three-dimensional modeling techniques enable the representation of structures, while physics-based numerical methods such as finite element analysis (FEA) and computational fluid dynamics (CFD) are used to analyze the system's behavior under various conditions.

   Model-based systems engineering, or **MBSE** (Madni & Sievers, 2018), is a subset of digital engineering that directly relates to systems engineering. MBSE leverages integrated digital models as the authoritative sources of truth for the end-to-end lifecycle management of large-scale systems. It is a broad concept encompassing several implementation methods (e.g., DoDAF, ARCADIA) (Estefan & Weilkiens, 2023), modeling languages (Unified Modeling Language, Systems Modeling Language) (De Saqui-Sannes et al., 2022), and software tools (e.g., MagicDraw, MATLAB/Simulink, Innoslate) (An MBSE Tools List for Systems Engineers, n.d.). MBSE has yielded positive results in several industries like automotive (Brenk et al., 2024; Góngora et al., 2012) and

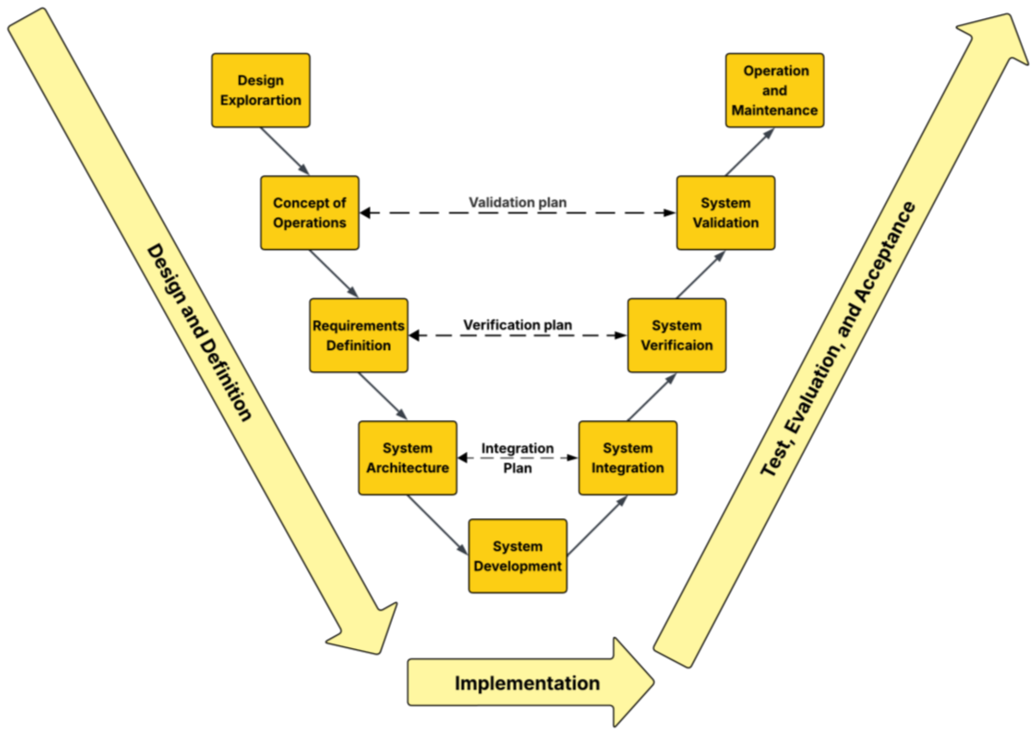

Figure 1. The systems engineering V-model for end-to-end system lifecycle management.

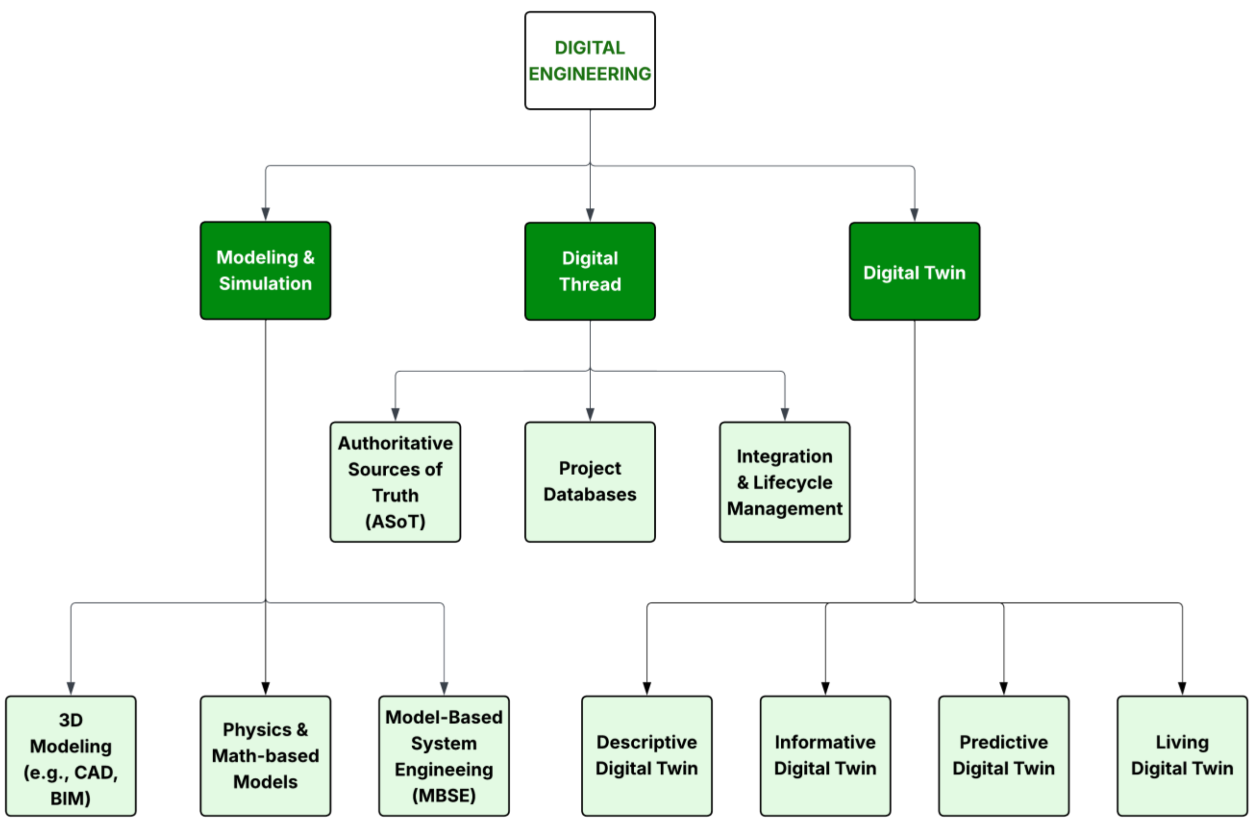

Figure 2. Hierarchical decomposition of digital engineering elements.

aerospace (Bayer, 2018; Malone et al., 2016; Simpson et al., 2012), where practitioners have noted advantages such as efficiency, improved communication and consistency, reduced costs, better analysis capability, and early error detection (Campo et al., 2023; Henderson & Salado, 2021). Integrated digital models can aid centralized requirements management, enhance collaborative system design, and enable simulations, risk and performance analysis, and system validation. Since all the teams contribute to the same model, errors or discrepancies can be detected early on, resulting in faster and cheaper projects (Carroll & Malins, 2016). Another advantage of this approach is the integration of various engineering domains (e.g., mechanical, electrical, thermal, and control) in a unified model. This allows modelers to capture the subsystem interdependencies, enabling multifaceted analysis under a range of operating conditions.

2. **Digital thread:** Digital thread (Dertien & Hastings, 2021; Gery, 2023) is another cornerstone of digital engineering. It may be defined as the information continuum across the lifecycle of a system or project. Different digital tools are often used to model different parts of the system across its lifecycle. For instance, a requirements management software may be used to specify system requirements, an MBSE tool may be used to define the architecture, and a finite element model may be used for structural analysis of some of the parts. Additionally, some system data may be sourced from digital databases created during the design and testing phase. Digital threads combine information from all the data sources associated with a system and ensure that they are connected in the correct order through the correct channels. The data comes directly from the original source where it was produced (authoritative sources of truth), thereby ensuring accuracy and minimizing errors. Digital threads enable efficient integration of multidisciplinary projects, ensure interoperability across systems, and facilitate seamless lifecycle management. They have been found to add value to several application areas, including manufacturing (Abdel-Aty & Negri, 2024; Bajaj & Hedberg Jr., 2018) and aerospace (Duverger et al., 2024; DXC Technology, 2021). Digital threads are created using commercial tools like PTC Windchill (Windchill PLM Software, n.d.) as well as niche in-house tools at individual organizations.

3. **Digital twin:** Digital twins (Grieves, 2023) can be defined as dynamic virtual representations of physical systems or processes. A twin is more than a computer model – it is connected to the physical asset and uses real-time data from sensors, actuators, and control devices for system monitoring, diagnostics, predictive analysis, or even live decision-making. Digital twins are being used in several industries and applications, including healthcare (Elayan et al., 2021; Vallée, 2023), manufacturing (Kritzinger et al., 2018; Soori et al., 2023), and urban planning (Austin et al., 2020; Schrotter & Hürzeler, 2020). Based on the developmental stage and capabilities, digital twins may be classified into the following types (Rasheed, 2022):

    - **Descriptive twin:** Aimed at understanding the system design and creating visual representations; can be used for design exploration, preliminary analysis, personnel training, and so on. In many cases, the descriptive twin may be created before a physical system exists, thus making it a digital twin prototype (Grieves & Vickers, 2017). For example, an interactive, data-rich 3D model of a nuclear power plant viewed in a mixed reality headset could be considered a descriptive twin.

    - Informative twin: Utilizes live data from the physical system to display system status, monitor its condition, and detect anomalies in real time. These can be used to track system health and inform maintenance decisions. For example, an informative digital twin of a nuclear power plant might use live sensor data to monitor current temperature and radiation levels at various locations.

- **Predictive twin:** Uses advanced methods like physics-based simulations, data-driven statistical models, and machine learning for predictive analysis of the future states of the system based on its current condition and operational history. Predictive twins can be valuable for early threat detection and operational strategy planning. For instance, a predictive twin of a nuclear power plant could estimate temperature and radiation levels a few minutes into the future based on live data and observed historical trends.
- **Living twin:** The most advanced version, where the digital model can be automatically updated to best represent the physical system, and multiple individual twins can be combined to form aggregates that represent a fleet or swarm. This can be used to optimize operations and improve the design in future iterations. For example, a living twin of a nuclear power plant would be able to fine-tune the predictive engine to minimize the error between the predicted and observed values.

A digital engineering ecosystem may be an amalgamation of some or all of the above-mentioned elements. These technologies can enable and facilitate each other to form a cohesive mechanism for lifecycle management, as shown in Figure 3.

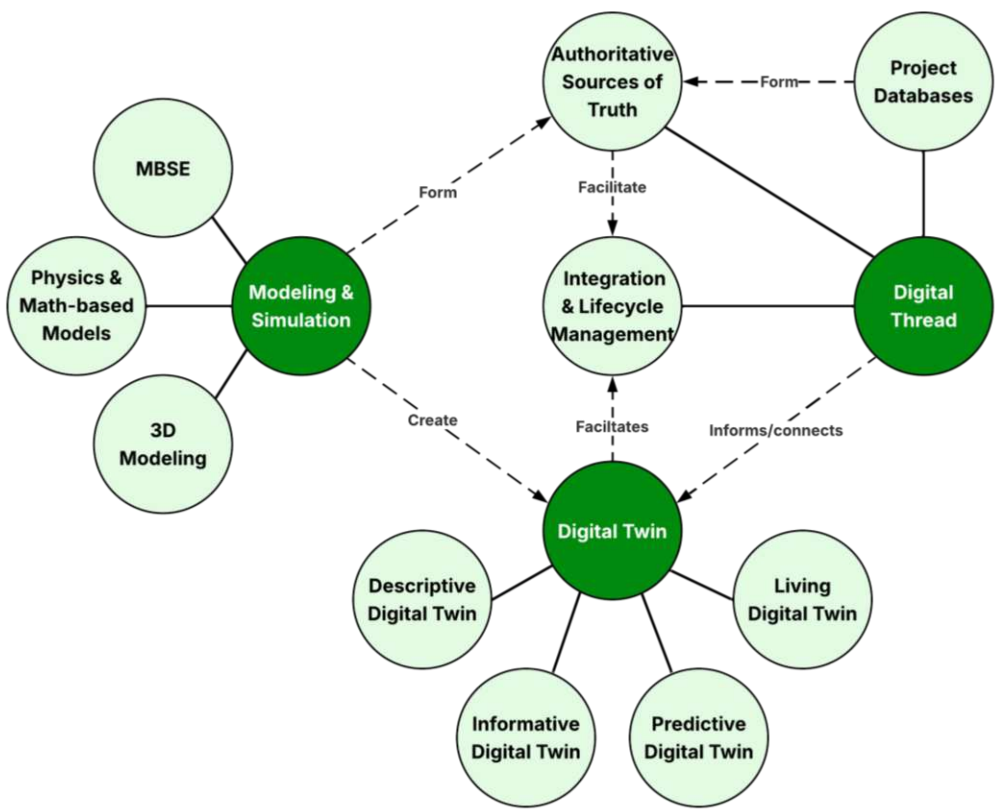

Figure 3. Interaction among the core digital engineering elements that contribute to integrated lifecycle management.

Artificial Intelligence

Artificial Intelligence (AI) encompasses technologies that enable machines to emulate cognitive functions typically associated with human intelligence, such as learning, language perception, and logical reasoning. While the concept of AI traces its origins to the 1950s (Haenlein & Kaplan, 2019), advancements in computational capabilities have catalyzed rapid progress in the field in the last decade. AI can be categorized (Types of Artificial Intelligence, 2023), based on capabilities (narrow AI, artificial general intelligence, and super AI) or functionalities (reactive machines, limited memory, theory of mind, self-aware AI). Over the years, AI has been used for various applications such as expert systems (rule-based logic for domain-specific applications), swarm intelligence (decentralized control, connected dynamics), and computer vision (object detection, facial recognition, etc.).

Most of the recent attention around AI has been directed at data-driven machine learning (ML) models, which are generally perceived as limited memory, narrow AI. ML (Alpaydin, 2021) is the most prominent subset of AI that enables computers to identify patterns in data and "learn" from them. This enables ML algorithms to execute tasks without needing to be explicitly programmed to do so. A few important concepts associated with ML are listed below.

- Supervised, unsupervised, and reinforcement learning are the three broad types of ML. Supervised learning uses structured, labeled data to train the model and is often used for regression (i.e., predicting continuous numerical variables) and classification (as-signing discrete categories input variables) applications. Unsupervised learning uses un-labeled data for model training and is useful for association (pattern recognition) and clustering (grouping data points based on similarity) tasks. A hybrid approach, semi-supervised learning, is often used for complex tasks. Reinforcement learning is an approach where the model learns through trial and error, continuously improving its performance through a feedback loop.

- Generative AI, or GenAI (Bengesi et al., 2024; Feuerriegel et al., 2024), is a subset of ML that can create various types of content, including text, images, and computer programs.

- Natural language processing, or NLP (Chowdhary, 2020), enables computers to interpret and generate human language. ML is used to train NLP models.

- Large language models, or LLMs (Shanahan, 2024), are trained on large amounts of da-ta, enabling them to understand natural language and generate various forms of content. LLMs are the basis for AI chatbots like OpenAI ChatGPT and Anthropic Claude.

AI, especially GenAI, is being used in many innovative ways in engineering, healthcare, finance, and other domains. In systems engineering, AI can be used to assess complex problems, accelerate tedious tasks, and optimize processes.

Systems Engineering Augmented by DE and AI

In many organizations, there has been a long-standing reluctance in, or even resistance to, the complete adoption of systems engineering due to the perceived complexity and cost of implementation (DiMario et al., 2021). With the emergence of digital engineering tools, systems engineering tasks can be accomplished quickly, with higher traceability and enhanced capabilities. This has encouraged many organizations, such as the U.S. Department of Defense, to adopt a systems engineering mindset (Bone et al., 2019; Noguchi et al., 2020; Zimmerman et al., 2019). Additionally, there is potential for ML to augment systems engineering processes through autonomous design, performance optimization, and configuration management (Adeyeye & Akanbi, 2024). Therefore, a combination of digital engineering and AI can enrich the systems engineering process, and enhance its rigor, and improve its efficacy.

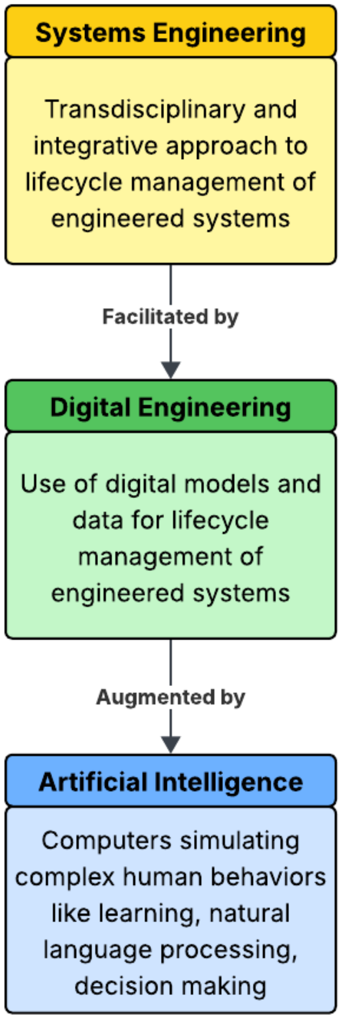

Figure 4. Digital engineering and AI as enablers for systems engineering.

The following subsections go through the systems engineering V-model and assess how digital engineering and AI are being used to accelerate the traditional systems engineering processes.

Project Assessment and Concept of Operations

The conceptualization phase of a system's lifecycle includes identification of stakeholder needs, system functions, and project constraints, followed by exploration of the feasible solutions. This leads to the concept of operations (ConOps), which is traditionally a document that describes the proposed system concept, preliminary design, and operational plan from the key stakeholders' perspective.

LLM tools can assist in this process. For example, Black (2024) used ChatGPT to evaluate project needs and transform them into process flows and tables, compile a list of stakeholders, and create product breakdown structures. Additionally, instead of a purely document-based approach, MBSE tools can be used for conceptual modeling in the early stages of the system lifecycle (Morris et al., 2016; London, 2012; Shoshany-Tavory et al., 2023; Anyanhun & Edmonson, 2018). A combination of AI and MBSE can accelerate design exploration, enable accurate stakeholder analysis, and accelerate the generation of ConOps. LLM-assisted conceptual model generation has been demonstrated by MITRE through their Systems Engineering Language Modeling Assistant (SELMA) tool (Gadewadikar et al., 2024). In a similar vein, NASA is developing an LLM-based multi-step tool to extract relevant system data from documents, knowledge graphs, databases, etc., and convert them to conceptual models using MBSE tools (VanGundy et al., 2024).

Requirements Definition

Definition and management of system requirements are crucial to the systems engineering process. The requirements, usually derived from stakeholder needs, specify the system's functions, design parameters, operational limits, expected performance, safety criteria, and so on. Well-defined requirements facilitate good system design and methodical verification. Unambiguous, actionable, and verifiable requirements help align the built system with the conceptual design. It is not uncommon for requirements to change over the system's lifecycle, especially during the development phase. Therefore, it is important to not only define good requirements but also manage any changes to the requirements and ensure they are reflected in the architecture and operations.

Requirement management tools like IBM DOORS (*IBM Engineering Requirements Management DOORS*, 2025) and Jama Connect (*Jama Connect*, n.d.) can be used to capture initial requirements, manage changes, integrate with modeling software or project management tools, and trace them across workflows, thus helping in digital thread implementation. While most MBSE tools can import requirements from requirement management tools, creation of the requirements is still primarily a manual process. Additionally, many organizations still use documents to define requirements, from which they are then copied to requirement management tools. The idea of model-based requirement engineering (B. London & Miotto, 2014; Inkermann et al., 2019) has generated some interest in the last decade, but its implementation has been sparse. However, ML and NLP are transforming the status quo. For example, requirement management tools like Jama (*Leveraging Artificial Intelligence in Requirements Management*, 2024) and MBSE tools like Innoslate (*Artificial Intelligence for MBSE*, n.d.) now include embedded NLP algorithms, which can automate requirement engineering tasks such as generating requirements from documents and other sources, assessing and improving the quality of requirements, dynamically tracing them to the corresponding system parameters, and analyzing the system-wide impact of requirement modifications. AI models have been used to identify similarities in the requirements of new systems and existing systems (Abbas et al., 2025), which can facilitate knowledge transfer and minimize rework. Motger & Franch (2025) have reviewed the use of NLP and ML-based methods to identify and extract relationships between pairs of requirements in complex systems. Requirement relation extraction can aid in the identification of interdependencies among different parts of the system. Arora et al., (2024) have explored the potential of LLMs in discovering "unknown" requirements, identifying inconsistencies or conflicts, and automatic quality assurance.

System Architecture

The architecture definition phase of the system's lifecycle converts the concept into a design. This is where the system's structure and functions are defined and decomposed. The structural architecture defines the hierarchical decomposition of the system into subsystems and components and identifies their interfaces. The functional architecture describes their functions and interactions.

Architecture definition is the most common application of MBSE (Lemazurier et al., 2017; Stirgwolt et al., 2022; Tepper, 2010). Specialized languages like System Modeling Language (SysML) and Unified Modeling Language (UML) include several types of diagrams to represent different views of the system's structure and functions, where the elements are connected through relationships and interfaces. As a result, models act as dynamic artifacts that can trace associations and dependencies across the system. This makes it easy to assess the impact of design modifications and identify weaknesses or vulnerabilities in the system architecture. Additionally, they can include various performance metrics and support simulations, thereby enabling system analysis, design evaluation, and optimization (Bussemaker et al., 2022; Ciampa & Nagel, 2021). Through the digital thread, system models can be linked to physics-based models, 3D models, or other artifacts (West & Pyster, 2015; David et al., 2021; Gery, 2023), which allows for real-time updates to system information directly derived from their source of truth. There is immense potential for machine learning to be used in system architecture definition. ML can be used to identify candidate architectures (Lin et al., 2023), iteratively optimize the system (Bucaioni et al., 2025), and auto-mate the connections across the digital thread (Xu et al., 2025). Additionally, AI-based tools can enrich other parts of the digital thread that connect to the system model. For example, AI-based tools for creating 3D models from text prompts (Lee et al., 2024) or autonomous risk assessment (Hegde & Rokseth, 2020) can accelerate the process of architecture definition and help in in-formed decision-making.

System Development and Integration

Once the architecture is finalized, it is used as a guide to build the system. System development can include construction, manufacturing, procurement, and installation for physical systems and programming various modules for cyber systems. All the individual elements must be integrated per the architecture to form the full system. In the traditional document-centric systems engineering approach, it is difficult to adapt to real-time challenges like component unavailability or natural disasters, often resulting in a negative impact on the project cost and schedule.

With digital engineering, the system models and associated artifacts can be updated throughout the lifecycle. This enables quick reassessment and dynamic decision-making. Moreover, the architecture model can evolve into a digital twin prototype (Lehner et al., 2024) in the developmental phase. Using a descriptive digital twin, various teams can collaborate in real time, ensure correct implementation of the system specifications at each step, and align their activities with the overall system-level goals (Douglas & Rios, 2019; Jiang et al., 2022; Sacks et al., 2020). For collaborative workspaces (e.g., construction and manufacturing), augmented reality (AR) can enable visualization of digital twins (Hossain, 2025; Schroeder et al., 2016; Tadeja et al., 2020), making it convenient to adhere to requirements, build systems as designed, and assess potential impacts before making any changes. AR-augmented descriptive digital twins can also be used to train technical operators on first-of-a-kind systems (Perno et al., 2025) and aid system design reviews. Various AI models can be used to improve and enhance the system development process. For example, AI-assisted AR is being used for smart manufacturing (Sahu et al., 2021), reinforcement learning algorithms are being used for production planning and quality control (Huang et al., 2021), NLP capabilities are accelerating procurement (Guida et al., 2023), and BIM-AI integration is transforming construction management (Pan & Zhang, 2023).

Verification and Validation

Verification and validation (V&V) are essential to the success of any system's development. This step ensures that all the requirements are fulfilled (verification) and the system performs its in-tended functions according to stakeholder needs (validation).

MBSE enables verification and validation as the systems are being conceptualized and designed (Cederbladh et al., 2024; Honcak & Wooley, 2024; Morkevicius et al., 2023). This facilitates early detection of errors and inconsistencies in the design phase, which can save the cost of correcting mistakes during deployment and operations (International Council on Systems Engineering, 2023). Many modeling and simulation tools offer test and evaluation capabilities for convenient V&V. For example, Simulink Test (Simulink Test, n.d.) allows users to create simulation-based test cases that can be used to verify specific requirements. The use of AI for automatic test case generation is gaining traction in software testing (Budnik et al., 2018; Olsthoorn, 2022), but there is an opportunity to expand this to other types of systems. LLMs can be used to parse text-based requirements and generate tests to verify them. Automated sequencing and execution of simulation-based tests under various operating conditions can facilitate holistic V&V and help create robust and resilient systems.

Operations and Maintenance

After the system is designed and tested to satisfaction, it is deployed for operation. The duration of the operational phase heavily depends on the type of system, ranging from a few minutes for missiles to decades for nuclear power plants. Systems with longer operational times require maintenance and upgrades for smooth operations.

In the operational phase of the system lifecycle, informative and predictive digital twins can have a tremendous impact. Digital twinning is driving innovation across several industries (Javaid et al., 2023; Singh et al., 2022). Informative twins are connected to the physical system and therefore have access to real-time operational data. When coupled with machine learning models (Huang et al., 2021; Minerva et al., 2023; Biller & Biller, 2023; Kreuzer et al., 2024), digital twins can enable real-time prognostics and diagnostics, predictive maintenance, anomaly detection, system optimization and multi-domain coordination. Twins can be designed to learn from operational data over time to identify possible areas of design improvement or risk reduction, which can inform hardware or software upgrades as well as design decisions for future systems. The inclusion of physics-based models in digital twins can expand their analytical capabilities. The data generated by high-fidelity models can be used to create reduced-order models or train data-driven ML models (Ritto & Rochinha, 2021; Srikonda et al., 2020), which can then be used by predictive digital twins for rapid, explainable insights.

Implementation in the Energy Sector

Energy systems are often highly complex and expensive. From nuclear power plants to integrated energy systems, megaprojects within the energy sector tend to suffer from cost and schedule overruns (Gilbert et al., 2017; Sovacool et al., 2014; Sovacool & Ryu, 2025), a sizeable fraction of which can be attributed to deficiencies in systems engineering and project management. AI-augmented digital engineering has the potential to bring about a paradigm shift in the lifecycle management of energy systems. Abdessadak et al. (2025) note that AI-powered digital twins for energy applications can result in a 35% reduction in unplanned downtime, an 8.5% increase in energy production, 98.3% accuracy in fault detection, and a 26.2% reduction in energy costs. Digital twins have been used for various energy applications, such as power generation, energy storage, grid optimization, and so on (do Amaral et al., 2023; Boreham, 2024; GE Vernova, n.d.). Aghazadeh Ardebili et al. (2024) emphasize the importance of data management and information continuum in their review of digital twins for energy applications. Well-designed data repositories and connected digital threads can facilitate multi-faceted analysis for safe and efficient design and operations. The benefits of digital engineering are amplified by the rapid adoption of artificial intelligence technologies within the energy sector (Karigiannis, 2025; Siemens, 2025; Honeywell, 2024).

An emerging field of interest is the symbiotic relationship between energy and AI. AI data centers are driving a surge in power demand (Goldman Sachs, 2025), which necessitates faster deployment and efficient operation of energy generation systems. Generative AI and machine learning can be used to optimize the design and operations of energy systems which will help increase the net energy output to meet the AI industry's rising power demands. The U.S. Department of Energy (DOE) has recently announced the Genesis Mission (Department of Energy, 2025), a national initiative to create an AI-powered platform for science, national security, and energy, including advanced nuclear energy applications, fusion power, and grid optimization. This is an evolution of prior efforts under which DOE national laboratories had identified five broad areas (Daniel et al., 2024) where AI has the potential to make a transformative impact – (i) nuclear energy, (ii) power grid, (iii) carbon management, (iv) energy storage, and (v) energy materials.

Several national laboratories are implementing AI in groundbreaking fundamental and applied research. For example, researchers at Oak Ridge National Laboratory (ORNL) have developed the AtomAI framework (Ziatdinov, Ghosh, Wong, & Kalinin, 2022) to analyze spectroscopy data. Chitturi et al. (2023) trained a machine learning platform to be able to obtain unknown parameters from experimental spectrographic measurements. At Lawrence Livermore National Laboratory (LLNL), Humbird and Peterson (2022) have applied transfer learning for inertial confinement fusion design optimization. At Los Alamos National Laboratory (LANL), Zhang et al. (2024) have developed a general reactive machine learning interatomic potential that matched simulated and experimental data for several elements in the condensed phase. Argonne National Laboratory's AI-NERD framework (Horwath et al., 2024) conducts unsupervised analysis of high data rate X-ray science experiments. Recent work at Pacific Northwest National Laboratory (PNNL) explores the use of vertical federated reinforcement learning for resilient control of microgrids (Mukherjee et al., 2024).

Additionally, DOE has funded several digital engineering efforts across its national laboratories. For example, a collaboration between PNNL and ORNL aims at creating digital twins for hydropower systems (Peckham, 2025). Liu et al. (2024) from

Argonne National Laboratory (ANL) developed a Graph Neural Network-based methodology to create digital twins of advanced reactors. Sandia National Laboratories (SNL) created a digital engineering ecosystem (Sandia National Laboratories, 2024) for the lifecycle management of national security projects.

Idaho National Laboratory (INL) is advancing the use of both digital engineering and AI to develop and demonstrate innovative energy solutions, accelerate their deployment, and maintain safe operations. INL researchers contributed to the demonstration of the first nuclear reactor digital twin (Goff, 2023) where machine learning was leveraged for anomaly detection (Stewart et al., 2025; Treviño et al., 2025). For the Virtual Test Reactor project, the use of digital engineering tools led to the development of a 3D model within the first 3 months, which is nearly 10 times faster than past projects of comparable scale (Ritter & Rhoades, 2023). Digital engineering has been applied to several other projects, such as testbeds for microreactors (Browning et al., 2022) and nuclear materials (Houck et al., 2022). These efforts are enabled by INL's DeepLynx data warehouse (*Deep-Lynx*, 2020/2025). Additionally, advancements in immersive visualization (Khadka & Koudelka, 2023), multi-physics simulation (*MOOSE*, 2014/2025), and high-performance computing (Whiting, 2020) have enhanced and expanded the capabilities of digital twins at INL.

Parallelly, the laboratory is applying artificial intelligence to various energy use cases. For example, research is underway to integrate control methods (including AI/ML-based control) with digital twins for advanced nuclear reactors (Al Rashdan et al., 2022). Since nuclear operations are highly sensitive, there is a conscious focus on human factors and explainability (Hall et al., 2024). MIRACLE (*MIRACLE: Machine Learning for Screening Nuclear Plant Conditions*, n.d.) is an ML-based application developed at INL for screening nuclear plant conditions. Like digital engineering, ML is being utilized for a plethora of applications, including thermal assessment of experimental nuclear reactor probes (Kajihara et al., 2024), prediction of battery performance (Kunz et al., 2021), and revenue prediction for integrated energy systems (Lin et al., 2022).

A few emerging areas of research across the DOE national laboratory ecosystem are autonomous design and autonomous operations of nuclear reactors and energy facilities. Under these thrust areas, the use of ML and GenAI is being explored for generating system architectures, designing various subsystems of nuclear power plants, exploring materials and structures, and identifying optimal designs for new reactors. Another focus area is the potential use of MBSE and AI for autonomous V&V and document generation from digital models and databases. This can accelerate licensing and regulatory processes, thereby reducing the time required for the deployment of new nuclear reactors. All these modern efforts in DE and AI are enabled by several decades of research and development in modeling and simulation methods, mathematics, statistics, data science, as well as high performance computing.

Challenges and Opportunities

Systems engineering is of utmost importance for the success of high-cost, high-complexity megaprojects, which are common in the energy sector. AI-augmented digital engineering has the potential to revolutionize these projects, accelerating their timeline, ensuring adherence to budget plans, and detecting deficiencies or errors before they cause disruptions. For example, nuclear power plants frequently face cost and schedule overruns during the design and construction phase. Stringent regulatory requirements can further add to the delays. Moreover, due to their long operational duration, they often suffer from inefficiencies due to outdated equipment and technologies. Systematic lifecycle management augmented by DE and AI can prevent most of these pitfalls and enable fast, efficient, high-frequency deployment of power generation capabilities to meet the energy demands of today's world. However, several challenges need to be addressed before fully integrating DE and AI into system lifecycle management. Some of the key issues are listed below.

- **Data security and intellectual property protection**: Complex energy systems often have multiple stakeholders who may own or operate different parts. These stakeholders may be unwilling to share their data, especially if they are related to sensitive areas like nuclear materials. Proprietary software and databases involve the additional challenge of intellectual property protection. As such, system integration through digital threads may not be feasible. Moreover, digital systems may be susceptible to cyberattacks targeting sensitive or proprietary information. Therefore, data compartmentalization and cybersecurity must be carefully considered when designing digital twins and digital threads.

- **Quality and reliability:** High-quality training data begets high-quality ML models. However, it is difficult to obtain reliable data in the energy sector, since many energy facilities are operated by private entities. Data related to nuclear reactors tends to be heavily protected, making it hard to train models. Moreover, LLMs are known to hallucinate (Perković et al., 2024) and generate unreliable results. Overall, results from AI tools are difficult to verify, which may result in a lack of trust in AI-augmented engineering processes. This can also have a negative impact on licensing and certification processes for novel energy systems. A few ways to mitigate this include incorporating explainable AI (Dwivedi et al., 2023) and using Retrieval-Augmented Generation (*What Is RAG?*, n.d.) to constrain and enhance LLMs.

- **Software integration and interoperability:** Digital threads are created by integrating models and data, often generated by multiple software tools. Many commercial tools are not inherently designed to be interoperable, making data transfer difficult. Proprietary file formats, data type incompatibility, lack of unified standards, and software version updates further add to the complexity of maintaining digital engineering ecosystems. For reusable, repeatable, and transferable digital twins, current efforts must be directed at not only building tools and models but also creating standards that facilitate interoperability and reusability.

- **Computational cost:** AI models and digital twins, especially those connected to physics-based models, can be computationally intensive. Real-time data integration relies on cloud infrastructure. AI-augmented digital engineering, especially with the incorporation of explainable AI, is expected to require massive computational resources and generate large amounts of data. As a result, complex digital twins may fail to maintain real-time synchronization with the physical system. This can lead to scalability issues for expandable systems like power grids and integrated energy systems. Reduced-order models and strategic data management can help overcome these hurdles.

- **Cultural transformation:** The shift from traditional, document-centric systems engineering to model-based and data-driven methods often elicits reluctance and skepticism from the engineering community. This may stem from skill gaps, unwillingness to adapt, fear of becoming irrelevant in the workforce, distrust toward new methodologies and technologies, or simply resistance to change. Cultural resistance to change is difficult to counter, but efforts must be made to ensure that the broader community understands the value of AI and digital engineering.

- **Knowledge transfer:** The stringent regulatory environment in some energy applications, coupled with data security concerns, can hinder the wider dissemination of tools and lessons learned. Without adequate knowledge transfer, the professional community remains unaware of the needs of the future, which may eventually lead to skill gaps in the workforce and add to the cultural resistance to digital transformation. For digital engineering implementation to be successful, it is important to adequately train the workforce, including developers who will build the tools and operators who will use them.

The value added by AI-augmented digital engineering to systems engineering in general and the energy sector in particular outweighs the challenges that need to be addressed. It is, therefore, a worthwhile investment to identify solutions to the abovementioned obstacles and ensure that the energy sector can safely transition to a digital, data-driven future. The combination of digital engineering and AI can help enforce good systems engineering practices in the energy sector, ensuring engineering rigor while accelerating the execution and deployment or delivery time for complex projects. This can lead to the deployment of new power generation capabilities at scale, on time, and within budget, enabling us to meet the growing energy needs of our species and make positive strides toward global energy security.

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Biography

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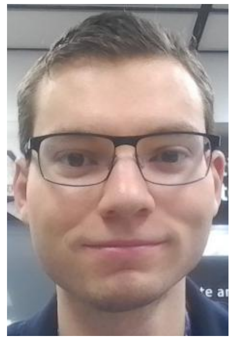

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