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Guest Editorial

Special Issue: Networks and Graphs for Engineering Systems and Design

1 Background and Motivation

The United States National Research Council defines network science as "*the study of network representations of physical, biological, and social phenomena leading to predictive models of these phenomena*" [1]. The modern chapter of network science emerged at the transition between the 20th and 21st centuries with two seminal works in 1998 and 1999, i.e., *Emergence of Scaling in Random Networks* and *Collective dynamics of "small-world" networks*, by Barabási and Albert [2] and Watts and Strogatz [3]. The former study found that a common property of many large networks is that their degree distribution (i.e., vertex connectivities) follows a scale-free power-law distribution. An important outcome of this study is the Barabási–Albert model, which can generate random scale-free networks using a preferential attachment mechanism [2]. This indicates that the development of large networks is governed by robust self-organizing phenomena that transcend the particulars of individual systems. The latter study discovered the famous "six degrees of separation" effect, which governs the hidden law in social networks. An important outcome of this study is the small-world model that can generate random networks with a high clustering coefficient and low distances. The high clustering coefficient implies a high probability that two neighboring nodes of a node are also neighbors themselves (e.g., two friends of one person are likely to be friends with each other). The low distances, on the other hand, mean that there is a short chain of social connections between any two people (that is, the six degrees of separation).

Since then, research in network science has experienced significant growth. Typical evidence is the explosive growth of citations to these papers, drawing a new and interdisciplinary audience. Indeed, the influence is huge. This is because the language of the network, with its nodes and links, offers a high level of abstraction, capable of representing a variety of systems. So, we see its application in almost every scientific field, ranging from biology [4] to social science [5], from business [6] to cosmology [7]. Yet, by no means is the concept of networks new. Graph theory, a prolific subfield of mathematics, has focused on networks since 1735. However, network science has become the science of the 21st century due to three driving forces: the Internet, the decreasing cost of data storage, and the exponential improvement in computing power. For example, with the advent of the Internet, disparate data were able to merge into a central database, offering the first opportunity for network scientists and engineers to explore the structure of networks behind systems. As quoted, "*In the past, we lacked the tools to map these networks. It was equally difficult to keep track of the huge amount of data behind them. The Internet revolution, offering effective and fast data sharing methods and cheap digital storage, fundamentally changed our ability to collect, assemble, share, and analyze data pertaining to real networks*" [8].

In the ever-evolving landscape of engineering, the fusion of network science has emerged as a dynamic force, revolutionizing the way we represent, design, model, and optimize complex systems [9]. Networks are particularly effective in modeling the interaction and interdependency among individual entities in complex engineered systems and have become the cornerstone for understanding the intricate relationships underlying a myriad of engineering domains. From transportation networks that optimize urban mobility to power grids that ensure energy efficiency and resilience, and from social networks that shape human interactions to biological networks that inspire human-engineered system design, the application of network science and graphs in engineering spans a broad spectrum of disciplines, just as its influence extends to nonengineering fields. In recent decades, several breakthroughs have been observed. For example, Albert et al. exposed the structural vulnerability of the North American power grid using graph theory [10]. By modeling the grid as a network of generators and transmission lines, they revealed that its small-world topology made it vulnerable to targeted attacks on highly connected hubs. In addition, network science has also redefined transportation engineering, as demonstrated by Porta et al. [11,12], who used dual graph representations to reveal how the topology of the street network governs the efficiency of urban mobility. Their approach enabled cities to optimize traffic flow by identifying and reinforcing critical high-centrality corridors. Moreover, network methods have emerged as powerful tools for architecting, governing, and enhancing the resilience of complex multiagent and sociotechnical systems. By strategically leveraging the network structure of agent-to-agent interactions, these methods facilitate more efficient resource allocation [13], improve system-level coordination, and guide the system along a robust recovery trajectory following disruptions [14].

Most recently, the rapid development of artificial intelligence (AI) and machine learning (ML) has advanced the integration of network science and graph theory, promoting a wider and deeper application and even a paradigm shift in engineering systems and design (ESD). One of the prominent developments is the graph neural network (GNN). GNNs leverage the fundamental principle that each node in a network is characterized by both its own features and the attributes of its neighboring nodes, which embed local topological information. This dual representation, commonly referred to as node embedding, enables a more comprehensive encoding of network structures. Once node representations are obtained, various downstream tasks, such as node, link, and graph classification or regression, as well as graph matching, can be effectively performed [15,16]. Due to their superior performance, GNNs have been widely adopted in ESD. For example, Zhang et al. [17] proposed a novel Conv-GCN model that integrates a graph convolutional network (GCN) with a three-dimensional convolutional neural network to improve the prediction of short-term traffic flow for subway passengers. Another key innovation is graph reinforcement learning (GRL), which combines graph mining with reinforcement learning to address tasks such as network pathfinding, node/link coloring, etc. In the ESD community, GRL has been widely applied, such as improving manufacturing system efficiency [18] and enhancing the safety and mobility performance of connected autonomous vehicle operations [19].

A more recent development is the integration of large language models (LLMs) with networks, which yields modeling techniques, such as Graph-based Generative Pre-trained Transformer (GraphGPT) and Graph-based Retrieval-Augmented Generation (GraphRAG). The fundamental objective of GraphGPT is to enhance LLMs' ability to understand and process graph-structured data, thereby improving their performance on graph-related tasks. It achieves this through a dual-stage instruction tuning process that first uses unlabeled graph structures to guide the model in understanding graph-specific knowledge and then fine-tunes the model on specific graph tasks, enhanced by chain-of-thought reasoning for step-by-step graph comprehension [20]. Because of this carefully designed training strategy, GraphGPT demonstrates powerful generalization and reasoning capabilities across both supervised and zero-shot graph learning tasks. These capabilities directly empower engineering applications: the same architecture that learns transferable patterns for unseen graph topologies (zero-shot) can (1) identify subtle defects in operational systems, while its ability to adapt supervised knowledge to new contexts allows it to (2) predict failures in novel designs. GraphRAG enhances query-focused summarization over large text corpora by integrating RAG with graph-based indexing. To address the limitations of traditional RAG in handling global queries, such as identifying overarching themes, it constructs an entity knowledge graph (KG) from source documents, enabling LLMs to generate more comprehensive and contextually relevant summaries [21]. Its efficient KG indexing makes it a powerful tool for fast retrieval and synthesis of multidomain knowledge for complex engineering systems, and also accurately summarizes system-wide behaviors or design trade-offs of ESD involving numerous entities and complicated relationships.

With the observation of these new advances, the guest editors are motivated to initiate a special issue dedicated to the topic of networks and graphs for the ESD community, aiming to promote the dissemination of knowledge related to complex networks in ESD research, while highlighting the latest advances at the intersection of network science, graph theory, AI/ML, and engineering.

2 Summary of Papers

This special issue has attracted community-wide attention and has finally accepted eight peer-reviewed articles for publication. The studies represent a variety of ESD applications ranging from manufacturing systems to supply chain networks, and from market systems to power networks. In what follows, we provide an overview of each paper and discuss the new network- or graph-based models the authors have developed.

The paper titled "Adaptive Network Intervention for Complex Systems: A Hierarchical Graph Reinforcement Learning Approach" by Heydari and Chen focuses on advancing the abilities of network-based governance for multiagent systems, which produces interaction patterns that naturally foster beneficial behaviors within the system. The approach is particularly valuable when direct control over individual decisions is impractical or undesirable and the strategic choices of the agents are influenced by their neighbors. The current challenges of network-based governance, complex and evolving agent dynamics, limited managerial authority, and the exponential growth of state and action spaces with the number of agents complicate its effective implementation. To address some of these challenges, the authors introduce a Hierarchical Graph Reinforcement Learning (HGRL) framework, which is GNN and reinforcement learning (RL)-based, to optimize network interventions in multiagent systems structured as dynamic networks. The work goes further to provide an in-depth demonstration of the value of understanding the impact of social learning in these contexts. A two-tier approach is proposed that first selects a node for intervention and then determines which links to add or remove around that node using GNNs and a hierarchical decision-making process. This method effectively reduces the action space, making the problem more tractable and enabling the framework to scale better compared to traditional flat reinforcement learning approaches. A novel hierarchical decomposition is used to simplify the complex task of network intervention and allows for more efficient policy learning. The integration of GNNs ensures that the framework can be generalized across various network topologies, enhancing its scalability and applicability to different real-world scenarios. Additionally, by acknowledging realistic constraints, such as limited managerial authority, the study adds real-life relevance. The empirical results demonstrate that HGRL consistently outperforms both Flat-RL and random strategies, particularly in larger networks and under varying levels of social learning, thereby underscoring the effectiveness of the hierarchical approach.

The paper titled "ReqNet and ReqSim: A Network and Semantic Similarity Dataset of Requirements from the Tree Structure of System Requirement Specifications" by Sahu, Rai, Wiecek, and Gorsich proposes a semiformal method to create a multipurpose requirement dataset that harnesses human knowledge in system requirement specification documents to facilitate the deployment of modern computing algorithms. The resultant dataset has three forms, all of which are openly available on GitHub, and is grounded by a tree structure. This work addresses the importance of clear and accurate requirements, which describe stakeholder needs for engineering systems and formalize the problem space, but a lack of a standardized requirement engineering dataset for use in machine learning. Challenges including system disclosure risks, meeting all ISO/IEC/IEEE 29148:2018 characteristics, the creative nature of the process, widespread usability, and the resource intensity of requirement annotation. Natural language processing and AI techniques are used to analyze the requirements and create a hierarchical tree structure that best supports network analysis techniques and from which a requirements dataset is created.

The paper titled "SafeZone*: A Graph-Based and Time-Optimal Cooperative 3D Printing Framework" by Stone, Ebert, Zhou, Akleman, Krishnamurthy, and Sha provides insights into cooperative 3D printing, a part of swarm manufacturing. The authors present SafeZone*, a collision-free and scalable cooperative 3D printing framework which improves multiprinter performance. The algorithm employed in SafeZone* combines Voronoi tessellation and graph coloring theory in a constrained optimization framework. The SafeZone* framework is validated using four robotic arm 3D printers operating in the same physical space. Of special interest to the ASME *JCISE* community is the algorithm's cosolving of the partitioning and scheduling problems via an integrated graph-based geometric-topological analysis. The SafeZone* framework results show that the framework is viable, scalable, and can reduce print time compared to more traditional cooperative 3D printing methods.

The paper "Demand Estimation for Evolving Products Considering Network Effects: A Networked Affinity Dynamics Model" by Walter, Paré, and Panchal, looks into the challenge of predicting how customer demand evolves in response to frequent product updates in rapidly changing markets. It employs a networked demand model that integrates decision field theory with social network dynamics to capture both individual decision-making and the influence of peers. This work extends traditional decision field theory frameworks by incorporating a consensus term that models how individuals' opinions converge through social interactions, as well as a dynamic decision threshold mechanism that accounts for transient update-induced engagement spikes. The model is validated through extensive simulation studies using stochastic block models that explore a variety of network configurations—ranging from equally sized populations with opposing preferences to more complex scenarios involving unequal population sizes and imbalanced product preferences. Moreover, the practical applicability of the model is demonstrated using real-world data from competing live-service video games. By effectively replicating observed transient surges in consumer engagement following product updates, the study offers valuable insights into the interplay between product design, social network structures, and dynamic consumer behavior. The paper provides a more nuanced and dynamic framework for predicting demand, with direct implications for optimal product release strategies and targeted marketing in competitive environments.

The paper titled "Network Analysis of Two-Stage Customer Decisions with Preference-Guided Market Segmentation" by Cui, Sun, Xiao, Sha, Koskinen, Contractor, and Chen demonstrates the importance of preference-guided segmentation in product design. A method is presented that uses Joint Correspondence Analysis to distinguish associations between customer attributes and preferred products. An Exponential Random Graph Model is applied to individual bipartite customer-product networks to compare product features that influence customer choices. Data from a consumer product survey are used to demonstrate the capabilities of the method. The case study shows that it is important to understand customer preferences at every decision stage which can be used to inform product design strategies. ASME *JCISE* readers will be particularly interested in how the method can be used to drive product design to ensure that diverse market needs are satisfied. The approach for identifying heterogeneous customer preferences in two-stage consideration-then-choice decision-making processes can better identify product attributes that play important roles in both the consideration stage and the choice stage. The approach is benchmarked against an existing model, which shows that the approach provides a practical interpretation of customer preferences as well as provides more accurate estimations of customers' considerations and choices.

The paper titled "Toward Early Design Modeling and Simulation of Distributed Situation Awareness" by Irshad and Hulse focuses on a unique problem, called situation awareness–the ability of operators to understand their environment and each other to achieve desired system functions. This is a key factor underlying the resilience of fully and partially autonomous systems, where operators (human and nonhuman agents) contribute to resilience by preventing, mitigating, and recovering from hazardous events. A system's situation awareness can be represented by a network of information elements where each agent within the system has a different view of this information network, and these views can change over time based on the goals and tasks performed. This paper proposes a framework to computationally simulate distributed situation awareness (DSA) via network representations to enable the study of operational resilience in complex engineered systems. This network representation can be used to understand DSA qualitatively and quantitatively through network theory, including the number of connections, node failure, and link failure. Also, because of the network representation, the proposed DSA modeling approach advances existing approaches, which analyze situation awareness-related constructs alone, by enabling the analysis of the dynamic interactions between DSA-related constructs and other system elements (e.g., software glitches and human error) and their effects on overall system behavior.

The paper titled "Unified System Modeling and Simulation via Constraint Hypergraphs" by Morris, Mocko, and Wagner describes the theory behind constraint hypergraphs: a novel modeling framework that can be used to universally represent and simulate complex systems. The authors are motivated to address the incompatibility issues that arise when dealing with multidomain system models, which are traditionally compiled from multiple frameworks, each based on a single domain. The incompatibilities between these frameworks prevent information from being shared, resulting in data silos, duplicate work, and knowledge gaps. In this study, a graph representation, specifically the constraint hypergraph, provides a universal modeling language and framework within which all model prescriptions can be expressed. The benefit of the graph representation is the ability to express the holistic behavior of a system and the relationships between system properties. Of special interest to the ASME *JCISE* community is that this work not only establishes what constraint hypergraphs are but also demonstrates how they can be used, with an example of an elevator lifting system, in representing uncertainties and computational cost in support of autonomous decision-making.

Finally, the paper titled "Decision-Centric Co-Design Exploration of Manufacturing Supply Networks for Resilience" by Baby, Mukundan, and Nellippallil presents a Co-Design Exploration of Manufacturing Supply Networks (MSNs) for Resilience framework to facilitate simultaneous consideration of conflicting network and group decisions in early-stage design exploration. In this study, MSN refers to a network of independent, interconnected enterprises that collaborate to physically produce and deliver products to customers. In this context, a "group" means a collection of all the enterprises that perform the same role in the MSN. The network-based framework offered several advantages, such as the ability to model multilevel system structures and the interaction between group decisions, managing disruptions, and visualizing and simultaneously exploring solution spaces. One uniqueness of this framework is that it integrates a combination of Preemptive (a rank of priority to reconcile conflicting decisions at different levels) and Archimedean (a weighted sum to aggregate different preferences for decisions at the same level) formulations with Resilience Index (representing network-level performance) and interpretable self-organizing map-based visualization to facilitate codesign exploration of MSNs. The ASME *JCISE* community will benefit from this study because the network-based decision-centric framework is generic and can be applied to many other complex systems with multilevel structures, which require design to be cooptimized across the levels.

3 Challenges and Closing Remarks

Despite the most recent advances, the use of network science and AI/ML in the engineering and design of complex systems is still challenging. This is manifested primarily in four aspects. At the end of this editorial, we would like to share our thoughts and visions with a broader *JCISE* community.

The first challenge is associated with the large and ever-increasing scale of modern complex systems, both in space and time, such as urban systems, transportation systems, and space exploration infrastructure. These systems are not only massive in size but also continuously expanding in complexity. For example, urban systems now integrate millions of IoT sensors and infrastructure networks, such as energy grids, generating petabytes of dynamic and heterogeneous data. Similarly, modern transportation systems integrate multiple modes of mobility, such as autonomous vehicles, ride-sharing platforms, high-speed rail, etc., requiring real-time coordination across vast networks. These systems must process exascale datasets with real-time constraints to optimize routing, minimize congestion, and enhance user experience. Traditional AI/ML and network science tools struggle to efficiently analyze these systems due to computational bottlenecks, data sparsity and noise, and dynamic growth of the system.

The second challenge is complex socio-technical interactions. Modern engineering systems increasingly integrate human behavior with technical infrastructure, creating complex interdependencies that introduce nonlinear and unpredictable dynamics to challenge traditional analysis. The paper titled "Toward Early Design Modeling and Simulation of Distributed Situation Awareness" by Irshad and Hulse showed a good example of how networks can help in this regard. Beyond the systems studied in this special issue, this challenge is exhibited in various complex sociotechnical systems. For example, in urban systems, the distribution of city services (technical system) interacts with the needs and political priorities of the community (social factors), often resulting in inequitable access or inefficient utilization. Two key limitations persist: (1) modeling difficulties: current models struggle to reconcile quantitative infrastructure metrics (e.g., facility placement efficiency) with qualitative social factors (e.g., community preferences), leading to suboptimal planning outcomes, and (2) lack of quantitative tools. Many sociotechnical studies are heavily based on qualitative methods, with few computational tools to validate the findings quantitatively. For example, in electric vehicle charging infrastructure, station placement and capacity planning must consider driver behaviors, such as preferred charging locations, willingness to detour, and sensitivity to wait times. However, many existing studies are based on user surveys or aggregated traffic data [22,23], making it challenging to capture fluctuations in demand for charging in real-time and behavioral adaptations. These qualitative analyses become particularly limiting when evaluating strategies such as dynamic pricing or reservation-based charging.

The third challenge involves managing uncertainties and sensitivities stemming from both human behaviors and emerging technologies, such as agentic AI. In shared mobility systems, for instance, user demand fluctuates dramatically with seasonal changes (peaking in favorable weather while declining during winter months) [24]. System designs that fail to account for these behavioral patterns often result in either resource underutilization or service shortages when demand suddenly shifts. Similarly, AI implementation in smart manufacturing introduces new forms of system sensitivity. For example, in smart factories, AI-driven production lines can enhance efficiency by dynamically optimizing processes in real time. However, this optimization may also introduce critical vulnerabilities, such as over-optimization fragility, where AI controllers eliminate all buffer capacity in pursuit of peak efficiency, leaving the system highly susceptible to supply chain disruptions.

The final challenge highlights the need for new bottom-up engineering and design approaches for modern complex systems. Complex systems (e.g., swarm robotics, distributed energy grids) feature *emergent behaviors* resulting from the interactions at the local level between individual entities in a decentralized and self-organizing manner. This challenges the traditional "V-model" of systems engineering, which relies on top-down controllability, although recent advances in Digital Twin pave the way for bottom-up AI-driven complex system development in sync with Digital Twin development [25] as part of a broader research push in Digital Twin [26]. A critical aspect of complex systems is that the statistically significant local connections of individual entities, embedding collective behaviors of entities, serve as crucial functional units, influencing global-level system performance. A paradigmatic example is the shared mobility network, such as bike-sharing systems. Compared to individual stations that only record users' rental and return behaviors, local service systems formed by several stations (e.g., a triangle of three stations) capture users' travel behaviors within the local network (e.g., a triangle transit). A better understanding of such a subsystem can help better probe into users' mobility patterns and local resource distribution, which are critical for the optimal decision-making of system engineers and operators. Similarly, microgrid communities self-organize through local energy trades, leading to emergent stability or cascading failures that cannot be fully understood through component-level analysis alone. To address this, network science must transition from a prescriptive, design-to-specification approach to an adaptive, learn-to-evolve paradigm. This shift requires advanced AI and machine learning techniques that integrate real-time graph learning with multiagent simulations to model and predict system dynamics more effectively.

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