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Neuro-symbolic Generative AI Assistant for System Design

Susmit Jha
SRI International
susmit.jha@sri.com

Sumit Kumar Jha
Florida International University
sjha@fiu.edu

Alvaro Velasquez
University of Colorado, Boulder
Alvaro.Velasquez@colorado.edu

***Abstract*—The design of complex cyber-physical systems involves balancing multiple, often conflicting performance objectives. In practice, some design requirements remain implicit, embedded in the intuition and expertise of seasoned designers who have worked on similar systems for years. These designers rely on their experience to explore a limited set of promising design candidates, evaluating or simulating them with detailed but computationally slow scientific models. The typical goal is to produce a diverse array of high-performing configurations that offer flexibility in trade-offs and avoid premature commitment to a specific design. In this invited talk, we describe an AI assistant that leverages neuro-symbolic machine learning to automate parts of the system design process. Our approach extends oracle-guided inductive synthesis by integrating a hierarchy of oracles, ranging from slow, detailed scientific models to faster but lower-fidelity deep neural network surrogates and symbolic rules. This approach accelerates design iterations, especially during early design phases. We employ deep generative models in the form of fine-tuned large language models to learn the valid design space, followed by joint exploration and optimization across this learned manifold. This allows the generation of a diverse set of optimal designs based on specified performance objectives.**

The automated design of systems has long been a goal of artificial intelligence (AI), with computer-aided design successfully applied in various fields, from microprocessors to software development [5], [13]. However, these successes are generally confined to domains [5], [13] where the design intent can be fully captured using complete and unambiguous specifications. Our focus is on the design of complex cyber-physical systems, such as ground or air vehicles, which pose unique challenges beyond the reach of traditional design automation methods.

First, the design process in these systems lacks adequate formalization and relies on a combination of explicit symbolic requirements, domain expertise, and data-driven insights informed by human intuition. Although the design space is vast, designers often have access to several examples of valid designs, created to meet different performance or functional goals. Using this knowledge, designers manually explore the design space to identify promising candidates. This design space exploration is accompanied with simultaneous refinement of requirements from high-level mission specification to gradually component-level specifications that can be implemented using software or hardware components.

Second, design space exploration in cyber-physical systems often involves complex multiphysics models [11], [14] that span various domains, such as mechanical, electrical, and fluid dynamics. These models are often non-differentiable, black-box, and proprietary, which limits the use of standard combinatorial search or gradient-based optimization techniques. As a result, minimizing the number of candidate designs evaluated during exploration becomes critical. Finding optimal designs with very evaluation relies heavily on the intuition and insight of human-experts. This also causes the emergence of design silos wherein different design houses rely heavily on prior design experience and make only minor modifications to minimize the number of iterations of design, evaluation, and improvement. As the designs have grown in complexity, this has led to further reduction in the extent of design space exploration.

Finally, the design process is typically incremental and involves optimizing multiple objectives [12]. Rather than simply finding one optimal design, designers aim to create a diverse set of high-performing designs that balance various objectives. This avoids premature commitment to a single design and allows flexibility for further refinement and integration when the overall requirements change or the environment in which the system has to operate evolves. Another need for adaptability comes from the maintenance of systems which might require replacing components and subsystems with no exact replica forcing other parts of the system to evolve to accomodate this change. This flexibility and adaptability is particularly crucial in systems that take years or even decades to build, and are in deployment for multiple decades.

In this invited talk, we present how a novel combination of generative AI models and formal methods can address these key challenges in system design achieving improved speed of design, flexibility of design to late changes in requirements and specifications, and ensuring the created design have high-assurance. Our proposed approach leverages a range of machine learning techniques, including exploration using oracle-guided inductive synthesis using surrogate models [3], [7], deep learning based likelihood-ratio estimation [4], robust surrogate models [1], out-of-distribution detection [8], [9], concept probing in foundation models [10], formal methods guided prompting of foundation models [6], and decision-procedures for design [15] to reduce reliance on human intuition, accelerate the scientific discovery of novel designs, and enhance both the quality and diversity of generated designs. We will use the design of aircrafts and our recently released dataset, AircraftVerse [2], of aircraft designs to illustrate the opportunities and limitations of neuro-symbolic design methods.

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