

Exploration of a Generative AI Assistant for Model-Based System Engineering (eGAIA4MBSE)

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ABSTRACT

Model-Based System Engineering (MBSE) has served as a formal model of systems engineering in terms of requirements, design, analysis, verification, and validation. This process is applied and updated throughout the lifecycle of a project. Such creative models provide the means to exchange information about the system. A consensus exists that the MBSE process has improved the systems engineering process especially when compared to the document-based approach. MBSE uses a form of XML called SysML to represent the MBSE model and a set of diagrams like UML diagrams used in the software development arena. MBSE has grown in use and expanded into other areas including simulation. This poster represents the ongoing work to incorporate and integrate avenues of Generative Artificial Intelligence (GenAI) into MBSE. GenAI has quickly reached a level of capability, maturity, and widespread use in recent years. The generation of content as well as supporting MBSE users in Development including the supporting SysML, positions GenAI to play an important role in the modelling with MBSE. Work is underway to explore how GenAI can generate the MBSE content and support the end user in providing crucial feedback on the rules and processes involved with MBSE while generating MBSE content. This work tends to show how GenAI along with RAG-based MBSE information can be incorporated into GenAI to serve as an AI agent which supports the development, validation, and documentation of said models. GenAI has been poised to be such an agent for this creative MBSE generation and user support in the systems engineering process. The application of GenAI with MBSE is still in the infant stages and this work seeks to explore the effectiveness of that integration.

Keywords: Generative artificial intelligence, Human systems integration, Systems engineering, Systems modelling language, Agent assistant

INTRODUCTION

As defined by the International Council on Systems Engineering (INCOSE), MBSE realizes a formal application in model form which incorporates requirements, design, analysis, verification and validation of a given system or system of systems. Just as important, the model and the process behind it can be utilized in the conceptual design phase as well as across all development cycles (Sampson, 2025; Hutchinson, 2020). MBSE utilizes domain models as a means for the exchange of information and moves away from the typical document-based information exchange (Douglass,

2016). Given these capabilities, the MBSE approach has been widely used in industries such as manufacturing, defence, aerospace, and transportation (Nauaer et al., 2026; Chen, 2018; Weiss et al., 2018; Hause, 2018). The model is described in systems modelling language (SysML) which is an open-source specification (Burger, 2014). SysML was designed to support systems engineering and is an extension of a subset found in the Unified Modelling Language (UML). MBSE has incorporated elements of the modelling and simulation to bring in more of software simulation in its processes (Gianni et al., 2014).

There are close to thirty (30) if not more MBSE-based tools or applications that have been developed since its inception in 2014. Many come from spin offs of UML tools. Some are very domain specific where others try to be generic in their approach to attract a variety of domain usages. These tools along with the structure of SysML and MBSE in general can be used to develop simple to very complicated models. The recent expansion of Generative AI tools has poised itself to be a powerful assistant to users of MBSE for model development and a guide to the various elements of SysML and structure to MBSE. Improvements to transform-based deep neural networks and the advancement of Large Language Models (LLMs) have provided a series of Generative AI tools which can generate, text, images, videos and other types of data. Interfaces to GenAI systems often provide a prompt-based interface which allows the end user to interact with the GenAI system in a natural manner with some caveats needed to help support the intricacies of these GenAI systems. Such systems have been used for software development, healthcare, art, writing, product design, finance, entertainment, video development, 3D models, and many more. The growth has been exponential when compared to other AI tools. Given this GenAI can be a natural fit as a human assistant as a guide and in the generation of MSBE models.

RELATED WORKS

Do MBSE systems exist that incorporate some form of Artificial Intelligence (AI) or end user support into their systems? Systems Strategies & Analysis (SSA) is a company trying to apply AI to MBSE in terms of supporting the requirements development and traceability process. More recently a book has been published (Rosenbert & Weilkiens, 2024) entitled “AI Assisted MBSE with SysML, An Integrated Systems/Software Approach”. The term AIM or AI Assisted MBSE is used to describe a process which is claimed to significantly accelerate systems and software engineering using AI. AI is used as a Subject Matter Expert (SME) and a code generation tool. The recognition is that software plays a significant role of the SysML Behaviour model. The goal of this approach is to also include the four known pillars of SysML which are Requirements, Structure, Behaviour, and Parametric modelling. The focus appears to be on the Behaviour model. Another company striving to incorporate AI into MBSE which is Spec Innovations with a tool called Innoslate. Innoslate is using AI for requirements quality checking and traceability. They also have produced an Intelligence View

dashboard which provide a summary score of how the developing model meets best practices. Innsolate is used for diagram generation, but it appears that this tool is still in development phase and has only been released as a trial application.

Research literature exists as a variety of authors have approached the topic of integrating Generative AI into the MBSE processes. Several works (Patel, Maheshwaran, & Santhya, 2024; Fuchs, Helmerich & Holland, 2024; Bourdon et al., 2025) examine the generation of requirements from unstructured documents based on a Natural Language Processing (NLP) model to provide a natural speech entry for the end user. In some cases (Crabb & Jones, 2024), SMEs are utilized to score existing models by completeness, consistency, correctness, simplicity and traceability. This was used to generate much of the needed information necessary for the model to ingest. The benefits suggested include a way to accelerate the overall model development process and answer detailed domain specific questions for end users to reduce the work in finding answers. A work (Longshore, Bell, & Madachy, 2024) tried to improve the efficiencies of the process via requirements generation and management. SysML version 2 models were utilized along with Retrieval-Augmented Generation (RAG) were used to add information to the LLM to improve model accuracy and specificity in the MBSE domain. Some works (Salornata, 2024; Bader, Vereno, & Neureiter, 2024; Camara, Torya, Burgueno, and Vallecillo, 2023) utilized existing tools based on UML and open-source Generative AI such as OpenAI's GPT-4o. One work (Erikstad, 2024) provided a MBSE GenAI implementation by the generation of python code while using a LLM model to generate the code which in turn generates the MBSE model. The use of also including the generation of simulation models for system physical properties has been examined (Zhang et al., 2025). The generation of artifacts were used as synthetic training data for AI assistants embedded in MBSE (Malmqvist et al., 2024). Some works just concentrated on a particular diagram within SysML such as flow-based diagrams (Alshareef, Keller, Carbo & Zeigler, 2024). It is noted that most of these works have occurred in the last two years.

PROPOSED METHODOLOGY

This is a preliminary report on the proposal to design, develop and test a system which can utilize the benefit of GenAI with RAG injection for MBSE AI assistant. This work has been examined, and the methodology has been formulated to assist in the design and development of this tool. The goals like many of the technical papers reviewed strive to gain efficiencies and improve the systems engineering process via mechanisms presented in the use of Generative AI. This would include the generations of models as well as support to query MBSE knowledge base with support to validate implementation methods.

ChatGPT was an apparent Generative AI tool to be used by many researchers on this topic. NIWC Pacific has access to a GPT system which is similar in nature to ChatGPT. ChatGPT is also available as an alternative to the Navy GPT. One or the other will serve as the AI engine to allow the end

user to prompt form both the generation of MBSE elements as well as gain support on the application of any portion of the MBSE/SysML definitions and implementations.

A little more unique to this work will be the use of a RAG component which not only specifies specific MBSE data and information but will also contain data on based on military systems and systems of systems. This will add to the corporate knowledge with the intent to improve on efficiencies of the model with respect to Naval systems.

A Naval Innovative Science and Engineering (NISE) project is projected as the means to research and design the system with the intent of finding sponsorship for a more complete and comprehensive development. With this in mind, a subset of MBSE or SysML will be examined in this work. The subset of the capability will be determined by the usage required by designers and developers of MBSE models for Naval systems. The methodology utilized is assumed to be the same for most all the MBSE elements with adaptation for any particular element.

EXPECTED RESULTS

MBSE is becoming a critical piece in modelling the complexity of Naval systems. This proposed work aligns with a minimal set of other researched striving to address this topic. The expected result is expected to be like other researchers, to improve efficiency, optimization and validation for the output of model generation and the support to the user in understanding MBSE processes via prompting the GenAI MBSE Agent. The expected results will also apply directly to a Naval domain usage which is why the use of RAG becomes a means to incorporate that with the selected LLM to be utilized.

The end expectation is not to have GenAI tell the user how it builds a model under a MBSE application. The real end use is how can the GenAI assistant help the end user to build a valid model and provide suggestions and corrections where needed. This would lead to the building of models where components, connections and other elements of MBSE can be created in ways not previously considered by the MBSE end user. This could lead to the creation of options for the model which can then be evaluated and presented to the end user for selection. Developing a choice versus a single model. From there the user with the GenAI assistant could then create a conglomerate of selected models that were generated to arrive at even a better option the is more in line with what the end user would like to see.

CONCLUSION AND FUTURE WORK

It is apparent that the use of Generative AI in MBSE is becoming more popular and it only a matter of time before a good source of tools to support MBSE will become available. Often Naval systems models tend to differ in several distinct ways and has specific domain knowledge to apply to the MBSE process. As such this work is unique in its attempt to fit it to this specific domain.

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