

Improving Efficiency in e-Axle System Development through the Integration of MBSE, MBD, and Generative AI

Masaru KATSUKI* Kazunori KAWASHIMA* Takuro KAWASUMI*
 Shota SATO** Junji KASHITANI***

Abstract

To improve the efficiency of e-Axle development, we digitized document-centered systems engineering and integrated it with generative AI. For the digitization, we implemented a meta-structure, introduced mechanisms to reduce the ambiguity in tool dependency, and streamlined the structure. For the AI integration, we compared vector retrieval-augmented generation (RAG) and graph RAG and showed that graph RAG, which is strong in relationship tracking, is effective for information extraction with high accuracy as well as for designers' verification of AI responses by visualizing the basis for the responses.⁽¹⁾

1. Introduction

With the rapid spread of electric vehicles in recent years, improving the quality and efficiency of systems development for electric axles (e-Axles), including the management and effective utilization of heat, has become an important issue.

In the conventional design process, information management based on Requirements, Functions, Logical, Physical (RFLP) is implemented by introducing the concept of systems engineering (SE).⁽²⁾ However, as shown in Fig. 1, a significant amount of SE information is managed as a large number of documents that are divided by hierarchy and corresponding systems. As such, designers must search for the necessary information by going back and forth between documents at different hierarchical levels. An example of this problem is that it is extremely time consuming to determine how a change in a certain design value affects the entire system.

In recent years, significant progress has been made in generative AI in the form of large language models (LLMs). In the field of SE, an approach for training generative AI to learn the system requirements of model-based SE (MBSE) has been reported.⁽³⁾

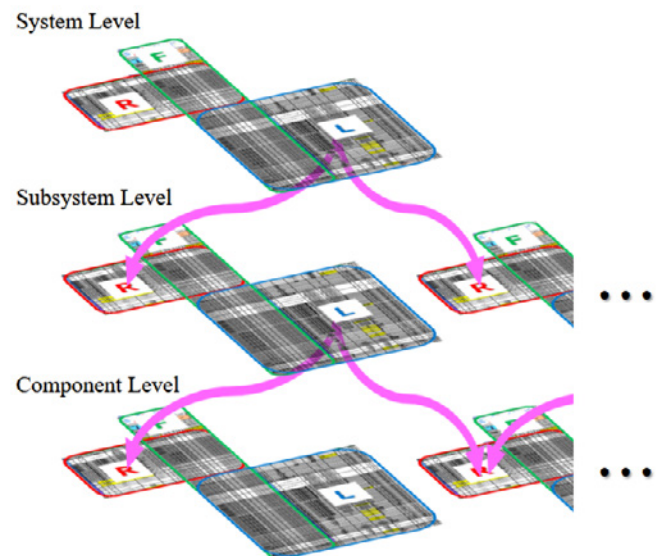


Fig. 1 SE Management form

*Innovative Technology Development Department **Lightblue K.K. ***Panasonic System Design Co., Ltd.

This study applied MBSE to RFLP across multiple levels. As shown in Fig. 2, using MBSE as a foundation, this study aimed to improve the efficiency of information extraction by integrating it with generative AI and to increase the efficiency of analysis preparation and result sharing in conjunction with model-based development (MBD), thereby increasing the development speed and competitiveness.

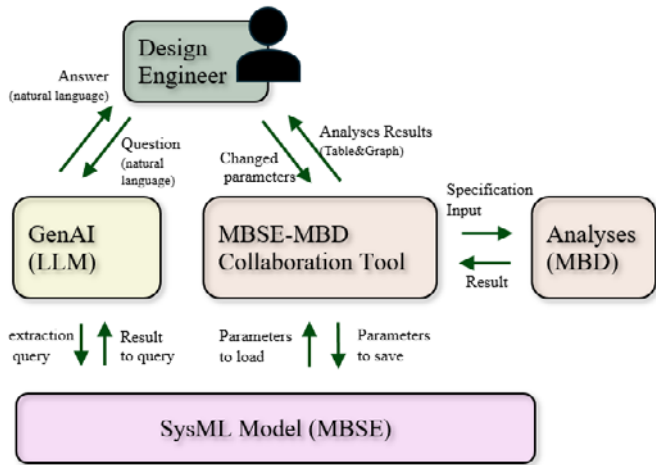


Fig. 2 Overview of this research initiative

2. Implementation of MBSE

MBSE is an SE approach centered on digital models, which are modeled using systems modeling language (SysML). MBSE is the foundation of this research and, when building an MBSE model based on SE information in the conventional document forms, there is the concern that if the structure of the MBSE model is not consistent owing to the degree of freedom of SysML tools or individual differences among designers, the answers obtained will be inaccurate even when integrated with generative AI. Therefore, we define a meta-structure as a set of rules that ensure uniformity in the structure of MBSE models and propose an implementation method that enables model construction according to this meta-structure. The meta-structure is based on the hierarchical structure shown in Fig. 3. The structure was constructed with the upper P and lower R as contact points between the hierarchies, considering that RFLP is managed at each hierarchy level according to the operation of a conventional SE management format with reference to public information.⁽⁴⁾

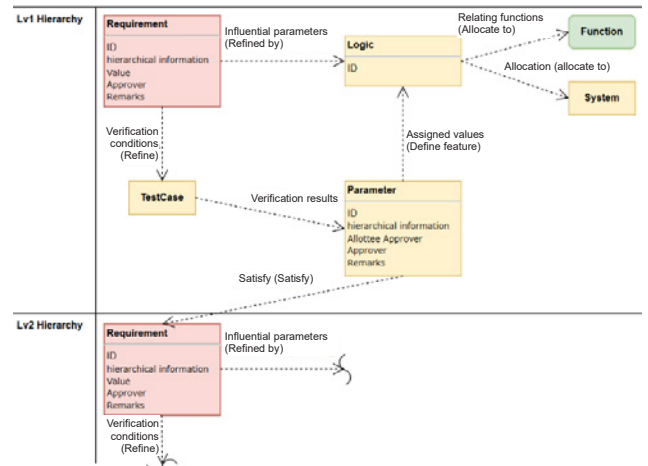


Fig. 3 MBSE meta-structure

The implementation method for the model with the meta-structure consists of a framework and validation rules.

- Framework: A process structure to form the structure of the MBSE model by automatically defining the relationships among elements in accordance with the meta-structure upon inputting information in order into the familiar charts prepared in advance. Figure 4 shows an example.
- Validation rules: A process mechanism to check the relationship between each element, and detect and notify of any omissions or errors. Table 1 presents an example.

These implementation methods enable the construction of a coherent MBSE model that serves as the basis for efficiency improvements.

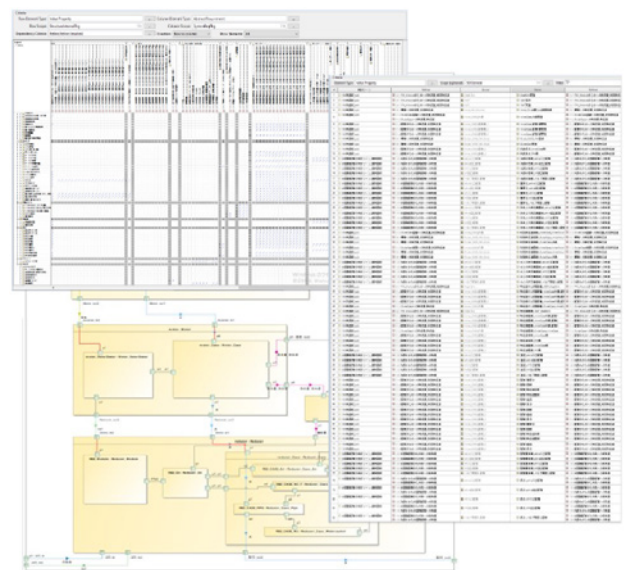


Fig. 4 Example of MBSE modeling framework

Table 1 Example of MBSE validation rules

#	Restraining factors	Validation rule
1	Function	There must be no factors in refining the Functions
2	Requirement	The destination of the refined Requirements is TestCase only
3	Requirement	Requirement is refined only by Logic and TestCase
4	Requirement	Requirement must be satisfied by Logic
5	Requirement	Requirement must be refined by Logic
6	TestCase	The destination of the refined TestCase is Requirements only
7	TestCase	Only Requirement and TestCase must refine TestCase

3. Design support methods using a combination of MBSE and generative AI

To improve the efficiency of information extraction from the relationships between documents at different hierarchical levels, the MBSE model described in the previous section was integrated with generative AI. The following two approaches were tested as the integration methods based on information retrieval.

The first method is known as vector retrieval-augmented generation (RAG). In this method, the MBSE model is segmented into appropriate units and each segment is converted into a numerical vector. The designer’s query is similarly converted into a vector and highly relevant information is retrieved based on the similarity between the two, up to the top-Nth information. This system is highly versatile because it can retrieve information based on similarities in context and meaning.

The second method is named graph RAG, in which the search targets are expressed as a knowledge graph. This method represents information entities as nodes and relationships among information as edges. The retrieval accuracy is expected to improve in terms of capturing the relationships between information and comprehensiveness compared with vector RAG, which is based only on similarity. In the MBSE model constructed in this study, we transformed graph RAG into a knowledge graph such that the meta-structure was maintained.

Figure 5 shows the structure of the graph RAG. When a designer asks a question, the generative AI automatically generates a query to obtain the information necessary to answer the question and look up the knowledge graph. After comparing the information obtained from the knowledge graph with the content of the question, the generative AI generates an appropriate response. To improve the query generation accuracy, few-shot learning is performed for each pattern described below, in which the AI is trained using a set of questions and appropriate queries as the training data.

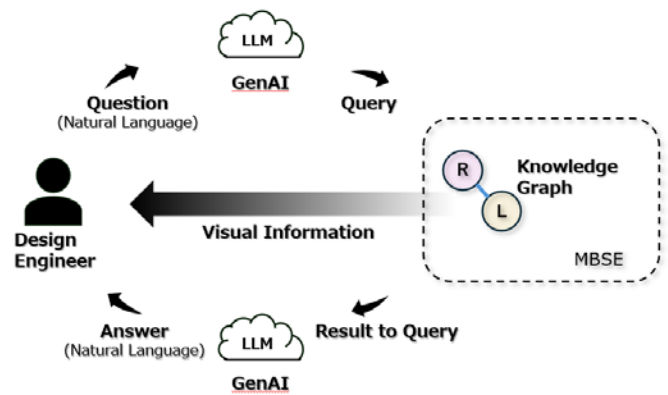


Fig. 5 Configuration of knowledge graph RAG

To verify the effectiveness of the two design support methods, we prepared a set of questions that simulated an actual design situation (Table 2), and evaluated the accuracy of the responses to each of the four question patterns (A to D). The results are shown in Fig. 6. Using the vector RAG, correct answers were obtained only for Pattern A, but not for Patterns B, C, and D. In contrast, Graph RAG provided a high percentage of correct responses for all patterns (A, B, C, and D).

Table 2 Question pattern classification for generative AI responses

Pattern	Classification	Example questions
A	Extraction of information of specific elements	What is the required value of the motor coil temperature [°C]?
B	Extraction of relationships within specific subsystems and components	Extract all elements that determine the A dimension of the XX part
C	Extraction of relationships across hierarchies	If the dimension A of part XX is changed, what are the dimensions of the other parts that are affected by the change?
D	Extraction of high-impact factors	What are the top 3 most influential factors in the e-Axle unit?

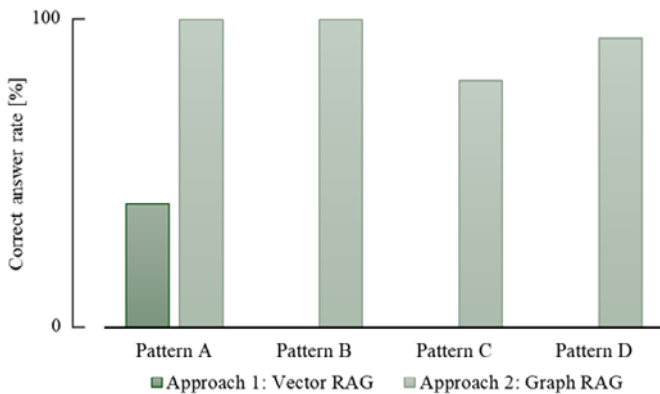


Fig. 6 Generative AI response accuracy evaluation results

In particular, it was confirmed that design parameters can be easily extracted in terms of the size of the influence, which is difficult to grasp solely through visual inspection of the model, such as pattern D. Figure 7 shows an example of actual questions and answers in the graph RAG. In this example, the knowledge graph returns the calculation results for the eigenvector centralities of the nodes.

Question
What are the top 3 most influential factors in the e-axle unit?

Answer
The top 3 most influential factors are listed.
If there are more than one factor with the same level of influence, all of them will be extracted.

1. ****Performance (Score: aaa)**
1. ****Performance (Score: aaa)**
2. ****Frequency (Score: bbb)**
3. ****Performance (Score: ccc)**
3. ****Conditions (Score: ccc)**

These are the most influential factors.

Fig. 7 Practical example of a question and answer in the graph RAG approach

It was also confirmed that the designer can verify the results of the responses and visually understand the complex dependencies by referring directly to the knowledge graph in conjunction with the results of the generative AI responses. Figure 8 shows an example of the visualization of the information extracted from the entire knowledge graph and referenced in the answers.

The results confirm that, based on the MBSE model with the meta-structure as an important factor, the graph RAG method can be used to extract information accurately and efficiently.

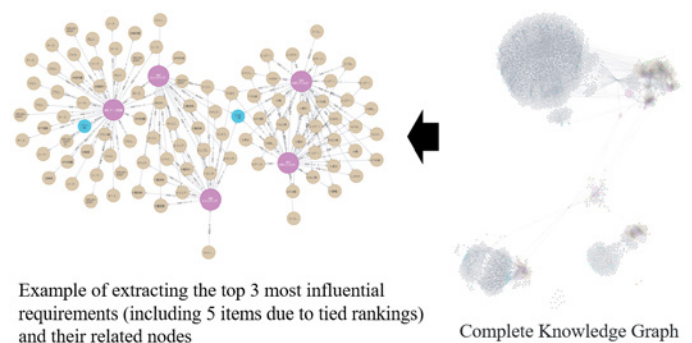


Fig. 8 Example visualization of the queried knowledge graph

4. Implementation of an MBSE model for increased analytical efficiency

The dispersion of information shown in Fig. 1 can affect the analysis, and a problem arises whereby significant time and effort are required to verify the latest information, input analysis data, and organize the results. In contrast, the implementation of a coherently structured MBSE model enables seamless connection via the MBSE-MBD collaboration tool. This collaboration reduces the designer’s workload and improves efficiency.

The effectiveness of this MBSE-MBD collaboration was confirmed by applying the integration to a small-scale design process. Figure 9 shows the flow of the application process used to determine the specifications in a thermal management analysis.

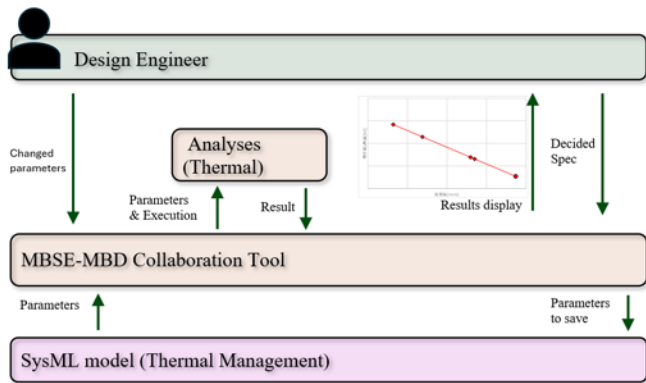


Fig. 9 Example of applying MBSE-MBD collaboration

It was confirmed that the MBSE-MBD collaboration enables the designer to automate the tasks of setting input conditions and organizing results, thereby reducing the time spent on analysis work by 30% (Fig. 10).

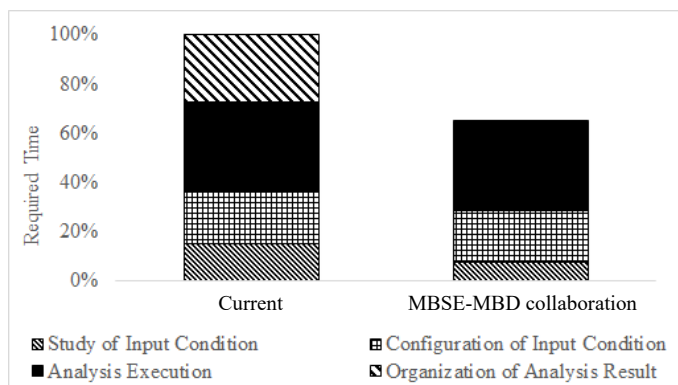


Fig. 10 Efficiency of MBSE-MBD collaboration

5. Summary

In this study, SE information in document form was reconstructed as an MBSE model, which was used to improve the efficiency of information extraction through analysis (MBD) and generative AI. In particular, it was demonstrated that graph RAG, which uses knowledge graphs, is superior to vector RAG in its integration with generative AI. It was confirmed that graph RAG enables information extraction with high accuracy in a manner that reflects the model structure. It was also shown that the analysis work itself can be performed efficiently by linking with MBD through the construction of an MBSE model.

In the future, we aim to improve the accuracy of the responses to questions that cannot currently be answered accurately, such as questions with a large number of relationships across hierarchical boundaries. In addition to directly answering the questions of designers, the system will be developed into a more active support tool that complements and expands designers’ thinking by providing designers with information on related quality issues and past design knowledge and predicting potential risks. Furthermore, the application scope of generative AI will be expanded to areas that currently need to be handled manually, such as the operation of MBD collaboration tools, to improve the efficiency of the entire design process further.

We will aim to create an environment in which designers can concentrate on more creative work by developing the tool into an AI agent that can understand the designer’s intentions, interpret the results by performing parameter selection and optimization analysis autonomously, and propose the next action.

6. References

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■ Authors ■



Masaru KATSUKI



Kazunori KAWASHIMA



Takuro KAWASUMI



Junji KASHITANI