

# Improving e-Axle System Development Efficiency through MBSE and Generative AI (LLM)

- (Part II) -

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**KEY WORDS:** software and its underlying technologies, generative AI, systems engineering/MBSE, e-Axle, knowledge graph, graph RAG [E3]

In our previous study, we proposed converting Model-Based Systems Engineering (MBSE) models into a knowledge graph and utilizing generative AI for engineering information retrieval. However, keeping the knowledge graph up to date requires continuously reflecting newly generated engineering knowledge, such as design review (DR) documents and technical reports. This maintenance effort has become a new bottleneck in practical engineering processes.

This study proposes a method for automatically extracting R-F-L-P (Requirement-Function-Logic-Physical) information from unstructured DR documents using generative AI and continuously reflecting the extracted information in an existing knowledge graph. As shown in Fig.1, the proposed method consists of an extraction phase and an integration phase. In the extraction phase, DR document pages are first converted into natural-language descriptions by a Vision-Language Model (VLM), and an LLM then extracts R-F-L-P elements. In the integration phase, the extracted results are compared with the existing knowledge graph and reflected only after review and approval by a designer.

To evaluate the proposed method, three extraction conditions were compared. Case1 used only text information and started extraction from the Requirement level. Case2 added VLM-based interpretation while keeping Requirement as the extraction origin. Case3 used the VLM and started extraction from the Logic/Physical elements associated with product changes. This backward extraction approach, which traces from product changes to the corresponding Function and Requirement, was adopted because DR documents often describe product changes and their concrete values explicitly.

The proposed method was applied to actual e-Axle development DR documents. As shown in Fig.2, the extraction rate increased from Case1 to Case3. In particular, after switching the extraction origin to product changes in Case3, extraction improved across the Requirement, Function, and Logic/Physical categories. This result indicates that product-change-based backward extraction is effective not only for identifying the changed Logic/Physical elements, but also for extracting the related Function and Requirement chain.

However, extraction errors still remain. Although the AI can extract factual information described in DR documents, some information, such as measured values and analysis results, may be incorrectly treated as Logic/Physical because the current meta-structure does not sufficiently distinguish design means from other information types. Addressing this issue is an important future challenge for the extraction phase.

In the integration phase, the extracted results are compared with the existing knowledge graph, and only the differences are presented to the designer, as shown in Fig.3. This enables the designer to review candidate updates without checking the entire graph, and the updates are reflected in the knowledge graph only after review and approval, thereby reducing the risk that incorrect extraction results are directly reflected.

Future work includes refining the meta-structure so that measured values and analysis results can be stored as distinct information types. By improving the validity check of extracted results and reducing classification errors, the proposed framework can support reliable continuous maintenance of engineering knowledge. We will also explore its extension to broader manufacturing processes beyond development.

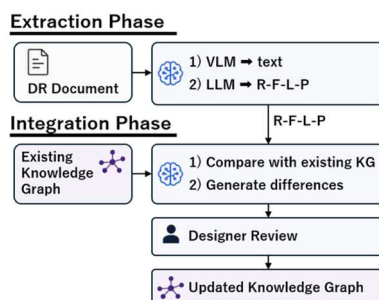


Fig.1 Overview of the automatic update flow

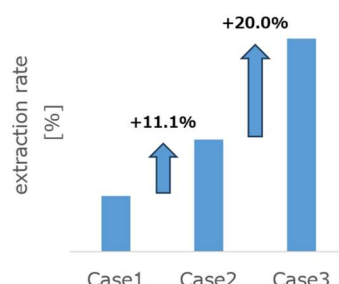


Fig.2 Change in extraction rate across extraction conditions

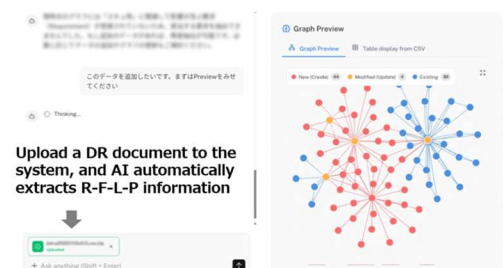


Fig.3 Example of graph comparison results and difference review