Towards the Capabilities of Large Language Models Regarding Functional Reasoning of Designed Products

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1 Introduction

A functional understanding of machines is crucial for their development (Matthiesen, 2021). As design tasks are usually based on the foundation of previous design activities with similar development objectives, the functional understanding of existing design results is an important basis for the development of new products (Pahl et al., 2007). Established methods for the analysis of functional relations between different components are for example product architectures or the C&C-Approach (Grauberger et al., 2020). The C&C-Approach leads to a definition of the embodiment-function relations and it needs a geometrical definition and tacit design knowledge of the applying engineers as input (Matthiesen et al., 2018). As this method is not yet automated, it is quite effortful. So, it might be an option to use digital geometric models like CAD as input and foster the automated definition of functional models with machine learning approaches, that inherit the required design knowledge within their model parameters (Fastabend et al., 2024). A challenge regarding machine learning approaches is the definition of suited training data sets with a sufficient amount of data tuples. Especially in CAD related tasks, this problem occurs, because the CAD-models are often handled as sensitive intellectual property of individual companies (Heidari and Iosifidis, 2024). A new trend in machine learning that might be capable of mitigating this challenge is the rise of foundation models. Foundation models are trained with an enormous amount of data aiming to learn a generalized capability like image generation or text understanding (Zhou et al., 2023). Those foundation models then can be parameterized with sparse training data for specified tasks as long as this specified task sets up on the generalized capability already learned by the model. ChatGPT is the most known foundation model and is used for text understanding and generation. The transfer of geometrical information into text makes them accessible for foundation models like ChatGPT as there are no qualitative foundation models for a direct 3D analysis available actually. Previous approaches on automated function retrieval investigate on the usage of the design structure matrix (DSM) as representation format for components physical interactions and their functional relations and it has been found that some functional relationships can be identified based on component names and the DSM (Lupinetti et al. 2017, Fastabend et al. 2024). As DSMs and component names can be represented as text, it should be accessible for large language models. In this paper the large language model ChatGPT is used to investigate, if a products functionality can be retrieved automatically by a foundation model using component names and a DSM as input, that specifies the components physical interactions in terms of contact faces. Use case for the experiment is a DSM of a drive shaft assembly with 7 components (Vajna et al., 2020).

2 Research Method

In this chapter the research method will be defined. The arguments already given in the previous chapter are leading to the following research question for this contribution:

Do Large Language Models have the ability to extract functional relations from the components DSM of a product?

The question will be answered by an experiment described in Figure 1. As input, a DSM representing the interactions of the components in terms of physical contacts is used. The DSM is chosen as a format for different reasons. It is text-based and therefore readable for a large language model. Additionally, it is a common framework in design methodologies for linking design entities like components semantically to each other. Therefore, it is suited to abstract the geometric information of a CAD assembly and as it is widely known since years (Eppinger and Browning, 2012), it is likely that a large language model is already familiar with the logical concept of the DSM.

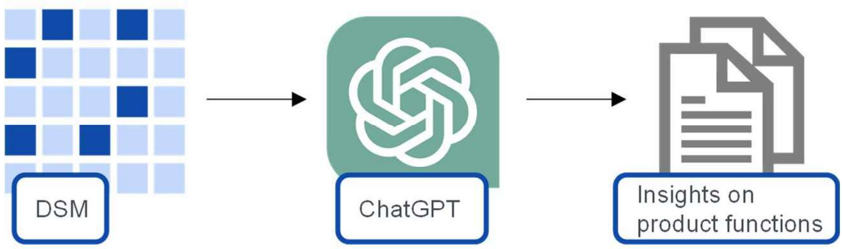
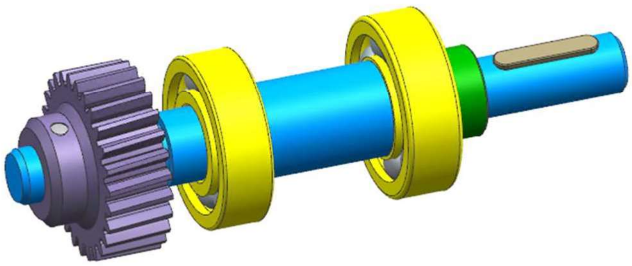


Figure 1. Workflow of the experiment

The DSM will be extracted directly from the CAD-assembly files of a drive shaft with 7 components (Vajna et al., 2020). The entries of the DSMs are binary and store an information on physical component contacts. If an entry equals one, both components share a physical contact through at least one pair of contact faces. If an entry equals zero, the components do not share a physical contact. Another information assigned to the DSM is the title of each row and column which is defined by the name of the components. As the matrix is symmetrical, each component is assigned to a row and a column. The (0,0) entry represents the assembly name. The CAD-assembly of the drive shaft and the DSM derived as input for the experiment is shown in Figure 2.



Drive_Shaft_Assembly	Ta	Fe	Sl	Gr	Gr	Ge	Dr
Taper Pin, A, GB,4x24	0	0	0	0	0	1	1
Feather_key_ISO_2491_25x5x3_A	0	0	0	0	0	0	1
Sleeve_15_21	0	0	0	1	0	0	1
Grooved_ball_bearing_15_42	0	0	1	0	0	0	1
Grooved_ball_bearing_17_40	0	0	0	0	0	0	1
Gearwheel_27_15	1	0	0	0	0	0	1
Drive_Shaft	1	1	1	1	1	1	0

Figure 2. Drive Shaft assembly and associated DSM

The large language model used for the experiment is ChatGPT 4.0 as it is most common and easily accessible. An initial prompt explains the experiment to the model and provides the DSM forming the basis for further prompts. Next, questions on the products functionality are delivered to ChatGPT as prompt. The questions are based on standardized characteristics of products functions like functional flows, main and secondary functions (Pahl et al., 2007). Additionally, they are inspired by previous work on automated force flow identification and the distribution of relative motions, as it has been shown that these functional relations could already be identified by the DSM and the component names by algorithms (Fastabend et al. 2024). The initial prompt and the questions on the products functionality based on that are standardized and given in table 1.

Table 1. List of standardized ChatGPT prompts for the experiment

Character	Prompt
Initial prompt	The given table represents a design structure matrix of a CAD-assembly with its components as entities and their physical contacts as relations. Spaces are separators. The (0,0) entry is the name of the assembly. The component names are given in row 0 and column 0. A non-zero entry means that the components have a physical contact. A zero entry means that the components do not have a physical contact.
Assembly function	What kind of assembly is represented by the matrix and what is its function?
Functional flow	What is the main functional flow (energy flow, mass flow or signal flow) and what components contribute directly to this flow? How do the components interact?
Functional hierarchy	What is the main function of the assembly and what are secondary functions? What components contribute to these functions?
Force flows	Which components are involved in the main force flows and therefore critical regarding their mechanical properties?
Relative motions	What are local spaces of relative motions and which components are moving as group with no internal relative motions?

3 Results

In this chapter the results are presented chronologically according to the prompt order in Table 1. The initial prompt has the objective to provide context information on the experiment and to deliver the DSM to the large language model. In return, ChatGPT clarifies, to what degree this context information is understood for further steps. ChatGPT reads the DSM and makes its reasoning transparent. First, the logical concept of the DSM is repeated in the answer. Next the DSM is modeled as table by ChatGPT. Lastly, a list of interfering components is generated. So, it can be stated, that ChatGPT represented the information without any mistakes. The second prompt asks for the assemblies' character and its function. ChatGPT identified the assembly correctly as drive shaft with the functions "power transmission" as well as "torque and motion conversion". In addition, a list of components with the components main functions is generated as given in Table 2. Single components function is described correctly through this prompt. The third prompt on the functional flow is answered as follows. The main flow value is identified correctly as "energy". All components were assigned as contributing to this main flow. However, this is not fully correct, as the sleeve does not transfer any forces while torque is guided through the shaft. The description of components interactions is semantically correct as ChatGPT identifies an interaction of feather key, gear wheel and drive shaft as critical for the energy transfer, but it does not match correctly to the DSM, because the taper pin connects gearwheel and shaft. The feather key is just an interface to adjacent assemblies as displayed in Figure 2. So, instead of using the information on the feather keys and the pins' interactions from the DSM, ChatGPT seems to hallucinate about the interfaces. Probably, the resulting conclusions are based on the general concepts of feather keys and pins stored in ChatGPT's model parameters.

Table 2. Identified component functions by ChatGPT

Component	Functional Description
Drive Shaft	The central component which transmits mechanical power from one part of the machine to another.
Taper Pin	Used for precise alignment and securing components together on the drive shaft.
Feather key	A type of key used to transmit torque between the shaft and a rotating machine element like a gear or pulley.
Sleeve	Likely a spacer or a coupling sleeve, possibly for aligning bearings or other components on the drive shaft.
Bearing	Bearings that allow the drive shaft to rotate smoothly, reducing friction.
Gearwheel	A gear that meshes with other gears to transmit torque and change the direction of mechanical power.

The fourth prompt is on functional hierarchy and is answered correctly by ChatGPT. Main function is the “Mechanical power transmission” and secondary functions are “Alignment and Securement”, “Support and Friction Reduction” and “Torque Conversion and Motion Control”. Components are assigned correctly to these main and secondary functions. The next prompt asks for components that are mechanically critical. All components were named as critical which is quite not correct, as the sleeve is not aimed to transfer any critical loads. The last prompt asks for relative motions within the assembly and is answered correctly. All components are linked and are moving together. The only relative motion identified is occurring within the bearings to support the movement of the drive shaft. In this prompt, ChatGPT identifies the function of the taper pin correctly as its objective lies in the linkage of gearwheel and shaft. This is interesting, because in a previous prompt ChatGPT assigned this function to the feather key. It needs to be stated that ChatGPT remains unclear on the specific interaction of feather key and taper pin as both are identified as linking elements between shaft and gearwheel.

4 Discussion and Next Steps

Summarized this experiment leads to the conclusion, that ChatGPT is capable of a senseful functional reasoning regarding assembly's analysis. Especially the functions of the different components were assigned correctly as given in Table 2. Most other reasoning is built up on this information. Therefore, it remains somewhat unclear what effect the DSM has exactly on the results. Questions referring to information on components interactions are more likely to be answered wrong or incomplete. The faulty assignment of the taper pin and feather key as well as the identification of the sleeve as mechanically critical component are examples for this. It makes sense that the names of the parts are more important for the prompt generation as ChatGPT is a large language model and not a matrix or graph-based foundation model. So, the hypothesis arises, that the DSM is only used sparsely during the prompt generation. Experiments just based on the list of components without the DSM might be capable of answering this for the given drive shaft example. But there are more experiments required with different assembled to certainly clarify, to what degree a large language model is capable of processing DSM information. Maybe there are prompting strategies that force ChatGPT to use the DSM more strictly for functional reasoning. Despite this somewhat down-to-earth hypothesis it could be proved, that ChatGPT is capable of functional reasoning based on component names. ChatGPT provides qualitative answers on functional questions as long as the reasoning is possible with language based semantic concepts encoded within ChatGPTs model parameters. Concepts of common machine parts like shafts, pins, gearwheels, etc. seem to match this requirement. So, it might be senseful to embed large language models as add-ons into engineering models that describe assemblies' characteristics and functions more text-based like testing reports and bill of materials.

5 Summary and Outlook

The given example shows, that a semantic interpretation of engineering models with artificial intelligent foundation models is possible. Additionally, it can be stated, that the DSM has the potential to serve as a text-based adapter model for engineering information with the objective to make this information accessible for large language models like ChatGPT. Unfortunately, it seems as the DSM is just used sparsely as information source in the given experiment. Maybe stricter prompting strategies or new versions of ChatGPT might be able to mitigate this phenomenon. Also, it might be an option to consider other types of foundation models more based on matrices or graphs. Overall, it is shown, that functional information on designed products can be derived reliably with ChatGPT based on a textual representation of the component names. So, Add-ons based on ChatGPT might help engineers with functional reasoning as long as the input formats are text based.

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