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Large language model based agent for process planning of fiber composite structures

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ABSTRACT

Process planning is a crucial activity, connecting product development and manufacturing of fiber composite structures. Recently published Large Language Models (LLM) promise more flexible and autonomous workflows compared to state of the art automation methods. An autonomous agent for process planning of fiber composite structures is implemented with the LangChain framework, based on OpenAI's GPT-4 language model. The agent is equipped with deterministic tools which encode a-priori process planning knowledge. It can handle different process planning problems, such as cycle time estimation and resource allocation. Combinations thereof are solved through executing a multi-step solution path.

1. Introduction

Improvement of process planning offers great potential to streamline and connect the design and manufacturing of products. Computer-Aided Process Planning (CAPP) involves the automated generation of manufacturing instructions based on design data, and agent-based planning systems utilize autonomous software agents to optimize and manage manufacturing processes. Large Language Models (LLM) like OpenAI's ChatGPT bridge the gap between natural language and intuitive thinking, and the formal languages used in engineering. Their reasoning and strategic thinking capabilities make them well-suited for complex and adaptive process planning tasks.

This paper showcases a proof of concept for an LLM-based agent for process planning of fiber composite structures. It provides initial insights whether an LLM-based agent is capable of solving process planning tasks autonomously.

2. State of the art

Interaction between product development and manufacturing poses a particular challenge in many industrial organizations [1]. *Agent-based planning* approaches for automating and optimizing process planning have been published in various contexts, such as integration of manufacturing planning, predictive machining models, and manufacturing control [2]. Jia et al. [3] propose a multi-agent system to integrate product development and manufacturing, using different functional agents representing domain experts. Multi-agent systems can involve different agents for design, process planning, manufacturing execution and many more [4]. Distributed planning systems can optimize process planning and scheduling simultaneously [5], where interaction between agents is possible through negotiation, coordination and cooperation [6]. Other planning strategies involve genetic optimization [7] and deep Q-networks agents [8].

Large Language Models show generic reasoning and multi-step strategic thinking and can thus act as agents to make decisions in a planning scenario. Establishing robust reasoning capabilities is still a primary challenge, but OpenAI's GPT-4 model, published in March 2023, already exposes remarkable strategic thinking capabilities [9]. Singh et al. [10] highlight the capability of LLMs to plan tasks, by scoring probable next steps based on a given sequence. In addition to prior approaches, they add situated awareness to autonomously plan actions within a dynamic environment. Models such as SayCan [11] highlight how LLMs propose feasible problem-solving sequences. Frameworks like LangChain [12] ease the creation of customized LLM agents, which can be equipped with tools like web search, database lookups, vector store embeddings, and customized planning tools.

Process planning links the design and manufacturing of a product [13], involving planning activities like operation sequencing

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and resource selection [14]. Many automation techniques have been developed, such as rule-based expert systems [15], and generative process planning with geometrical feature recognition in manufacturing [16] and assembly planning [17]. While many solutions focus on metallic parts, the process planning of fiber composite aerostructures is addressed in [18] with a model-driven approach based on graph-based design languages.

This work focuses on process chains for Carbon-fiber reinforced polymers (CFRP) based on *automated fiber placement (AFP)*. Fig. 1 shows a Coriolis C1 robot-based fiber placement machine [19]. The AFP head is mounted on a robot and places CFRP tows on a layup tool, applying heat and pressure to ensure a strong bonding between the incoming tows and the substrate [20]. Subsequent processes include curing, forming, milling, edge sealing, varnishing, non-destructive testing and others. The cycle time of each step can be estimated with physics-based process models [21]. For example, the cycle time of the AFP layup process is estimated based on parameters such as tape width, feed velocity, tool dimensions and fiber orientation. Such cycle time estimation tools will be provided to autonomous planning agents in the presented approach.

3. Approach

This paper presents a proof-of-concept autonomous process planning agent for fiber composite structures using an LLM augmented with custom process planning tools. The agent is supposed to solve these problems autonomously:

1. *Time Estimation:* Estimate the cycle time, i.e., duration from start to end, for a manufacturing task.
2. *Process Chains*: Determine which tasks are required in which order to manufacture a specific component.
3. *Resource Allocation:* Identify the resources, e.g. machines, required to manufacture a specific component.
4. *Integrated Planning:* Estimate the total cycle time for a chain of tasks required to manufacture a component.

The agent receives planning tasks in natural language, see Fig. 2. To solve these autonomously, it must unite reasoning capabilities, provided by the pre-trained LLM, and process planning knowledge. The core planning tools include Job Selection, Process Chain Setup, Cycle Time Estimation, and Resource Allocation for different manufacturing tasks. The Expert-in-the-Loop and Search tools assist when external information is needed.

The autonomous planning agent is implemented based on the *OpenAI Functions agent* of the LangChain [12] framework, using the GPT-4-0613 model by OpenAI. The planning tools are implemented as Python methods, which are called by the agent. The approach does not require any fine-tuning of the LLM.

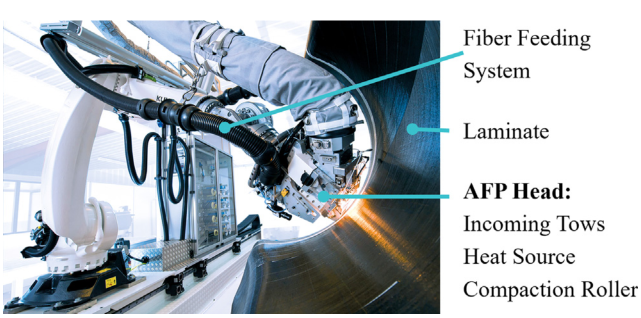

Fig. 1. Automated Fiber Placement Process [18].

4. Results

The agent's solution paths for the planning problems (1)–(4) are illustrated in Fig. 3. This figure depicts the observed solution as a workflow, where colored boxes represent tool calls and arrows depict data flow between them.

Time Estimation (1): The agent is asked for the duration of the AFP layup process for a component with an area of 5 m^2, laminate thickness of 1.5 mm, a fiber orientation of 0°, and dimensions 2.5 m × 2 m. It calls the *Cycle Time Estimation* tool for AFP layup, hands over the component parameters and retrieves the answer *3.18 h*.

Process Chains (2): The agent is asked to list the tasks required to manufacture a thermoplastic composite component. It first uses the *Job Selection* tool with the inferred component type ('CompositeComponent') and component material ('Thermoplast-CF'). The return value '2dAfpManufacturingJob' is propagated to the *Process Chain Setup* tool, which returns the task sequence *ToolPreparationTask – AfpLayupTask – PressFormingTask – PostProcessingTask*.

Resource Selection (3): The user asks for resources required to manufacture a thermoset composite component. As in the preceding case, the agent correctly invokes *Job Selection* and *Process Chain Setup*, which now yields a slightly different process chain for thermoset instead of thermoplastic composites, including a 'AutoclaveCuringTask'. After the task sequence was determined, the agent calls the *Resource Selection* tools for tool preparation, AFP layup, autoclave curing and post processing, and provides a summary of the required resources, such as an AFP machine, an autoclave and mechanics.

Integrated Planning (4): This problem is a combination of problems (1)–(2). The console log is given in Listing 1, and showcases multistep problem-solving capabilities of the LLM-based process planning agent. The agent is asked for the necessary manufacturing tasks and the total duration of a thermoset composite component. It calls the *Job Selection* and *Process Chain Setup* tools for the thermoset route. Subsequently, the *Cycle Time Estimation* tools for each of the four involved tasks are invoked with the given component parameters. The final answer is the summed up total time of 9.56 h. This excludes logistics, buffer, and unexpected downtimes.

The *Expert-in-the-Loop* and *Search* tools provide additional flexibility when information is missing. For example, when asked how long the manufacturing of a 3 m × 2 m composite skin panel takes, the agent invokes the *Expert-in-the-Loop* tool, asking for missing parameters like the thickness of the laminate. Following the expert's reply that the laminate consists of 8 plies of M21 prepreg, *Search* is applied to obtain the ply thickness of M21 prepreg

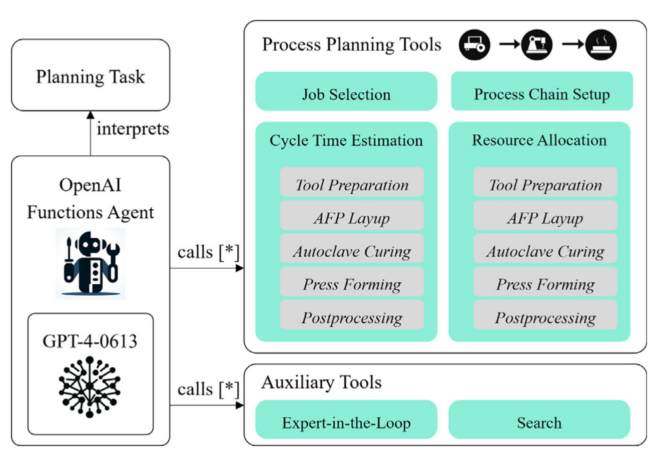

Fig. 2. LLM planning agent scheme.

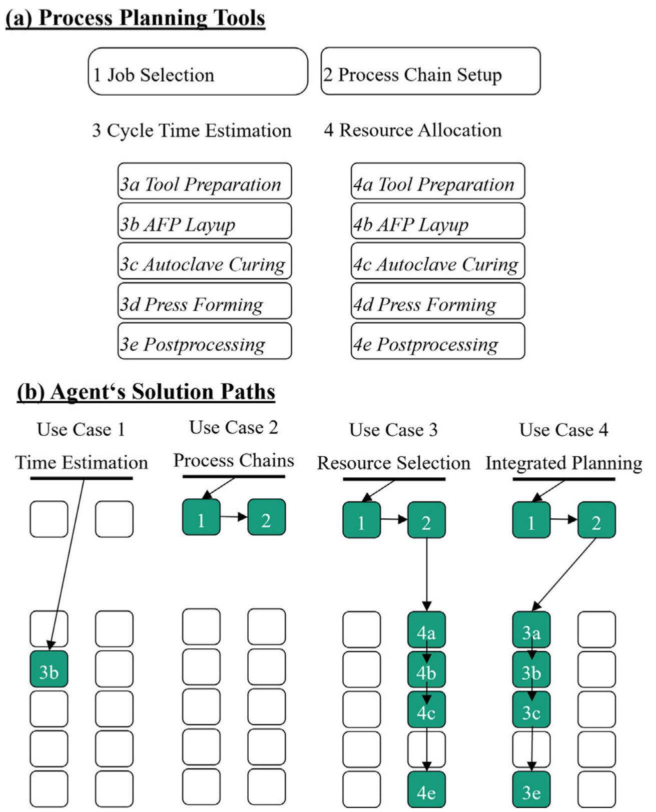

Fig. 3. (a) Process planning tools and (b) Agent's solution paths for planning problems 1–4.

```
Task:    Which tasks are required to manufacture my
         thermoset composite component and how long does
         it take in total? The component has an area of
         1.2m², laminate thickness of 2.25mm, a mean fiber
         orientation of 0°, and its dimensions are 1.7m x
         1.5m.
Agent:   Invoking: `job_selection` with `{'componentType':
         'CompositeComponent', 'componentMaterial':
         'Thermoset-CF'}`
Return:  3dAfpManufacturingJob
Agent:   Invoking: `process_chain_setup` with `{'jobType':
         '3dAfpManufacturingJob'}`
Return:  ['ToolPreparationTask', 'AfpLayupTask',
         'AutoclaveCuringTask', 'PostProcessingTask']
Agent:   Invoking: `cycle_time_estimation_for_
         tool_preparation` with `{'surfaceArea': 1.2,
         'laminateThickness': 2.25, 'fiberOrientation': 0,
         'longEdge': 1.7, 'shortEdge': 1.5}`
Return:  0.5036231884057971
Agent:   Invoking: `cycle_time_estimation_for_AFP_layup`
         […]
Return:  2.9929133858267716
Agent:   Invoking: ` cycle_time_estimation_
         for_autoclave_curing` […]
Return:  5.375
Agent:   Invoking: `cycle_time_estimation_for_
         postprocessing` […]
Return:  0.6861904761904761
Agent:   The tasks required to manufacture your thermoset
         composite component are:
         1. Tool Preparation Task: 0.50 hours
         2. AFP Layup Task: 2.99 hours
         3. Autoclave Curing Task: 5.38 hours
         4. Post Processing Task: 0.69 hours
         The total time required for the manufacturing
         process is approximately 9.56 hours.
```

Listing 1. Protocol for integrated planning (problem 4).

(0.184 mm) from a search engine. In another call of the *Expert-in-the-Loop* tool, the agent asks for the average fiber direction. After this, it has all the information to run the *Job Selection*, *Process Chain Setup*, and *Cycle Time Estimation* tools like in problem (4).

If any of the process planning tools is removed from the toolbox, the agent is not able to solve the presented planning problems in the same precise way. By implementing tools with restricted arguments, we have implicitly defined *system boundaries and a parameter space*. These can be modified without any form of training, allowing for a quick adaptation to a company's actual process planning knowledge and process portfolio.

5. Summary and outlook

This study demonstrates the feasibility of LLM-based process planning agents, providing adaptive planning capabilities to non-experts. Using a GPT-4 model within the LangChain framework, our agent successfully solves core problems like job selection, process chain setup, cycle time estimation, and resource allocation. Currently focused on fiber composite AFP processes, the approach can be extended to other manufacturing domains. The LLM's reasoning is guided by structured tools, removing the need for process planning expertise from the end user. Decision-making can be traced back to these tools, allowing for subsequent verification of the results.

A promising area of further research lies in explicit model representation. Storing process plans, and any interim results of process planning, in persistent graph databases could significantly expand complexity handling of the LLM agent. Further improvements may originate from the use of class models and ontologies to create a more defined solution space.

Integration of advanced simulation tools into the process planning toolset can further increase planning accuracy. More potential for improvement arises from fine-tuning models to process planning instead of applying off-the-shelf pretrained LLMs. In summary, there remains great potential to further improve the capabilities of LLM-based agents in process planning scenarios. We believe that our approach can be generalized to any planning scenario which is similar in complexity.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI GPT-4 and Google Gemini Ultra 1.0 in order to revise, shorten and streamline their original manuscript. They applied OpenAI DALL-E 2 for generating graphical elements of the presented figures. After using these services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Maximilian Holland: Conceptualization, Writing - original draft, Writing - review & editing. **Kunal Chaudari:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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