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AI4CE: BOTTOM-UP AI SUPPORT FOR CONCEPTUAL DESIGN

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Abstract

AI for Concurrent Engineering (AI4CE) is a research project to combine the advantages of AI tools with the efficiency of Concurrent Engineering, to support and improve the design process. An AI system capable of generating conceptual space mission designs can support the preliminary design phase in a number of ways. Following a bottom-up approach, this AI-support tool assists the CE study teams by generating system designs with Deep Reinforcement Learning, instead of extracting knowledge from historical mission data. A first prototype could demonstrate the general functionality of this approach and future research will focus on expanding the system creation capabilities as well as a solid integration into existing MBSE workflows.
Keywords: Artificial Intelligence, Concurrent Engineering, MBSE.

Acronyms

AI Artificial Intelligence
CE - Concurrent Engineering
CELab - Concurrent Engineering Lab
DRL - Deep Reinforcement Learning
MBSE - Model Based System Engineering
ML Machine Learning
PLC - Product Life Cycle
RL - Reinforcement Learning

1. Introduction

To continue designing space missions fast and efficiently users of Concurrent Engineering (CE) such as space agencies or industries have to adapt their design approach constantly to cope with the challenging opportunities provided by the *NewSpace* era. New companies and start-ups increase with new components and new ideas an ever-growing design space, which calls for a faster, more efficient and thereby cheaper space mission design process.

One important aspect of innovation is the adoption of new technologies. The Concurrent Engineering Lab (CELab) at the TU Darmstadt, as part of the ESALab@-Network, performs research on adopting new methods like agile processes, AR/VR and AI technology to the design process of complex systems. Of particular interest is the design of innovative space and ground segment system.

The adoption of the capabilities of AI systems has been elaborated in other research projects before, but recent improvements in the field of Reinforcement Learning (RL) offer new possibilities for the conceptual design phase, which has so far remained largely unexplored, as described in Section 2.

Originating in robotics, RL has shown convincing capabilities in numerous disciplines. [1] This opens the question, whether there are unexplored research approaches for AI-supported CE, which can be filled by the application of RL.

As highlighted in Section 2, the approach to design a system "from the bottom-up" remains largely unexplored. The idea is to use the same established approach of applying engineering calculations to build a system from scratch, the same way CE experts build their concepts, instead of extracting knowledge from historical missions and building a knowledge database. The special characteristics of RL can offer a solution for this approach.

RL *agents* learn their strategy by gaining experience in a purpose-built *environment*. Starting with random actions, the agent learns which actions work best in which *state* (the current scenario/situation) by observing the environments response in form of a numerical *reward* value. The environment makes an assessment for every given state, by performing a set of calculations. These calculations can reach from simple if-statements, up to extensive physical simulations, depending on the use case and performance requirements. By tailoring the calculations performed by the environment, RL systems can be adapted to the specific use case. In Deep Reinforcement Learning (DRL) a Neural Network is used to perform the action-state mapping, which was recommended for these kind of tasks, because of a property called Value Function Approximation. With this, the DRL agent is capable of using a complete design space, without the need of training on every element.

With this, it is possible to design a DRL system, that is capable of gaining knowledge of a dedicated design space based on evaluations defined in the environment. Further, this opens the possibility to build an AI concept creator that is capable of creating concept designs in the aforementioned "bottom-up" approach, where the DRL-based AI agent gains experience in the designed environment.

2. Related Work

Artificial Intelligence (AI) has proven its value in the past to offer capable solutions and is especially reliable in data-driven situations. Besides many other applications to support the space mission design, Reinforcement Learning (RL) was shown to be capable of generating CubeSat designs [2] by applying regular engineering calculations. Besides the fact, that no following work after the master thesis has been published,

The main difference between the AI4CE project to to others lies in the approach on how the system design is approached on a fundamental level. While the demonstrated work follows the aforementioned "bottom-up" approach, the remaining research to this topic followed a more "top-down" approach.

Berquand et al. [3] proposed an AI system to support CE studies by providing a knowledge base of historical missions, with the idea to "provide easy and quick access to previous design decisions". As a key challenge of their work, the challenge of extracting relevant information from technical documentations, data sheets and alike is highlighted. The proposed system would help the designing team with knowledge from previous missions using Natural Language Processing (NLP), which is a different approach, than generating designs based on engineering calculations and the experience of the designing CE team. Buettner et al. [4] developed the iCASD tool which is capable of creating satellite designs, based on simple selction algorithms. The work primarily focuses on component placement within the satellite, but also offers simple component selection capabilities. The iCASD project is a capable visualisation and component positioning tool, but the proposed PhD research offers increased component selection functionalities and integration in an existing MBSE/CE workflow. In addition to the machine learning (ML) discussed here, Expert Systems have been studied as another branch of AI to support the CE process, like [5]. In summary, AI has been explored to be used for CE studies before, but the main focus relied on extracting information from historical missions, using Experts Systems or NLP to support the designing teams. The proposed research uses a method to generate systems without the challenge to analyse the documents, mails and technical descriptions of other missions.

A survey paper by the German Aerospace Agency DLR highlighted the bottom-up approach as promising. [6]

3. AI4CE - The vision

The Artificial Intelligence for Concurrent Engineering (AI4CE) research project describes the approach to combine the advantages of AI tools to the design process, to support and elevate the design decision process in a bottom-up approach. The general idea can be distinguished in 3 major aspects: the DRL concept creator (DCC) itself, a module for the translation from an MBSE model to the design tool (DCC2MBSE) and a translation layer from operations to the mission design process (OPS2Design).

The Deep Reinforcement Learning Concept Creator (DCC) functions as the core of the system creation process. In it, the AI takes system requirements together with a component database as an input and generates mission concepts as a result. Figure 1 illustrates the underlying functionality and conceptual integration into a CE workflow. Starting with a set of system requirements, the AI selects components from the database and combines them to a system concept, which is represented as a list of selected components. This concept will then be evaluated by the CE team, to tweak the requirements of the designed system or the AI evaluation criteria. The CE team has full control about the criteria and mechanisms the AI uses to comprise the system design and can adjust them by simply changing the implemented calculations. Further, when moving to the next design iteration, the mission requirements can be adjusted to represented the current state of mission design, which will be used by the tool to create an updated mission design. The final system design can function as a general process optimisation, inspiration, training purposes or just a test implementation to check, how the current system design could be realised using real-world components, in case of a a database of commercial off-the-shelve components.

To integrate the concept creation into an existing MBSE workflow, the DCC2MBSE module will offer an interface for MBSE models. System requirements defined in the model will be read from the model and the created system designs will be introduced back into the same model.

Another aspect and benefit of applying MBSE is digitisation of the complete Product Life Cycle (PLC). With this it is possible to collect valuable information from the fist idea and Phase0/A designs up until the disposal of the satellite. Especially making use of the knowledge gained during the operation phase (OPS) is of value for a sufficient mission design.

To close the PLC loop from the operation phase back

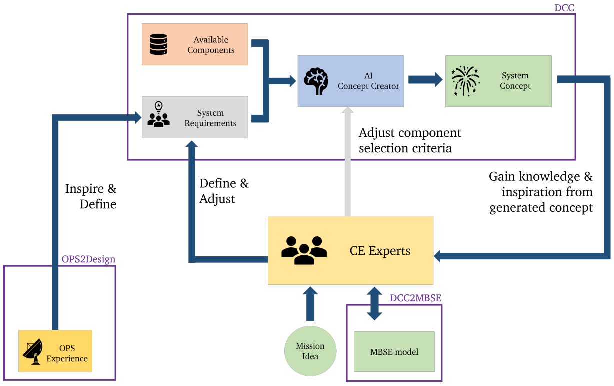

Fig. 1. Overview of the AI4CE concept creation procedure. The CE team receives information about the system's purpose and an MBSE model. Building on that, the team adjust the AI system's mission requirements. Together with additional information coming from the operations and a component database, a concept gets created. The CE experts will then review the created system and start a new iteration, until the final design is reached, which gets exported as an updated MBSE model. The three models of the AI4CE project are highlighted as purple boxes.

to the design phase, AI4CE contains a OPS2Design module. It will function as an interface for the operational teams to the MBSE model, where design-relevant information can be introduced. Since these information will then be used by the DCC, a formalisation of these information is necessary.

4. Current State of Work

The AI4CE project is a processor a preceding master thesis, where a first prototype and the prove of the underlying implementation idea were made.

It was shown in the context of a master thesis, that DRL can be used to build a satellite design where the decision process is based on engineering calculations. It was possible to select suitable components and to build up a satellite design automatically, satisfying formalised design constraints. This process resembled the trade-off studies performed during CE studies, however performed by making use of AI: The agent makes a component selection from the component database based on user-defined system design constraints. The evaluation and optimisation of a design thus can be done inside the learning environment: This is done by calculating a reward, which is a numerical number characterising the benefit value of a given design variant. The reward acts as a feedback to design agent who can learn from this experience and adjust its component selection accordingly to achieve an even higher reward. As a result, AI4CE can gradually evolve a design towards an optimum. Figure 2 illustrates the gen-

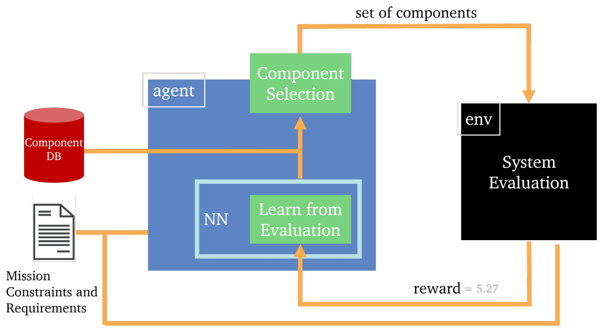

Fig. 2. Complete overview of the selection process. The agent takes a component selection from a database (action) which gets evaluated by the learning environment. Inside the environment multiple classical engineering parameters get calculated to access the performance of the current component selection in form a reward. This reward is used by the agent to learn from its taken action. Since a Neural Network (NN) is used for the action-reward mapping, the technology is called Deep Reinforcement Learning (DRL).

eration of such a system reward. The agent calculates an individual reward for every single component, based technical performance calculations in the same way as the domain experts perform their calculations for the CE design activity. Each reward is based on a variety of general and domain-specific parameters such as power, mass, performance parameters, which are read from the database. Subsequently, all individual rewards get combined into one single system reward.

The user has control over the DCC tool, by adjusting 2 setup file: the orbit file holds information about the desired satellite orbit and information about the design are stored in a dedicated system architecture file.

5. Future Development and Open Questions

After the first prototype implementation demonstrated the underlying applicability of the concept creation approach, future research will focus on further expanding on all three aspects of the project.

The DCC was designed with high modularity in mind. Expending existing component support and implementing creation functionality for entirely different systems is therefore part of the implementation.

The supported types of system are not yet defined, but plausible candidates are: a generic satellites representation, satellite constellation, the ground segment (in cooperation with ESA/ESOC), moon rover and moon base.

An essential step in the development of AI4CE is the integration in existing CE processes. It is therefore important, to have a distinguished/detailed understanding, on how the concept creation can interact with already existing MBSE models. The DCC2MBSE module therefore will define the interface between the DCC and the used MBSE Software like RHEA's COMET or DLR's Virtual Satellite. Managing the various requirements will be among the first steps towards that functionality. In the described prototype, requirements are are defined rudimentary in the system architecture file, where the amount of pre-defined supported components can be defined, as well as a few system-wide parameters. While this implementation can be sufficient for CubeSats because of the systems's high level of standardisation, support for more general /abstract requirement definition is required. It will be possible to state general mission constraints, like Ground Sampling Distance or daily data volume transmission requirements.

6. Conclusion

In this paper the Artificial Intelligence for Concurrent Engineering (AI4CE) research project has been introduced. AI4CE enables bottom-up system concept creation based on Deep Reinforcement Learning as support for CE studies. The DRL Concept Creator (DCC) as the core of the project, enables CE teams to generate system designs based on a set of requirements and a database of components to support their studies in various ways. To integrate this capability into an existing CE process, the DCC is is accommodated by an interface to communicate with the MBSE model used by the CE teams. Additionally, to make use of the knowledge gained during the actual usage in operation and thereby closing the PLC loop the OPS2Design interface forms the third aspect of the AI4CE project.

AI4CE is currently in its early steps. The feasibility of the underlying approach could be demonstrated with a first prototype and future development will focus on defining the interfaces for the MBSE model and OPS experience integration.

Acknowledgements

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