Investigating the Use of AI Planning Methods in Real-World CPS Use Cases

Niklas Widulle*, Luis Miguel Vieira da Silva*, René Heesch*, Julian Putzke*, Oliver Niggemann*
*Institut für Automatisierungstechnik
Helmut Schmidt Universität
Hamburg, Deutschland
{niklas.widulle, miguel.vieira, rene.heesch, julian.putzke, oliver.niggemann}@hsu-hh.de

***Abstract*—AI based planning methods are promising tools to allow CPS to achieve independent and optimal behaviour. Many research projects have developed a variety of planning algorithms with encouraging results. However, many of the developed algorithms are not yet capable to handle the complexity of real world problems. A roadblock in the development of more advanced solutions is the lack of real world benchmarks and applications. In this work we investigate how AI based planning methods can be applied to real world CPS use cases. These use cases are part of the research projects KIPRO, EKI and RIVA which are all part of the KIIPS research focus by dtec.bw. We show how these projects bring research into real world applications and help advance the state of the art of AI planning methods.**

***Index Terms*—cyber-physical systems, artificial intelligence, planning, machine learning**

I. Introduction

Cyber-physical systems (CPS) are characterized as highly complex, interconnected systems which combine physical and computational elements [1]. Examples of CPS are industrial manufacturing systems which are called cyber-physical production systems (CPPS), robotics systems or autonomous vehicles [2]. Depending on the type of CPS, the governing algorithms have different goals, including control, anomaly detection, diagnosis, (re-) configuration and especially planning, the process of making decisions towards a goal. Whether it is production sequence in a CPPS or a route generation for an autonomous vehicle, planning as a high level functionality plays a key role.

Recently, progress has been seen in the field of artificial intelligence (AI) based planning solutions. AI can be grouped into symbolic and subsymbolic methods. The former methods deal with discrete symbols and their relationships, while the latter focus on statistical relationships in data with the best known subgroup being machine learning (ML). Both groups provide methods that can be applied to planning as is shown in e.g.: [3], [4].

A big research community is working with the *planning domain definition* language (PDDL). It is a formal language that can be used to describe planning problems and falls in the symbolic category [5]. Another symbolic way to describe planning problems is within the formalisms of *boolean satisfiability problems* (SAT) and *satisfiability modulo theories* (SMT). SAT requires the planning problem to be described as a set of boolean statements and a SAT solver is then used to find a solution. SMT extends this to include background theories and is thus more expressive. ML is typically grouped in the three main directions supervised, unsupervised and reinforcement learning. Each of these three main categories has been applied to planning problems, with varying results.

The maturity of the approaches covered so far is very varied. Some have been applied only to very small toy problems, while for example PDDL has been used as a basis for scientific competitions. However, the application of these methods to real world problems is still limited. This is at least partially due to a chicken or the egg dilemma: Most approaches so far are not yet usable to cover real world problems but the scientific community lacks real world data to improve the approaches.

The solution can take the form of joint research projects that bring industry and scientific community together, as the research projects KIPRO [1], EKI [2] and RIVA [3] do. Each of these projects has its own scope on different aspects of research for CPS. In each one however, planning plays a significant role and therefore these projects are candidates for the application of AI planning approaches. Every project can provide additional insight into the application of these approaches and also provide much needed feedback and data for the research community.

In this work, the use of AI planning within the scope of these research projects is investigated. Potentials of the individual approaches within the use cases are highlighted and potential pitfalls and limitations are named. This lays the foundation for future work on AI planning within these projects.

The remainder of this paper is structured as follows: In the next section, a short overview of the state of the art in AI planning is given. Then the aforementioned research projects are introduced, highlighting use cases and potential benefits. This is followed by a more general discussion of these applications and resulting challenges. The conclusion and future work finish this paper.

[1] KIPRO – KI-basierte Assistenzsystemplattform für Produktionsprozesse
[2] EKI – Engineering für die KI-basierte Automation in Produktionsumgebungen
[3] RIVA – IT-Konzepte & -Lösungen für Verbünde autonomer Fahrzeuge

https://doi.org/10.24405/14547

II. State of the Art

In the following two subsections, an overview of AI planning methods is given. Requirements resulting from their use in CPS are also introduced.

A. Symbolic Planning Methods

Symbolic AI deals with high level symbols and their relationships. For planning, it can be used as follows: The planning problem needs to be described using these symbols and the solution can then be inferred from them. Thus, the solution process always consists of two steps: Describing the problem within the formalism of the chosen method and then applying a solver to derive the solution. The development of solvers is a large research topic on its own, but outside of the scope of this work. Here we focus on the modelling languages. Generating a formal description of a planning problem is not trivial in itself.

One common approach is the use of PDDL. The language helps to define a description format for planning problems. Depending on the version of the language, many common features of planning problems can be described, such as temporal constraints, numeric parameters or parallelism [6]. However, real world problems are often still too complex to be described within the stiff framework of the language [7]. Connected with PDDL, a number of solvers were developed, some solve the problem directly, while others translate the problem into another description such as SMT [8]. Solvers usually support only a subset of all features of a PDDL version, which makes the problem of the limited expressiveness of PDDL even worse [7].

The basis for using SAT for planning was laid by Kautz et al. in 1992 [9]. The basic method is to describe the problem within the formalism of SAT and then use a regular SAT solver to find the solution. Describing a planning problem in SAT is nontrivial however. Since SAT only supports boolean symbols, it is very limited. This can be overcome by employing SMT [3]. Using SMT for planning can be done by describing the problem directly as SMT or by using another problem description formalism and then translating it to SMT. SMT has its own widely used standardized language, specified as smt-lib. A notable extension for SMT is called OMT, which additionally includes methods for optimization [10]. This is obviously very beneficial for planning, since we are typically interested in an optimal solution.

B. Machine Learning based Planning Methods

Where symbolic methods typically fall short is in their inclusion of data. Modern CPS create vast amounts of data, and using them to create or improve plans can benefit the solution. This is where ML based methods can step in. The main drawback of these methods is that they require vast amounts of data that may not yet be available when the CPS is still in the design phase. Simulations can alleviate this problem. For an overview of ML based planning approaches refer to [11], only a brief impression is given here.

Supervised learning uses labeled data for training. Examples of recent applications of supervised learning for planning include STRIPS-HGN by Shen et al. [12] and GGS-NN by Li et al. [13]. The need for labeled data is a major drawback, since generating labels for data sets is usually labor-intensive and often impractical.

For this reason, unsupervised learning is promising, which does not require labels for training. Work in this direction is still in its infancy. An example is the work by Segovia-Aguas et al. [14], in which planning instances are classified using an unsupervised algorithm.

Recently, first benchmarks have been created for the use of AI and more specifically ML planning methods [15].

C. Requirements for the Application of Planning Algorithms

In a previous work, we derived requirements for the use of AI-based planning algorithms in CPPS, but they remain relevant to the more general case of CPS [16]. The requirements for the algorithms are:

- Optimization: The ability to provide an optimal solution
- Dependencies: Handling dependencies between tasks
- Loops: Managing recurrent actions
- Explainability: Be understandable by a human user
- Low Effort: Does not require too much human input
- Data: Makes use of existing data

For a more in-depth look at the reasoning for these requirements please refer to our previous work. In the description of our use cases and in the discussion we will refer back to these requirements.

III. Applications

In the following an introduction to the projects KIPRO, RIVA and EKI and the specific use cases within them is given.

A. KIPro

Modern production facilities still incorporate manual tasks. These manual production steps are frequent especially for assembly and in high variance or low volume production, which is common within the machine tool industry. Fully automating these production steps is typically unfeasible given the low volume, however, increases in efficiency are still required. This is especially true in high-wage countries such as Germany.

Worker assistance systems can alleviate the issue. They support the worker by providing information on the assembly task and therefore reduce idle time especially for inexperienced workers. Creating the assistance function with traditional methods still requires a lot of effort. Here, AI can step in: Using AI based planning algorithms creating assistance can be automated. Additionally it can be embedded into the automated planning and scheduling system of the factory to further increase productivity. This is the goal of the project KIPro: To create an AI enabled assistance system.

KIPro is a joint project by HOMAG[4], DUALIS[5], ITAC[6], TH OWL[7] and the Professorship Computer Science in Mechanical Engineering at HSU[8]. HOMAG is a leading manufacturer of woodworking machines. DUALIS is a solution provider for automatic planning and scheduling (APS) systems as well as other industrial software. ITAC creates manufacturing execution system (MES) software and related tools. Together with the input from the academic institutions these companies have the required know how and capabilities to create the assistance functionality envisioned in KIPro.

The assistance system needs to plan the assembly process in order to provide assistance to the worker. This makes the connection to AI planning methods clear. However, the input to the planning system can be CAD and video data from assembly sequences, and therefore not directly suitable for symbolic planning. The description of the planning problem is one of the areas of concern. There is a dedicated community to assembly sequence planning [17] which has created its own notations. A high level of automation for the generation of assembly plans is required in order to keep the solution economically viable. Therefore, in order to solve the issue we require an automatic creation of a problem description which can then be solved using a planner or we can alternatively rely on an integrated RL based approach. Both approaches are current research topics and solutions can benefit the wider community.

Additionally the assembly assistance functionality needs to be embedded in the APS and MES contexts. APS systems themselves can benefit from ML as the created schedules can be adapted automatically to changes in production context. The assistance functionality also needs to adjust to the worker, since they will require individual and adaptive levels of assistance. Here the integration into the MES context can be helpful as it provides information about the user.

B. EKI

The project EKI aims to develop an open, vendor independent and expandable engineering platform which enables the integration of AI components within the engineering process. In this case, engineering describes the process of creating or adapting the automation software of CPPS in order to manufacture new products or react to failures. The project tackles two challenges. On the one hand, AI applications such as predictive maintenance are getting more and more important and have to be integrated during the engineering process. Furthermore, due to the trend of CPPS, there are also new approaches to facilitate the engineering using AI-based assistance features for example, to automate the creation of sequences in PLCs. However, there is a lack of engineering methods enabling the usage of these new developments. On the other hand, due to the lack of the engineering methods, there are also only few CPPS. To solve this chicken or the egg dilemma, an AI-capable engineering platform is developed together with Weidmüller Interface GmbH & Co. KG and evaluated by engineering a CPPS for automotive glass finishing built by BBG GmbH & Co. KG.

Within the EKI project, AI planning methods will be used as the basis of the AI-based assistance feature to facilitate the engineering. For this purpose, it is assumed that within a modular CPPS, the functionality of a module is accessed as a so-called *skill*. The skills already programmed on the module's PLCs and can be called, for example via OPC UA, from a higher-level controller by specifying various required parameters [18]. Thus, the output of the assistance feature will be a sequence of parameterized skills, a high-level controller has to call in order to manufacture a desired product. An AI planning algorithm will take a description of the raw materials as the initial state and a description of the desired as the goal state. The possible actions, which can be performed to reach the goal state, are represented by the descriptions of the functionalities of the available modules, the so-called *capabilities* applied in [19].

In this project, we try to solve the planning problem from two different sides. On one hand, the symbolic approach, where we use logic solvers to resolve the planning problem. On the other hand, a subsymbolic method, which uses ML algorithms to generate the output sequence. The general input and output of both systems are the same, although the implementation is different. The two need a formal description of the domain, as well as the initial state of the process and the desired goal. The output is a sequence of actions leading from the initial to the goal state. On top of that, for each action, the individual parameters are defined in the planning tool. Consequently, the planning tool can output a combination of production sequence and parameters.

C. RIVA

The RIVA project aims to enable teams of robots of different modalities (land, water, air) to perform missions autonomously in real time. Autonomous robot teams have an enormous economic and societal potential, as many use cases can be realized more effectively and efficiently than with single robots. Such teams range from unimodal robot teams (e.g., drone swarms for fighting forest fires) to trimodal robot teams (e.g., search & rescue using boats, drones and rovers). An important part of the project is the planning and execution of missions based on the knowledge of the different capabilities of each robot, where changing environmental conditions or capabilities of the team participants can directly affect the tasks of the individual robot and must be taken into account. Various other challenges such as path planning, environment model creation or ensuring safe behaviour are addressed in this project. Mission accomplishment is to be demonstrated both in simulation and in practice. This problem is addressed in cooperation with IT-objects GmbH and Third Element Avi-

[4]HOMAG GmbH
[5]DUALIS GmbH IT Solution
[6]ITAC Software AG
[7]OWL University of Applied Sciences and Arts (TH OWL)
[8]HSU Helmut Schmidt University University of the Federal Armed Forces Hamburg

TABLE I: THE REQUIREMENTS OF AI PLANNING IN THE RESEARCH PROJECTS
●/◐/○: Important/Partly relevant/Less relevant

	Optimization	Dependencies	Loops	Explainability	Low Effort	Data
KIPro	●	●	○	◐	●	◐
EKI	●	●	●	●	◐	○
RIVA	◐	●	○	●	○	◐

ation GmbH, who provide the required hardware (multimodal robots) and the simulation environment.

In the RIVA project, AI planning methods will be used for mission planning. Teams of robots are used to implement complex scenarios. Due to this complexity, but also due to the diversity of the scenarios, the missions for the fulfillment of the scenarios are to be planned automatically. Accordingly, the wide range of possible applications for robot teams also requires a domain-independent approach to planning the desired missions. In contrast to the CPPS considered so far, a sequence of robot capabilities is output here instead of a sequence of production steps. The project is not about considering different approaches to solving the planning problem, but about creating the planning problem based on a formal model of autonomous robot capabilities to be developed in the project. The goal is to enable planning for all possible scenarios and robot types by basing the planning on the uniform description of the robots, which only needs to be transformed into the planning problem. Consequently, no individual planning problems have to be set up manually. Furthermore, three modalities are considered, which have hardly been applied so far. In addition to describing the robots and their capabilities, the initial situation of the robots and their environment as well as the mission objective must be considered. For example, the goal may be to transport an object from A to B, and the transport can be realized only by cooperation of multimodal robots due to obstacles. The output is also a sequence of actions or capabilities leading from the initial state to the goal state.

IV. DISCUSSION

Each of these projects use AI planning as a central part of their solution. The different projects applications, requirements and goals however still require distinct approaches.

A. Requirements for the Planning Approaches

Which methods are the best fit for each project is a difficult question. The requirements for planning algorithms established in our previous work can give a good indication [20]. For each of the projects, different requirements are more relevant. Since the planning methods only satisfy the requirements to varying degrees, this can give an indication which methods are best suited for the different use cases within the projects.

For KIPro, the assistance system needs to provide optimal solutions for the workers, otherwise the overall benefit is too low. Assembly processes are inherently interdependent. Loops and repetitive instructions are of less concern, while explainability is of some interest. The solution should overall remain economically viable and therefore low effort is essential. The usage of existing data is relevant to the improvement of APS results.

For an engineering tool like that created by EKI, explainable behaviour is highly important in order to be transparent to the user. Still, dependencies need to be resolved and an optimal solution should be provided. Loops will be part of the solution and need to be addressed accordingly. Currently, a lot of research is being done in the field of semantic descriptions of production facilities. It is hoped that in future, it is possible to use these descriptions to reduce the effort required to integrate the domain knowledge in planning algorithms. Thus, the effort is less important in this project.

In mission planning for autonomous and heterogeneous robots, as envisioned in RIVA, an optimal solution is not as necessary. Finding a solution for complex scenarios is challenging in itself. Dependencies between robots or between inputs and outputs of capabilities are on the other hand of importance, so that for example the battery life can be calculated. Loops are less of a concern for the RIVA project. Of high importance is explainability, since the behaviour of autonomous robots is already difficult to comprehend due to their highly automated capabilities. Therefore, planning should be explainable in order not to make the behavior of robots even more unpredictable. The effort required to create and maintain the solution is not as much of a focus. Neither is the use of the data in the focus. The data is of course important for the control of the internal state and consideration in the execution of their capabilities, but for the basic planning it should be considered and included in a rather limited way.

These notions are summarized in TABLE I. Together with the knowledge of the advantages and shortcomings of the different planning methods, some recommendations for the projects at hand can be derived.

B. Challenges and Potentials for Planning Approaches

For KIPro, using symbolic planning approaches, especially SMT to create optimal assembly plans is promising, especially since resolving dependencies becomes trivial. However, the form of the input models, be it CAD or video data, makes using just these methods impossible. What is required is an interconnected method which utilizes the power of ML to create input models suitable for symbolic AI methods. Alternatively, an end-to-end RL approach might resolve the task, here the computational effort could be the limiting factor. The additional inclusion of optimization for the APS results

creates a scenario which resembles supervised learning because planning results can be matched with known outcomes.

Considering the strengths and weaknesses of the different AI planning methods, two approaches seem to be the most useful in the context of the EKI project. If the platform is used at the beginning of the operating phase of a CPPS, there is less or no labeled data available to train an ML-model. Thus, at this point in time, only a symbolic approach is feasible. As PDDL is not expressive enough to describe and consider the complex dependencies between the input and output products as well as the parameters, it has to be an SMT-based approach. But, in the course of the operating phase of a CPPS, it is possible to collect the data about the different products as well as the corresponding sequences of actions leading to the products. Therefore, also an ML-based approach may be an interesting option at a later point in the operating phase. As the collected data will be labeled, a supervised learning algorithm might be promising. However, using ML-based methods brings new challenges, as learning extensive ML-models cannot be done on a PLC. This makes the integration of cloud computing or edge devices with sufficient computing power necessary. There is also the question whether inference must be real-time capable and run on the PLC, and how this can be ensured. These challenges will also be addressed within the EKI project.

In the RIVA project, the use of symbolic planning approaches for mission generation is promising. On the one hand, formal capability models have a close proximity to these planning approaches, on the other hand, the advantageous properties of sub-symbolic planning approaches are hardly relevant here and take place in the use of a robot's autonomous capabilities, such as in environment perception. Especially PDDL is in strong focus for planning in the field of autonomous robots. Therefore, the focus is on symbolic planning approaches in conjunction with formal capability models for the robots.

In each of these projects, a combination of symbolic and subsymbolic methods is most promising. While the reasons for this are diverse, it highlights the necessity for research into combining these domains for planning approaches.

V. Conclusion and Future Work

The three research projects KIPro, RIVA and EKI each show the potential for successful applications of AI based planning. While their applications - autonomous vehicles, engineering tools and assembly systems - are very different, each project offers the opportunity to apply these methods. In the future, this will hopefully allow us to overcome one of the main limitations in the development of AI based planning methods, which is the lack of real world benchmarks and data.

The analysis of existing planning approaches for the projects showed that combining symbolic and subsymbolic methods holds the greatest potential. This is an exciting and promising field for future research in the planning domain.

Acknowledgment

This Paper is funded by dtec.bw – Digitalization and Technology Research Center of the Bundeswehr which we gratefully acknowledge [project KIPRO][project RIVA][project EKI].

References

[1] R. Baheti and H. Gill, "Cyber-physical systems," *The impact of control technology*, vol. 12, no. 1, pp. 161–166, 2011.

[2] J. Shi, J. Wan, H. Yan, and H. Suo, "A survey of cyber-physical systems," in *2011 international conference on wireless communications and signal processing (WCSP)*. IEEE, 2011, pp. 1–6.

[3] A. Bit-Monnot, F. Leofante, L. Pulina, and A. Tacchella, "Smt-based planning for robots in smart factories," in *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*. Springer, 2019, pp. 674–686.

[4] J. P. Usuga Cadavid, S. Lamouri, B. Grabot, R. Pellerin, and A. Fortin, "Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0," *Journal of Intelligent Manufacturing*, vol. 31, no. 6, pp. 1531–1558, 2020.

[5] C. Aeronautiques, A. Howe, C. Knoblock, I. D. McDermott, A. Ram, M. Veloso, D. Weld, D. W. SRI, A. Barrett, D. Christianson *et al.*, "PDDL— The Planning Domain Definition Language," Technical report, Tech. Rep., 1998.

[6] A. Anis, W. Schäfer, and O. Niggemann, "A comparison of modeling approaches for planning in cyber physical production systems," in *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*. IEEE, 2014, pp. 1–8.

[7] A. Rogalla, A. Fay, and O. Niggemann, "Improved Domain Modeling for Realistic Automated Planning and Scheduling in Discrete Manufacturing," in *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, vol. 1, 2018, pp. 464–471.

[8] M. Cashmore, M. Fox, D. Long, and D. Magazzeni, "A compilation of the full pddl+ language into smt," in *Proceedings of the Twenty-Sixth International Conference on International Conference on Automated Planning and Scheduling*, ser. ICAPS'16. AAAI Press, 2016, p. 79–87.

[9] H. Kautz and B. Selman, "Planning as Satisfiability," in *Proceedings of the 10th European Conference on Artificial Intelligence (ECAI 92)*, 1992.

[10] F. Leofante, E. Giunchiglia, E. Ábrahám, and A. Tacchella, "Optimal planning modulo theories," in *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI 2020*, C. Bessiere, Ed. ijcai.org, 2020, pp. 4128–4134.

[11] S. Jiménez, T. de La Rosa, S. Fernández, F. Fernández, and D. Borrajo, "A review of machine learning for automated planning," *The Knowledge Engineering Review*, vol. 27, no. 4, pp. 433–467, 2012.

[12] W. Shen, F. Trevizan, and S. Thiébaux, "Learning domain-independent planning heuristics with hypergraph networks," in *Proceedings of the International Conference on Automated Planning and Scheduling*, vol. 30, 2020, pp. 574–584.

[13] Y. Li, D. Tarlow, M. Brockschmidt, and R. Zemel, "Gated graph sequence neural networks." [Online]. Available: http://arxiv.org/pdf/1511.05493v4

[14] Javier Segovia-Aguas, Sergio Jiménez, and Anders Jonsson, "Unsupervised classification of planning instances," *Proceedings of the International Conference on Automated Planning and Scheduling*, vol. 27, pp. 452–460, 2017.

[15] J. Ehrhardt, M. Ramonat, R. Heesch, K. Balzereit, A. Diedrich, and O. Niggemann, "An ai benchmark for diagnosis, reconfiguration planning," in *2022 27th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA2022)*, 2022.

[16] A. Köcher, R. Heesch, N. Widulle, A. Nordhausen, J. Putzke, A. Windmann, and O. Niggemann, "A research agenda for ai planning in the field of flexible production systems," in *2022 IEEE 5th International Conference on Industrial Cyber-Physical Systems (ICPS)*. IEEE, 2022, pp. 1–8.

[17] B. Deepak, G. Bala Murali, M. R. Bahubalendruni, and B. Biswal, "Assembly sequence planning using soft computing methods: a review," *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, vol. 233, no. 3, pp. 653–683, 2019.

[18] A. Köcher, T. Jeleniewski, and A. Fay, "A Method to Automatically Generate Semantic Skill Models from PLC Code," in *IECON 2021 - 47th Annual Conference of the IEEE Industrial Electronics Society*. Piscataway, NJ: IEEE, 2021, pp. 1–6.

[19] A. Köcher, C. Hildebrandt, L. M. Vieira da Silva, and A. Fay, "A Formal Capability and Skill Model for Use in Plug and Produce Scenarios," in *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, vol. 1, 2020, pp. 1663–1670, ISSN: 1946-0759.

[20] R. Heesch, N. Widulle, A. Köcher, A. Nordhausen, L. M. Vieira da Silva, J. Putzke, and O. Niggemann, *Methoden der künstlichen Intelligenz für die automatisierte Planung von modularen Produktionsprozessen*, ser. Automation 2022: Automation creates Sustainability. Düsseldorf: VDI Verlag, 24.08.2022 2022, pp. 439–452. [Online]. Available: https://doi.org/10.51202/9783181023990-439