Potentials of Symbolic AI Planning for Construction

Shermin Sherkat[1], Thomas Wortmann[1] and Andreas Wortmann[2]
[1]Institute for Computational Design and Construction,Chair for Computing in Architecture, University of Stuttgart,Keplerstrasse 11, 70174 Stuttgart, Deutschland
[2]Institute for Control Engineering of Machine Tools and Manufacturing Units, University of Stuttgart,Keplerstrasse 11, 70174 Stuttgart, Deutschland
E-mail(s): shermin.sherkat@icd.uni-stuttgart.de, thomas.wortmann@icd.uni-stuttgart.de, andreas.wortmann@isw.uni-stuttgart.de

Abstract: AI planning aims to automate the reasoning process that underlies the plan formulation to achieve a particular goal for a particular problem. Research in this field has focused on symbolic methods -which represent knowledge with human readable symbols- to efficiently and systematically produce plans, i.e., sequences of actions to be performed, from well-defined problem statements. Despite advances in leveraging AI for construction planning and scheduling, most construction projects still adopt fully manual work templates. We outline the current state, challenges, and potentials of using symbolic AI in construction process planning. We first discuss the challenges in construction process planning. Then, we summarize potential applications of symbolic AI planning methods in the construction industry providing a resource for both practitioners and researchers to familiarize themselves with the potential of these powerful AI methods.

Keywords: Model-based planning, Construction industry, motion planning, TAMP, Task planning

1 Introduction

Today, artificial intelligence (AI) is frequently linked with machine learning methods, such as deep learning, that leverages neural networks. Traditionally, there have always been two main paradigms of AI: symbolic vs. subsymbolic, model-based vs. function-based, or knowledge-driven vs. data-driven [1]. While advances in the availability of data training, data transmission, and data processing have given rise to the resurgence of data-driven AI methods, which were considered being of little use in the “AI winter” of the 1980s, symbolic AI methods enable a plethora of successful applications based on structured knowledge, such as expert systems, path planners, or production planning. Despite not being in the spotlight currently, symbolic AI has been with us all the time.

AI planning is an abstract, explicit reasoning process that selects and organizes sequences of actions based on their anticipated outcomes. This reasoning seeks to achieve predetermined goals as efficiently as possible. Automated planning is an AI subdomain that studies this reasoning process computationally [2]. We believe that automated planning methods, particularly model-based planning (or so called symbolic AI planning), can facilitate construction planning.

In model-based planning, the controller that selects the next action to be performed is derived automatically from models of the actions, states, and goals defined in a declarative language like the Planning Domain Definition Language (PDDL) [3]. Our aim is to provide insights for researchers who want to use this technique in construction process planning.

Several challenges have hindered the scalability and widespread use of automated planning systems in construction planning [4]. Construction planning is consequently still mostly done manually, which results in inefficient plans and arguably contributes to construction's large environmental impact [5]. Model-based planning can address challenges related to knowledge formalization, inflexible work templates, and the disconnected nature of planning and scheduling. Towards leveraging model-based planning in construction, the contributions of this paper are:

1. Summarizing model-based planning methods and their corresponding environmental characteristics;
2. Reviewing selected applications of model-based planning in fields other than construction; and
3. Discussing the potential application of these planning methods in construction.

Our key insights are twofold: First, complex problems in the construction industry require a hybrid of model-based planning methods, and these problems all need the probabilistic method. Second, for the problem of robotic assembly, integrating task and motion planning methods is the most promising approach, while other problems can be modeled and solved with task planning methods.

We focus more on task planning methods in this paper and do not discuss motion planning methods in detail. In the remainder, Section 2 discusses construction planning and related automation challenges. Section 3 introduces the methods of planning, and Section 4 discusses the use of these methods in other fields. Finally, Section 5 outlines potential use-cases of each method for construction planning challenges.

2 Planning in Construction

Planning is required for many activities of construction processes, such as allocating labor, equipment, and material for efficient and economical operations. Sarker, Egbelu, Liao, *et al.* [6] categorize these activities into 10 categories, out of which model-based planning can potentially be applied to six: (1) delivery process of ready mixed concrete (RMC) trucks, (2) resource allocation and leveling (to reduce peak requirements and resource fluctuation), (3) inspection of partially completed work at the end of one activity and before the start of the next known as buffer stocks (modeling the link between processes), (4) planning for linear projects such as railroads and pipelines, (5) time and cost estimation, and (6) controlling the cost escalation in big infrastructure projects [6]. Additionally, model-based planning can support automated assembly (cf. Table 1). Several methods and systems

Table 1: This table shows construction industry planning categories, their scope and application

Planning categories	Scope	Application
Scheduling and dispatching	Dispatching space	RMC trucks
Resource allocation and leveling	All projects	Equipment. manpower balancing
Buffer stocks	Project sites, Procurement	Work in progress, work flow reduction, cycle time
Linear projects	Highway and road construction	Schedululing, traverse operations, cost estimation
Time and cost estimation	All projects	Risk management, quality assurance, intellectual property
Infrastructure	Public project, bridge and highways construction	Cost escalation factor
Automated assembly	Project sites, prefabrication	Task and motion planning

have been developed so far to automate planning processes. However, construction planning is done mostly manually because (C1) flexible knowledge formalization is missing for storing construction models and templates for sequencing algorithms, (C2) current automated scheduling methods are dependent on manually formed and maintained work templates, (C3) research on automated planning and scheduling is decoupled, (C4) existing automated planning systems are only partly validated in real-life construction projects, and (C5) automated learning methods are needed to learn construction knowledge from existing records without extensive human input [4]. Model-based planning, as illustrated in the following sections, has the potential to address C1-C3.

3 Planning Methods

Model-based planning for creating the sequence of actions to be performed to reach a specific goal consists of two main parts: (1) the domain models that define the states, goals, and actions, specified in a planning language; and (2) the algorithms that use the models to generate the plan [4]. A planner then inputs the domain models and derives a sequence of actions required for reaching the goal state. Thus, given an initial state (e.g., concrete hollow core slabs on the ground) and a goal state (e.g., concrete hollow core slabs in their position on the roof) of a problem, planners will use various search and reasoning techniques to find a sequence of actions leading from the initial state to the goal state.

Depending on the problem environment, search and reasoning techniques differ. For planning in construction, classical planning, temporal and numerical planning, probabilistic planning, and hierarchical task networks appear to be promising techniques, which can be used together (hybrid planning) to address more complex problems. Table 2 defines important characteristics of the planning environment. Based on the environment characteristics we defined in Table 2, we now define planning methods.

Classical planning is the problem of planning in deterministic, fully observable, and discrete environments [7]. While classical planning answers what to do and in which order, **temporal planning** answers when an action takes place and how long it takes for planning in a continuous environment [7]. The difference between temporal and **numerical planning** is that in temporal planning, the only continuous variable is time and all other variables are discrete [8]. However, continuous variables

Table 2: This table shows the the definitions of environmental characteristics [7]

Task environment characteristics		Definition
Observability	Fully observable	The sensors detect all environmental aspects that are relevant to the choice of action.
	Partially observable	The sensors are noisy and inaccurate or parts of the state are missing from the sensor data.
	Unobservable	There is no sensor.
State transition	Deterministic	The next state of the environment is fully determined by the current state and the action executed
	Stochastic	Actions are characterized by their possible (not deterministic) outcomes.
Time and perception	Discrete	The state, time and actions are used as discrete variables.
	Continuous	The state, time and actions are used as continuous variables.

are allowed other than time in numerical planning, but it is insufficient for defining high dimensional geometrical problems [8].

Probabilistic planning is planning in partially observable, stochastic environments [7]. Markov Decision Process (MDP) planning is used when the actions have effects that can only be predicted probabilistically, but the state of the problem is always observable [3]. Partially Observable Markov Decision Process (POMDP) planning problem is used for problems where the actions have stochastic effects, but the state cannot be fully observed [3].

Hierarchical Task Networks (HTNs) are methods for solving planning problems that consist of abstract tasks and their methods (decomposition). Therefore, instead of going through all possible actions in each state, the methods decompose high-level relevant tasks to build a task network containing both compound and primitive tasks (actions) [9]. This approach can make the large problems more manageable.

The methods mentioned above are widely used for solving task planning problems. We also briefly discuss the problem of motion planning as it is relevant to construction industry challenges: The challenge of **Motion planning** is finding a feasible trajectory in space and time [2]. It includes (1) finding a path in an environment for moving a mobile system from the start position to the goal position and (2) the control law along the path considering the mobile system's dynamic limitations (speed, kinematics, and acceleration). Motion planning requires a geometric CAD model of the environment with the obstacles and free space; Methods of this planning problem deal with high dimensional geometry in a continuous environment [2]. Table 3 shows a summary of the mentioned planning methods and their main environmental characteristics.

Table 3: This table shows the main characteristic of each planning method

Planning methods		Environmental characteristics		
		Observability	State transition	Time and perception
Classical planning		Observable	Deterministic	Discrete
Numeric and temporal planning		-	-	Continuous
Probabilistic planning	MDP	Observable	Non deterministic	-
	POMDP	Partially observable		
	Conformant	Unobservable		
Motion planning methods		-	-	Continuous

4 Applications of Model-Based Planning

4.1 Classical Planning

Classical planning has applications including planning military logistics [10], and RoboCup Logistics League (RCLL) [8]. However, to use classical planning in non-deterministic and partially observable real-world problems, abstraction and hierarchy both in activities and in states have been used [8]. In robotics, a classical planner is rarely used to control a robot's motors directly. Instead, they usually assume the robot can perform a set of tasks (tasks defined with classical planning methods). Then, these tasks could be implemented in a lower-level probabilistic process [11], in custom rule-based systems [12], or in other ways to control the robot's motors. In the RCLL scenario for example, the classical planner does not need to know about the continuous coordinates of the robot and only plans the discrete move actions between the different machines [8].

4.2 Temporal and Numeric Planning

Robots could use temporal planning to (1) meet a deadline (e.g., complete a task before 6 PM), (2) meet a time window (e.g., the charging station is only operating between 2 and 4 PM), or (3) coordinate concurrent activities. Combinations of numeric and temporal planning allow modeling numeric changes over time, which is useful for resource management (e.g., the battery level) [8]. But, the duration of actions being executed by robots can only be observed and not controlled directly because many external factors will affect these durations. To handle this, robots need to determine when to dispatch each action for execution and to understand when the deviation of observed durations from those in the model has invalidated the plan [8].

4.3 Probabilistic Planning/ Planning Under Uncertainty

MDPs and POMDPs have been used for optimizing dam management in hydroelectric power plants because, for example, a valve can get stuck and not respond correctly to a signal from the controller (stochastic actions), errors in the flow measurement in pipes are common (uncertainty in the state), or the level in a steam reservoir is a variable that cannot be observed directly (partial observability) [13]. But probabilistic planning requires a precise representation of the possible states and actions, which leads to exponential growth of the problem space and limits their use for real-world problems. In dam management, the challenge of state and action exponential growth has been addressed through factored representations, which uses Bayesian networks [13]–[15]. Another challenge with using MDP is that they become difficult to solve for large problems with hundreds of state variables. In this case, abstraction or decomposition strategies might help [16].

4.4 Motion Planning

Free-space motion is the most basic motion planning problem, in which the agent must just move across space without colliding with anything [17]. Multimodal motion planning extends the problem

Table 4: This table shows potential planning methods for each of the construction process categories.

	Construction planning categories	Planning methods				
		Classical	Temporal and Numeric	Probabilistic	Hierarchical task network	Motion planning methods
1	Scheduling and dispatching of RMC trucks	×	×	×	-	-
2	Resources allocation and leveling	-	×	×	-	-
3	Impact of buffers in construction processes	-	×	×	×	-
4	Scheduling linear projects	-	×	×	×	-
5	Time, cost and quality	-	×	×	-	-
6	Large infrastructure projects .	-	×	×	×	-
7	Robotic assembly	×	-	×	×	×

space to include changing the state of other objects in the world [17], [18]. However, for a robot to act fully autonomously, planning needs to be in a hybrid environment that contains both discrete and continuous actions and variables. For example, if the problem is packing some boxes into a defined region, we need to model both discrete (e.g., move, pick, boxes) and continuous (e.g., robot trajectory, box poses) variables and actions [19]. To solve this, research has devised fully integrated task and motion planning tools, such as PDDLStream [19].

5 Potential Uses of Model-Based Planning in Construction

Model-based planning can be applied to construction process planning categories and challenges mentioned in Section 2 . However, construction processes are non-deterministic and large; thus, we should solve them by combining several planning methods. For instance, scheduling and dispatching of RMC trucks can be modeled as a hybrid of (1) classical planning for finding the shortest path to the construction sites, (2) temporal and numeric planning for dispatching hours, costs, and revenues, (3) probabilistic for considering delays, accidents and other things that can interrupt the delivery process. Table 4 shows the potential methods for the rest of the construction planning categories.

As shown in Table 4, probabilistic planning is a part of all the construction processes since they are rarely deterministic. The plan should consider all the possibilities that might happen after performing an action. However, this is not possible in real world construction problems and requires other measures as mentioned in Section 4.3.

Temporal and numeric planning can automate schedule planning and schedule optimization in construction projects. For example, costs, labor, material and time are linear continuous variables that can be planned and scheduled automatically using temporal and numerical planning methods (Table 4).

Classical planning is used for planning parts of the process that include discrete objects. It can be used to sequence and allocate the tasks in a construction process, since the tasks are discrete variables.

Motion planning is concerned with geometry. So, the kinematic limits of the robots and their trajectory and path planning in the construction site is done by motion planning. For robotic assembly of building parts, integrating task and motion planning methods looks promising as it includes both discrete and continuous actions and variables. For example, the building components are discrete variables and the location of them are continuous variables.

Additionally, we can use abstraction and hierarchy (HTN) for modeling larger problem domains, as shown in the examples in Section 4.

Model-based planning also has the potential to address the challenges In Section 2 : Formal representation (C1): each method of planning provides the essential language requirements for formally representing the problem. Inflexibility of knowledge base (C2): once the model is properly built for a problem, it can solve any instance of that problem automatically. Also, using probabilistic planning methods can increase the flexibility of the knowledge base. Decoupled nature of planning and scheduling (C3): planning and scheduling are merged in temporal and numerical planning.

5.1 Conclusion

Model-based AI planning uses symbols to model the problem and then logic to solve them. Recent reviews on automated planning in construction suggest that formal representation, the rigidity of process templates, and the decoupled nature of planning and scheduling are among the reasons that hinder the use of existing automated planning systems [4]. Based on these insights, we conclude that different methods for task planning, e.g., classical, temporal, probabilistic, and motion planning have different advantages, limitations, and applications. Classical planning can be used for parts of the problems that are discrete, like finding the shortest path in a delivery process. Temporal planning can be used for processes that include resources and scheduling. Probabilistic planning is a part of all construction processes. These methods should be used together as construction processes are complex and cannot be modeled with a single planning method. Finally, a hybrid of task and motion planning methods has the potential for automating robotic assembly in construction. Discussing the languages for modeling these methods and planners that solve them using different algorithms and heuristics, and learning methods are beyond the scope of this paper, but are discussed in [2]–[4], [7], [20].

Acknowledgements

Financial support was provided by Artificial Intelligence Software Academy (AISA), University of Stuttgart.

References

[1] P. Hitzler and M. K. Sarker, editors, *Neuro-symbolic artificial intelligence: the state of the art* (Frontiers in artificial intelligence and applications / FAIA 342). Washington: IOS Press, 2022.

[2] M. Ghallab, D. S. Nau, and P. Traverso, *Automated planning: theory and practice.* Amsterdam ; Boston: Elsevier/Morgan Kaufmann, 2004.

[3] H. Geffner and B. Bonet, *A concise introduction to models and methods for automated planning* (Synthesis lectures on artificial intelligence and machine learning 22), eng. San Rafael: Morgan & Claypool Publishers, 2013.

[4] F. Amer, H. Y. Koh, and M. Golparvar-Fard, “Automated Methods and Systems for Construction Planning and Scheduling: Critical Review of Three Decades of Research”, en, *Journal of Construction Engineering and Management*, vol. 147, no. 7, (ASCE)CO.1943–7862.0002093, 03 121 002, Jul. 2021.

[5] S. O. Abioye, L. O. Oyedele, L. Akanbi, *et al.*, “Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges”, *Journal of Building Engineering*, vol. 44, 2021.

[6] B. R. Sarker, P. J. Egbelu, T. W. Liao, and J. Yu, “Planning and design models for construction industry: A critical survey”, en, *Automation in Construction*, vol. 22, pp. 123–134, Mar. 2012.

[7] S. J. Russell, P. Norvig, and E. Davis, *Artificial intelligence: a modern approach* (Prentice Hall series in artificial intelligence), 3rd ed. Upper Saddle River: Prentice Hall, 2010.

[8] E. Karpas and D. Magazzeni, “Automated Planning for Robotics”, en, *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 3, no. 1, pp. 417–439, May 2020.

[9] D. Holler, G. Behnke, P. Bercher, and S. Biundo, “Language Classification of Hierarchical Planning Problems”, in *ECAI*, Prague, Czech Republic, 2014, pp. 447–452.

[10] S. S. Chouhan and R. Niyogi, “Multi-agent planning with quantitative capability”, in *2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, Jaipur, India: IEEE, Sep. 2016, pp. 602–606.

[11] G. Konidaris, L. P. Kaelbling, and T. Lozano-Perez, “From Skills to Symbols: Learning Symbolic Representations for Abstract High-Level Planning”, *Journal of Artificial Intelligence Research*, vol. 61, pp. 215–289, Jan. 2018.

[12] T. Niemueller, T. Hofmann, and G. Lakemeyer, “CLIPS-based Execution for PDDL Planners”, in *Proceedings of the 28th International Conference on Automated Planning and Scheduling (ICAPS), Workshop on Integrated Planning, Acting, and Execution (IntEx)*, Delft, The Netherlands, 2018.

[13] A. Reyes, L. E. Sucar, P. H. Ibargüengoytia, and E. F. Morales, “Planning Under Uncertainty Applications in Power Plants Using Factored Markov Decision Processes”, en, *Energies*, vol. 13, no. 9, May 2020, ISSN: 1996-1073.

[14] C. Boutilier, R. Dearden, and M. Goldszmidt, “Stochastic dynamic programming with factored representations”, en, *Artificial Intelligence*, vol. 121, no. 1-2, pp. 49–107, Aug. 2000.

[15] A. Darwiche and M. Goldszmidt, “Action Networks: A Framework for Reasoning about Actions and Change under Uncertainty”, en, in *Uncertainty Proceedings 1994*, Elsevier, 1994, pp. 136–144.

[16] A. Reyes, P. Ibargüengoytia, L. E. Sucar, and E. Morales, “Abstraction and Refinement for Solving Markov Decision Processes. In Workshop on Probabilistic Graphical Models”, in *Citeseer*, Prague, Czech Republic, 2006, pp. 263–270.

[17] C. R. Garrett, R. Chitnis, R. Holladay, *et al.*, “Integrated Task and Motion Planning”, en, *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 4, no. 1, pp. 265–293, May 2021.

[18] K. Hauser and V. Ng-Thow-Hing, “Randomized multi-modal motion planning for a humanoid robot manipulation task”, en, *The International Journal of Robotics Research*, vol. 30, no. 6, pp. 678–698, May 2011.

[19] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling, “PDDLStream: Integrating Symbolic Planners and Blackbox Samplers via Optimistic Adaptive Planning”, *arXiv:1802.08705 [cs]*, Mar. 2020.

[20] P. Haslum, editor, *An Introduction to the Planning Domain Definition Language* (Synthesis Lectures on Artificial Intelligence and Machine Learning 42), eng. S.l.: Morgan et Claypool Publishers, 2019.