SMarTplan: a Task Planner for Smart Factories *

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Abstract. Smart factories are on the verge of becoming the new industrial paradigm, wherein optimization permeates all aspects of production, from concept generation to sales. To fully pursue this paradigm, flexibility in the production means as well as in their timely organization is of paramount importance. AI is planning a major role in this transition, but the scenarios encountered in practice might be challenging for current tools. Task planning is one example where AI enables more efficient and flexible operation through an online automated adaptation and rescheduling of the activities to cope with new operational constraints and demands. In this paper we present SMarTplan, a task planner specifically conceived to deal with real-world scenarios in the emerging smart factory paradigm. Including both special-purpose and general-purpose algorithms, SMarTplan is based on current automated reasoning technology and it is designed to tackle complex application domains. In particular, we show its effectiveness on a logistic scenario, by comparing its specialized version with the general purpose one, and extending the comparison to other state-of-the-art task planners.

1 Introduction

In recent years manufacturing is experiencing a major paradigm shift due to a variety of drivers. From the market side, the push towards high product customization led to a higher proliferation of product variants. From the organizational side, the need to take into account customer feedback led to shorter product cycles. From the technological side, the convergence between traditional industrial automation and information technology brought additional opportunities by combining fields such as, e.g., intelligent Cyber-Physical Systems, additive

* The research of Arthur Bit-Monnot and Luca Pulina has been funded by the EU Commissions H2020 Programme under grant agreement N. 732105 (CERBERO project). The research of Luca Pulina was also partially supported by a grant from Regione Sardegna (Italy), POR FESR 2014/2020 - Asse Prioritario I "Ricerca Scientifica, Sviluppo Tecnologico e Innovazione" (PROSSIMO project).
manufacturing, cloud computing, and the Internet of Things – see, e.g., [1] for a recent survey.

The short planning horizons and product life cycles induce the decrease of batch sizes and do therefore require manufacturing flexibility. In order to make the right management decisions, real-time information and the direct realization of the decisions are mandatory. The term smart factory is often used to refer to the combination of industrial automation and information technology that should respond to the change drivers, and become the prevalent industrial paradigm, wherein optimization permeates all aspects of production, from concept generation to sales.

To fully pursue this paradigm, flexibility in production processes as well as in their timely organization is of paramount importance. AI planning has the potential to play a major role in this transition, allowing for more efficient and flexible operation through an on-line automated adaptation and rescheduling of the activities to cope with new operational constraints and demands.

However, the scenarios encountered in practice might be challenging for current state-of-the-art tools. For instance, task planning for production logistics often requires reasoning on expressive models that combine ordering constraints, time windows and spatial relations which most tools cannot handle and solve efficiently. Furthermore, task planning for high product variety may pose additional challenges to planners that rely on grounding procedures. Even if solving the problem might actually be easy, instantiation of the entire planning task may swamp the memory and hamper the search for a feasible solution.

With the above considerations in mind, in this paper we present SMARTplan, a task planner specifically conceived to deal with real-world scenarios in the emerging smart factory paradigm. Including both special-purpose and general-purpose algorithms, SMARTplan is based on current automated reasoning technology, namely Satisfiability Modulo Theories (SMT) and Optimization Modulo Theories (OMT) solving — see, e.g., [2, 3] and [4, 5] for related solvers. SMT solvers developed into a crucial technology in many areas of computer-aided verification — see, e.g., [6, 7]; their application has also been explored in task planning [8, 9]. OMT solvers have been introduced more recently, but they already showed promise in some tasks, including task planning [10, 11]. The combination of leading-edge SMT and OMT decision procedures with effective encodings, is our recipe to tackle relevant application domains.

In particular, we show the effectiveness of SMARTplan on a logistic scenario based on the RoboCup Logistics League (RCLL) [12], wherein two teams of autonomous robots compete to handle the logistics of materials through several dynamic stages to manufacture products in a smart factory scenario. Using the RCLL as a testbed, we aim to (i) compare the performances of SMARTplan with other general purpose planners and (ii) compare the performances of its specialized version with the general purpose one to highlight strengths and weaknesses of each. The main contribution of our paper is to show that, while considerable investment in research and tech-transfer is required to cope with smart factory needs as a whole, task planners can be made fit to leverage
either domain knowledge or suitable encodings towards state-of-the-art decision
procedures.

The remainder of this paper is structured as follows. Section 2 introduces
background knowledge on which SMarTplan builds, while Section 3 gives an
overview on its architecture and internals. The logistic scenario used to assess the
performance of our tool is presented in Section 4 followed by Section 5 where
experimental results are discussed. Concluding remarks together with future
directions are discussed in Section 6.

2 Background

2.1 Task Planning

Task planning is a field of Artificial Intelligence concerned with finding a set of
actions that would result in desirable state. It is traditionally formulated as a
state transition system in which actions allow to transition from one state to
another. Solving a planning problem means finding a sequence of actions, i.e. a
path, from an initial state to a goal state.

Most research in automated planning has focused in heuristic search tech-
niques in which forward search planners explore the set of states that are reach-
able from the initial one. Such techniques have proved to very efficiently handle
large problems in classical planning, through development of targeted heuristic
functions. Such techniques have however proved to be difficult to extend to richer
problems such as those involving a rich temporal representation or continuous
variables, leading to a renewed interest in constraint-based approach (e.g. [8,13]).

2.2 Planning as Satisfiability

As shown first shown in [14], classical planning problems can be naturally for-
mulated as propositional satisfiability problems and solved efficiently by SAT
solvers. The idea is to encode the existence of a plan of a fixed length \( p \) as the
satisfiability of a propositional logic formula: the formula for a given \( p \) is satis-
fiable if and only if there is a plan of length \( p \) leading from the initial state to
the goal state, and a model for the formula represents such plan.

Classical planning abstracts aways from time and assumes the actions and
state changes to be instantenous. In contrast, temporal planning considers ac-
tion durations and temporal relations between (possibly concurrently executed)
actions. For instance, in logistics plans might need to meet deadlines in or-
der to satisfy some production requirements. The natural encoding of temporal
planning problems requires an extension of propositional logic with arithmetic
theories, such as the theory of reals or integers. Recent advances in satisfiability
checking [2] led to powerful Satisfiability Modulo Theories (SMT) solvers such
as [4,15,16], which can be used to check the satisfiability of first-order logic
formulas over arithmetic theories and thus to solve temporal planning problems.
2.3 SMT and optimization

Satisfiability Modulo Theories is the problem of deciding the satisfiability of a first-order formula with respect to some decidable theory $\mathcal{T}$. In particular, SMT generalizes the boolean satisfiability problem (SAT) by adding background theories such as the theory of real numbers, the theory of integers, and the theories of data structures (e.g., lists, arrays and bit vectors).

To decide the satisfiability of an input formula $\varphi$ in Conjunctive Normal Form (CNF), SMT solvers (see Fig. 1) typically first build a Boolean abstraction $\text{abs}(\varphi)$ of $\varphi$ by replacing each constraint by a fresh Boolean variable (proposition), e.g.,

$$
\varphi : x \geq y \land (y > 0 \lor x > 0) \land y \leq 0
$$

$$
\text{abs}(\varphi) : \ A \land (B \lor C) \land \neg B
$$

where $x$ and $y$ are real-valued variables, and $A$, $B$ and $C$ are propositions.

A SAT solver searches for a satisfying assignment $S$ for $\text{abs}(\varphi)$, e.g., $S(A) = \top$, $S(B) = \bot$, $S(C) = \top$ for the above example. If no such assignment exists then the input formula $\varphi$ is unsatisfiable. Otherwise, the consistency of the assignment in the underlying theory is checked by a theory solver. In our example, we check whether the set $\{x \geq y, y \leq 0, x > 0\}$ of linear inequalities is feasible, which is the case. If the constraints are consistent then a satisfying solution (model) is found for $\varphi$. Otherwise, the theory solver returns a theory lemma $\varphi_E$ giving an explanation for the conflict, e.g., the negated conjunction of some inconsistent input constraints. The explanation is used to refine the Boolean abstraction $\text{abs}(\varphi)$ to $\text{abs}(\varphi) \land \text{abs}(\varphi_E)$. These steps are iteratively executed until either a theory-consistent Boolean assignment is found, or no more Boolean satisfying assignments exist.

Standard decision procedures for SMT have been extended with optimization capabilities, leading to Optimization Modulo Theories (OMT). OMT extends SMT solving with optimization procedures to find a variable assignment that defines an optimal value for an objective function $f$ (or a combination of multiple objective functions) under all models of a formula $\varphi$. As noted in [17], OMT solvers such as [5, 18] typically implement a linear search scheme, which can be summarized as follows. Let $\varphi_S$ be the conjunction of all theory constraints that are true under $S$ and the negation of those that are false under $S$. A local optimum $\mu$ for $f$ is computed under the side condition $\varphi_S$ and $\varphi$ is updated as

$$
\varphi := \varphi \land (f \bowtie \mu) \land \neg \bigwedge \varphi_S , \ \bowtie \in \{<,>\}
$$

Repeating this procedure until the formula becomes unsatisfiable will lead to an assignment minimizing $f$ under all models of $\varphi$.

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4 For instance, if $f$ and $\varphi_S$ are expressed in QF_LRA, this can be done with Simplex
3 The architecture of SMarTplan

SMARTplan is a task planner that leverages the latest SMT and OMT technology to solve smart factory problems. It comes with two planning components:

– RCLLPlan is specifically tailored for the RCLL problems. Given problem description in PDDL format, it generates domain specific encodings for both SMT and OMT, thus supporting both satisfiability as well as optimal planning.

– LCP is the domain-independent component and accepts as input arbitrary PDDL domain and problem files. LCP internally generates time-oriented SMT encoding which are solved using an off-the-shelf SMT solver.

For both planning components, the resulting plan is extracted from the SMT/OMT encoding and validated against VAL [19].

3.1 Special purpose solution

RCLLPlan implements domain-specific encodings of the state-based planning problem defined over the scenario we target here. This module builds upon previous work [10, 20] and extends it with the ability to generate different types of encodings specifically tailored to be able to cope with the complexity of the domain. In particular, we present here (i) a fine-grained encoding where single actions are encoded separately and (ii) an encoding which leverages domain-specific knowledge to build more compact encodings that enable macro planning by grouping action constraints together. In both cases, RCLLPlan can leverage SMT or OMT technology to produce either feasible or optimal plans, solving a planning as satisfiability problem defined as follows.

World states are described using an ordered set of real-valued variables $x = \{x_1, \ldots, x_n\}$. We also use the vector notation $x = (x_1, \ldots, x_n)$ and write $x'$ and $x_i$ for $(x'_1, \ldots, x'_n)$ and $(x_{1,i}, \ldots, x_{n,i})$ respectively. We use special variables $A \in x$ to encode the action to be executed at each step and $t \in x$ for the associated

![Diagram of the SMT solving framework](image-url)

**Fig. 1.** The SMT solving framework.
time stamp. A state \( s = (v_1, \ldots, v_n) \in \mathbb{R}^n \) specifies a real value \( v_i \in \mathbb{R} \) for each variable \( x_i \in x \).

The RCLL domain is represented symbolically by mixed-integer arithmetic formulas defining the initial states \( I(x) \), the transition relation \( T(x, x') \) (where \( x \) describes the state before the transition and \( x' \) the state after it) and a set of final states \( F(x) \). The transition relation is defined in terms of actions that can be performed at each step. A plan of length \( p \) is a sequence \( s_0, \ldots, s_p \) of states such that \( I(s_0) \) and \( T(s_i, s_{i+1}) \) hold for all \( i = 0, \ldots, p - 1 \), and \( F(s_p) \) holds. Thus, plans are models for the formula:

\[
I(x_0) \land \left( \bigwedge_{0 \leq i < p} T(x_i, x_{i+1}) \right) \land \left( \bigvee_{0 \leq i \leq p} F(x_i) \right)
\]  

(1)

In general the length of a plan is not known a priori and has to be determined empirically by increasing \( p \) until a satisfying assignment for \( \mathbb{P} \) is found. However, RCLLPlan, being tailored for the domain considered, exploits domain specific knowledge to determine an upper bound on \( p \) and simplify plan search. In order to be able to support generation of optimal plans with OMT, the bounded planning approach is extended to enable optimization over cost structures expressed in first-order arithmetic theories. We introduce additional variables \( c \in x \) to encode the cost of executing action \( A \) at time \( t \). We define the total cost \( c_{tot} \) associated to a plan as:

\[
c_{tot} = \sum_{0 \leq i < p} c_i
\]

(2)
Optimal bounded planning is then defined as the problem to find a path of length at most $p$ that reaches a target state and achieves thereby the smallest possible cost, i.e., to minimize Eq. 2 under the side condition that Eq. 1 holds.

The same ideas presented above are applied when generating encodings for macro actions. In this case, domain-specific knowledge is encoded explicitly at the logical level, so as to produce encodings that are more compact and easier to solve. Macro actions are encoded based on the following observation. Plans for production in the RCLL often involve action sequences that yield better performance if performed by the same agent. For instance, if a robot is instructed to prepare a base station to provide a base, then it makes sense that the same robot also retrieves the base (under the realistic assumption that in the RCLL providing a base is less expensive than motion planning and navigation for another robot). Following such observations, a logical encoding is built in RCLLPlan where the transition relation contains constraints for macro actions only.

### 3.2 General purpose algorithm

This domain-dependent planner is complemented by LCP (Lifted Constraint Planner) a domain-independent planner that aims at providing good performance over a large set of problem. LCP supports both temporal PDDL \[21\] and a subset of ANML \[22\] to define planning problems.

Like RCLLPlan, it uses a constraint-based encoding where multi-valued variables are related through a set of constraints that can be exploited by SMT solvers. Unlike RCLLPlan’s state-oriented representation, LCP relies on time-oriented encoding where the effects and conditions of actions are placed on temporal intervals which are related through temporal constraints ensuring the consistency of a plan.

**From PDDL and ANML to Chronicles** LCP uses chronicles \[23\] as a building block for its internal representation. Chronicles were first introduced in the IxTeT planner \[24\]. They allow an expressive representation of temporal actions that leverages a constraint-based representation close to the one found in state-of-the-art scheduling solvers such as CP Optimizer \[25\].

The environment is represented by a finite set of state variables, that describe the evolution of a particular state feature overtime, e.g., the location of a robot over the course of the plan.

A chronicle is composed of a set of decision variables, a set of constraints relating those variables as well as some conditions and effect statements. Condition statements require a particular state variable to have a given value over a temporal interval while effect statements change the value of a state variable at

\[5\] RCLLPlan exploits a simple cost definition in its current state, i.e., minimize time to delivery for each product. However, richer goal structures could be specified.
given point in time. In essence, a chronicle is thus a CSP extended with additional constructs to represent the conditions and effects that are at the core of AI planning.

Chronicles offer a natural representation for the action models present in both the PDDL and ANML languages that are supported by our tool. In practice, one simply needs to map an action’s parameters and timepoints into to variables of the chronicles. The action’s condition and effect can be straightforwardly encoded into the corresponding condition and effect statements. Additional requirements, e.g. on the duration of an action, are encoded as constraints on the chronicles variables. For this translation, we follow the process demonstrated by other planners such as IxTeT [24] and FAPE [13].

The planning problem itself is also encoded as a chronicle, with effect statements defining the initial state and condition statements representing the goals of the problem.

From Chronicles to Constraint Satisfaction Problems Planning differs from scheduling in that the actions that will be part of the solution plan are not known beforehand. We escape this problem by generating bounded problems in which a finite set of actions are allowed to be part of a solution plan. More precisely, a bounded planning problems has a finite set of action chronicles, each representing a possible action in the solution plan. Action chronicles are optional: they are associated to a boolean decision variables that is true if the action is part of the solution plan and false otherwise.

Finding a solution to a bounded planning problem means finding an assignment to decision variables that represent action parameters (i.e. variables inside the chronicles) and action presence (the boolean variables) such that the set of actions that are present form a consistent plan.

Plan consistency is defined through a set of constraints over the chronicles. Those constraints are detailed in [9] and are sketched below:

- **consistency constraints** enforce that no two effects statements are overlapping. Namely, if two effect statements are part of actions that are present in the solution, they must either affect different state variables or be active on non-overlapping temporal intervals.
- **support constraints** ensure that any condition statement in an action that is part of the solution is supported by an effect statement. More precisely, it means that there exists an effect statements that changes the state variable to the value required by the condition. In addition, the effect statement must be active before the condition, and they must be no other effect affecting the same state variable active between the start of the effect and the end of the condition.
- **internal constraints** ensure that all constraints defined inside a chronicle hold if the corresponding action is part of the solution.

For a given bounded planning problem, a CSP is built by taking the conjunction of all consistency, support and internal constraints.
This formulation has some important similarities with lifted plan-space planning \cite{13,24,26}. It differs from the former in that the CSPs in LCP contain no dynamic part since possible actions are fixed beforehand. This facilitates the use of off-the-shelf solvers while plan-space planner typically require ad-hoc constraint solving engines. The representation is also closely related to the one of recent constraint programming engines for scheduling that support of optional temporal intervals but lack a notion of condition and effects \cite{25,27}.

Planning Planning is done by generating increasingly large bounded planning problems. At each step, an SMT solver is used to prove the existence or absence of a plan for a bounded planning problem, i.e., whether a plan exists with the limited number of actions allowed. The SMT solver is used to find a satisfying assignment (model), which can then be translated into a solution plan. When the solver proves the inconsistency of the CSP, a new bounded planning problem allowing more actions is generated and the process restarts.

In addition to this iterative deepening setting, LCP also supports a configuration that defines the size of the planning problem to solve: specifying for each action in the planning domain its maximal number of occurrences. In this setting, LCP will generate a single bounded planning problem and attempt to find a solution for it, allowing a simple domain-dependent configuration of the planner.

4 Case Study: The RoboCup Logistics League

The RoboCup Logistics League (RCLL) provides a simplified smart factory scenario where two teams of three autonomous robots each compete to handle the logistics of materials to accommodate orders known only at run-time. Competitions take place yearly using a real robotic setup, however, for our experiments we made use of the simulated environment (Fig. 3) developed for the Planning and Execution Competition for Logistics Robots in Simulation\footnote{http://www.robocup-logistics.org/sim-comp} \cite{29}.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3.png}
\caption{Simulated RCLL factory environment \cite{28}.}
\end{figure}
Products to be assembled have different complexities and usually require a base, mounting 0 to 3 rings, and a cap as a finishing touch. Bases are available in three different colors, four colors are admissible for rings and two for caps, leading to about 250 different possible combinations. Each order defines which colors are to be used, together with an ordering. An example of a possible configuration is shown in Fig. 4.

Several machines are scattered around the factory shop floor (positions are different in each scenarios and announced to the robots at runtime). Each machine completes a particular production step such as providing bases, mounting colored rings or caps. There are four types of machines:

- **Base Station (BS):** acts as dispenser of base elements (one per team).
- **Cap Station (CS):** mounts a cap as the final step in production on an intermediate product. The CS stores at most one cap at a time (empty initially). To prefill the CS, a base element with a cap must be taken from a shelf in the arena and fed to the machine; the cap is then unmounted and buffered. The cap can then be mounted on the next intermediate product taken to the machine (two CS per team).
- **Ring Station (RS):** mounts one colored ring (of specific color) onto an intermediate product. Some ring colors require additional tokens: robots will have to feed a RS with a specified number of bases before the required color can be mounted (two RS per team).
- **Delivery Station (DS):** accepts finished products (one per team).

The objective for a team of autonomous robots is to transport intermediate products between processing machines and optimize a multistage production cycle of different product variants until delivery of final products.

Orders that denote the products which must be assembled are posted at run-time by an automated referee box and come with a delivery time window, therefore introducing a temporal component that requires quick planning and scheduling.

## 5 Experimental evaluation

### 5.1 Experimental Setup

We evaluate our various planning components against the RCLL set of benchmarks. Unlike the setting for the RCLL competition that features two competing
### Table 1. Results for the C0 configuration. For problems with 1 to 3 robots (R1–R3), it indicates for each planner the number of problems solved and the average runtime when a plan was found before the timeout of 60 seconds.

| Planner               | C0 – R1 |          | C0 – R2 |          | C0 – R3 |          |
|-----------------------|---------|----------|---------|----------|---------|----------|
|                       | Solved  | Runtime (s) | Solved  | Runtime (s) | Solved  | Runtime (s) |
| RCLLPlan-Sat          | 20      | 0.98     | 20      | 2.52     | 20      | 2.73     |
| RCLLPlan-Opt          | 20      | 15.22    | 17      | 42.18    | 4       | 54.26    |
| RCLLPlan-Macros-Sat   | 20      | 0.13     | 20      | 0.14     | 20      | 0.14     |
| RCLLPlan-Macros-Opt   | 20      | 0.40     | 20      | 0.53     | 20      | 0.60     |
| LCP-Gen               | 20      | 7.25     | 20      | 9.72     | 20      | 11.52    |
| LCP-Spe               | 20      | 1.61     | 20      | 1.93     | 20      | 2.74     |
| Optic                 | 13      | 24.39    | 2       | 57.60    | 0       | –        |
| SMTPlan+              | 0       | –        | 0       | –        | 0       | –        |

### Table 2. Results for the C1 configuration. For problems with 1 to 3 robots (R1–R3), it indicates for each planner the number of problems solved and the average runtime when a plan was found before the timeout of 60 seconds.

| Planner               | C1 – R1 |          | C1 – R2 |          | C1 – R3 |          |
|-----------------------|---------|----------|---------|----------|---------|----------|
|                       | Solved  | Runtime (s) | Solved  | Runtime (s) | Solved  | Runtime (s) |
| RCLLPlan-Sat          | 20      | 11.55    | 16      | 10.35    | 18      | 24.11    |
| RCLLPlan-Opt          | 0       | –        | 0       | –        | 0       | –        |
| RCLLPlan-Macros-Sat   | 20      | 0.37     | 20      | 0.43     | 20      | 0.60     |
| RCLLPlan-Macros-Opt   | 20      | 1.82     | 20      | 9.57     | 17      | 6.48     |
| LCP-Gen               | 2       | 30.07    | 1       | 56.12    | 1       | 48.67    |
| LCP-Spe               | 20      | 7.03     | 15      | 10.59    | 12      | 12.45    |
| Optic                 | 12      | 23.46    | 0       | –        | 0       | –        |
| SMTPlan+              | 0       | –        | 0       | –        | 0       | –        |
teams of robots, we use a single team which is closer to the real-world setting in which robots in the same factory are expected to collaborate in the production steps.

The PDDL domain is taken, unmodified, from the referee box of RCLL competition. Problems are generated for different game settings and vary on the number of robots available (from 1 to 3 robots). The complexity of the product to manufacture varies between complexities C0 and C1, respectively corresponding to no-ring and one-ring configurations of the final product.

### 5.2 Tested planners

Our special purpose planning component is evaluated in its two versions, both declined in two subversions depending on whether they seek feasible or optimal plans.

- RCLLPlan-Sat & RCLLPlan-Opt represent the basic RCLL-specific planning component, respectively configured to seek feasible and optimal plans. While this encoding is domain specific, it closely mimics the actions available in the executive system.
- RCLLPlan-Macros-Sat & RCLLPlan-Macros-Opt represent the RCLL-specific planning component with macro actions. They are respectively configured to seek feasible and optimal plans. Unlike, RCLLPlan-Sat/RCLLPlan-Opt, the use of macro actions allows for much smaller encoding at the expense of divergence with the underlying execution system and more complexity in its development.

The LCP component is evaluated in two configurations:

- LCP-Gen is our domain-independent planning component running with default options.
- LCP-Spe is our domain-independent planning component with a configuration tailored to the RCLL domains. Namely, the bounded planning problem is restricted to actions that might be useful in the RCLL domain. This configuration is purely external and does not require touching the internals of the planner.

Finally, we compare SMARTPlan to two state-of-the-art temporal planners:

- Optic is a forward-search heuristic planner evolved from the POPF planner which was a runner-up the penultimate International Planning Competition (IPC). Optic is a forward search heuristic planner that uses a temporal extension of the $h^F$ heuristic. TFD and YAHSP, the other top competitors of the latest IPCs, were not considered because (i) they are not complete with respect to the semantics of PDDL 2.1 and (ii) they do not support the PDDL encoding of the RCLL domain that mixes instantaneous and durative actions.

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[7] https://github.com/timn/ros-rcll_ros/tree/master/pddl
SMTPlan+ is a recent SMT-based planner for the PDDL+ language [8]. SMTPlan+ is more expressive than the other planners considered as it supports the full range of PDDL+ features, including continuous processes inducing non-linear changes over numeric state variables. It uses a state-oriented SMT encoding, over plans of increasing length.

All SMT-based planners use Z3 in version 4.6.3 as an off-the-shelf solver.

5.3 Results

All benchmarks were run on an Intel i7-3770 @ 3.40GHz with a timeout of 60 seconds. The timeout is low compared to the usual setting of 30 minutes of the International Planning Competition but is more adequate to an online planning setting such as the one of RCLL.

C0 configuration Results for the C0 configuration of the RCLL problem are given in Table 1. For each planner, the table provides the number of problems solved and the average runtime for successful runs.

For the C0 configuration, all components of SMARTPLAN are able to solve all 60 problems. The only exception is the base configuration of the domain-dependent approach that fails to prove optimality for a number of problems (RCLLPlan-Opt). Runtimes are largely dominated by the domain-specific encoding with macro actions: runtimes are well below a second for both feasibility and optimality (RCLLPlan-Macros-Sat/RCLLPlan-Macros-Opt). Given their generality, both versions of LCP provide good performance solving all problems in handful of seconds. Notably, performance of the configured version of LCP (LCP-Spe) is on par with that of RCLLPlan-Sat.

Optic has overall poor performance on those domains, solving only 13 problems involving 1 robot and 2 problems involving 2 robots. SMTPlan+ fails to solve any attempted problem.

C1 configuration Problems for configuration C1, where an additional ring must be mounted on the product, show more differentiated results (Table 2). The benchmark is still dominated by the domain specific macro-encoding, that only fails to prove the optimality of three of the most difficult problems.

RCLLPlan-Sat and LCP-Spe continue to show comparable performance both in runtime and number of problems solved in R1 and R2. Both RCLLPlan-Opt and LCP-Gen show their limits, solving respectively none and 4 problems.

Optic almost maintains its performance from the C0 configuration, solving 12 of the 20 problems involving 1 robot.

6 Discussion and Conclusion

In this paper we have presented and evaluated SMARTPLAN, a planner that leverages the latest SMT technology for solving typical problems that arise in
smart factories. Evaluation of the domain-specific and domain-independent components of SMarTplan on the RCLL benchmarks highlight different trade-offs.

The most involved domain-specific solver, shows unchallenged performance on the RCLL benchmarks highlighting the work that remains to be done on fully automated task planners. Of course the development of such a domain-specific planner induces many difficulties as it is more error prone and time consuming. Perhaps most importantly, adapting it to new operational constraints is challenging as the process must be restarted to account for violated assumptions.

On the other hand, fully domain-independent planners provide a great promise of reusability and adaptability to a wide variety of contexts. The development of LCP as a part of SMarTplan is meant to leverage those benefits. While the gap with domain specific solvers remains important, experiments show that LCP does reduce this gap with respect to existing domain-independent planners. In its current state, it would stand as a valid solution when provided with minimal configuration.

The performance gap indicates two directions for future work on LCP. First there is the never-ending quest for performance improvement, the performance of RCLLLPlan defining a challenging target to reach. Second, we believe the performance gain from injecting domain-specific knowledge (being in specific solvers or in the configuration of LCP) raises the question of how to inject such knowledge in a principled and solver-independent way. The optional specification of Hierarchical Task Networks (HTN) in the ANML language provide a good opportunity to do this in an incremental and non-intrusive manner. The ANML subset for HTN is currently not supported by LCP and will be the subject of future work.

Acknowledgements

The authors would like to thank Igor Bongartz for his help with the implementation and validation of RCLLPlan.

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