SCALING UP METRIC TEMPORAL PLANNING

by

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ABSTRACT

This dissertation aims at building on the success of domain-independent heuristics for classical planning to develop a scalable metric temporal planner. The main contribution is *Sapa*, a domain-independent heuristic forward-chaining planner which can handle various metric and temporal constraints as well as multi-objective functions. Our major technical contributions include:

- The temporal planning-graph based methods for deriving heuristics that are sensitive to both cost and makespan. We provide different approaches for propagating and tracking the goal-achievement cost according to time and different techniques for deriving the heuristic values guiding *Sapa* using these cost-functions. To improve the heuristic quality, we also present techniques for adjusting the heuristic estimates to take into account action interactions and metric resource limitations.

- The "partialization" techniques to convert the position-constrained plans produced by *Sapa* to generate the more flexible order-constrained plans. Toward this objective, a general Constraint Satisfaction Optimization Problem (CSOP) is developed and can be optimized under an objective function dealing with a variety of temporal flexibility criteria, such as makespan.

- *Sapa*^{ps} , an extension of *Sapa*, that is capable of finding solutions for the Partial Satisfaction Planning Net Benefit (PSP Net Benefit) problems. *Sapa*^{ps} uses an anytime best-first search algorithm to find plans with increasing better solution quality as it is given more time to run.

For each of these contributions, we present the technical details and demonstrate the effectiveness of the implementations by comparing its performance against other state-of-the-art planners using the benchmark planning domains.

To my family.

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I am and will always be grateful to my parents for their love and for their constant belief in me. Saving the best for last, my wife is special and has always been there understanding and supporting me with everything I have ever needed. My son, even though you can not say more than a few “uh ah”, I know that you meant: “I can always give you a nice smile or a good hug when you need one”.

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TABLE OF CONTENTS

Page

Page

Page

Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

Figure Page

CHAPTER 1

Introduction

Many real-world planning problems in manufacturing, logistics, and space applications involve metric and temporal constraints. Until recently, most of the planners that were used to tackle those problems such as HSTS/RAX [68], ASPEN [14], O-Plan [15] all relied on the availability of domain and planner-dependent control knowledge, the collection and maintenance of which is admittedly a laborious and error-prone activity. An obvious question is whether it will be possible to develop *domain-independent* metric temporal planners that are capable of scaling up to such domains. The past experience has not been particularly encouraging. Although there have been some ambitious attempts–including IxTeT [37] and Zeno [75], their performance has not been particularly satisfactory without an extensive set of additional control rules.

Some encouraging signs however are the recent successes of *domain-independent* heuristic planning techniques in classical planning [70, 7, 41]. Our research is aimed at building on these successes to develop a scalable metric temporal planner. At first blush search control for metric temporal planners would seem to be a very simple matter of adapting the work on heuristic planners in classical planning [7, 70, 41]. The adaptation however does pose several challenges:

- Metric temporal planners tend to have significantly larger search spaces than classical planners. After all, the problem of planning in the presence of durative actions and metric re-

sources subsumes both classical planning and a certain class of scheduling problems.

- Compared to classical planners, which only have to handle the logical constraints between actions, metric temporal planners have to deal with many additional types of constraints that involve time and continuous functions representing different types of resources.

- In contrast to classical planning, where the only objective is to find shortest length plans, metric temporal planning is *multi-objective*. The user may be interested in improving either temporal quality of the plan (e.g. makespan) or its cost (e.g. cumulative action cost, cost of resources consumed etc.), or more generally, a combination thereof. Consequently, effective plan synthesis requires heuristics that are able to track both these aspects in an evolving plan. Things are further complicated by the fact that these aspects are often inter-dependent. For example, it is often possible to find a "cheaper" plan for achieving goals, if we are allowed more time to achieve them.

This dissertation presents *Sapa*, a heuristic metric temporal planner that we developed to address these challenges. *Sapa* is a forward chaining planner, which searches in the space of time-stamped states. *Sapa* handles durative actions as well as actions consuming continuous resources. Our main focus has been on the development of heuristics for focusing *Sapa*'s multi-objective search. These heuristics are derived from the optimistic reachability information encoded in the planning graph. Unlike classical planning heuristics (c.f,[70]), which need only estimate the "length" of the plan needed to achieve a set of goals, *Sapa*'s heuristics need to be sensitive to both the cost and length ("makespan") of the plans. Our contributions include:

- We present a novel framework for tracking the cost of literals (goals) as a function of time. We present several different ways to propagate costs and terminate this tracking process, each gives different tradeoff between the heuristic quality and the propagation time. These "cost

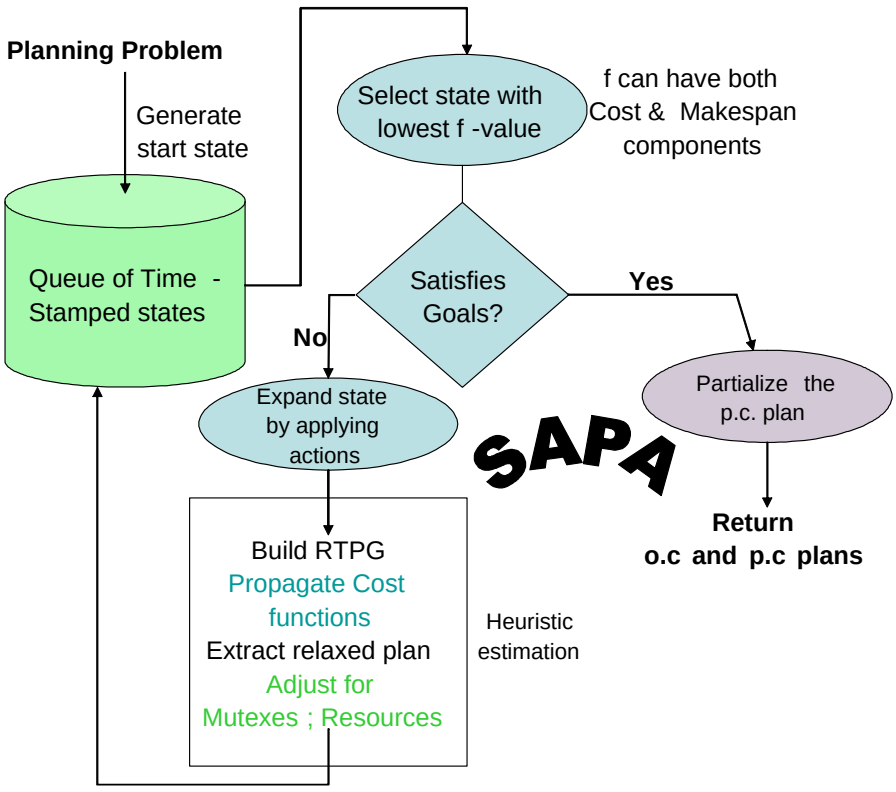


Figure 1. Architecture of *Sapa*

functions" are then used either directly or through relaxed-plan extraction to derive heuristics that are capable of directing the search towards plans that satisfy any type of cost-makespan tradeoffs.

- *Sapa* generalizes the notion of "phased" relaxation used in deriving heuristics in planners such as AltAlt and FF [70, 41]. Specifically, the heuristics are first derived from a relaxation that ignores the delete effects and metric resource constraints, and are then adjusted subsequently to better account for both negative interactions and resource constraints.

Architecture of *Sapa*: Figure 1 shows the high-level architecture of *Sapa*. *Sapa* uses a forward chaining A* search to navigate in the space of time-stamped states. Its evaluation function (the "$f(.)$" function) is multi-objective and is sensitive to both makespan and action cost. When a state

is picked from the search queue and expanded, *Sapa* computes heuristic estimates of each of the resulting child states. The heuristic estimation of a state S is based on (i) computing a relaxed temporal planning graph (RTPG) from S, (ii) propagating cost of achievement of literals in the RTPG with the help of time-sensitive cost functions (iii) extracting a relaxed plan P^r for supporting the goals of the problem and (iv) modifying the structure of P^r to adjust for mutex and resource-based interactions. Finally, P^r is used as the basis for deriving the heuristic estimate of S. The search ends when a state S' selected for expansion satisfies the goals. After a plan is found, we have an option to post-process the "position constrained" plan corresponding to the state S by converting it into a more flexible "order constrained" plan. This last step, which is the focus of the second part of this dissertation, is done to improve the makespan as well as the execution flexibility of the solution plan.

A version of *Sapa* using a subset of the techniques discussed in this paper performed well in domains with metric and temporal constraints in the third International Planning Competition, held at AIPS 2002 [27]. In fact, it is the best planner in terms of solution quality and number of problems solved in the highest level of PDDL2.1 used in the competition for the domains *Satellite* and *Rovers* (both are inspired by NASA applications.)

While the main part of the dissertation concentrates on the search algorithm and heuristic estimate used in *Sapa* to solve the metric temporal planning problems, we also investigate several important extensions to the basic algorithm in *Sapa.* They are: (i) the partialization algorithm that can be used as a post-processor in *Sapa* to convert its position-constrained plans into the more flexible order-constrained plans; and (ii) extending *Sapa* to solve the more general Partial Satisfaction Planning (PSP) Net Benefit planning problems where goals can be "soft" and have different utility values.

Improving *Sapa* Solution Quality: Plans for metric temporal domains can be classified broadly

into two categories–"position constrained" (p.c.) and "order constrained" (o.c.). The former specifies the exact start time for each of the actions in the plan, while the latter only specifies the relative orderings between the actions. The two types of plans offer complementary tradeoffs *vis a vis* search and execution. Specifically, constraining the positions gives complete state information about the partial plan, making it easier to control the search. Not surprisingly, several of the more effective methods for plan synthesis in metric temporal domains search for and generate p.c. plans (c.f. TLPlan[1], *Sapa*[19], TGP [81], MIPS[24]). At the same time, from an execution point of view, o.c. plans are more advantageous than p.c. plans –they provide better execution flexibility both in terms of makespan and in terms of "scheduling flexibility" (which measures the possible execution traces supported by the plan [87, 71]). They are also more effective in interfacing the planner to other modules such as schedulers (c.f. [86, 59]), and in supporting replanning and plan reuse [90, 45].

A solution to the dilemma presented by these complementary tradeoffs is to search in the space of p.c. plans, then post-process the resulting p.c. plan into an o.c. plan. Although such post-processing approaches have been considered in classical planning ([49, 90, 2]), the problem is considerably more complex in the case of metric temporal planning. The complications include the need to handle (i) the more expressive action representation and (ii) a variety of objective functions for partialization (in the case of classical planning, we just consider the least number of orderings)

Regarding the conversion problem discussed above, our contribution in this dissertation is to first develop a Constraint Satisfaction Optimization Problem (CSOP) encoding for converting a p.c. plan in metric/temporal domains produced by *Sapa* into an o.c. plan. This general framework allows us to specify a variety of objective functions to choose between the potential partializations of the p.c. plan. Among several approaches to solve this CSOP encoding, we will discuss in detail the one approach that converts it into an equivalent Mixed Integer Linear Programming (MILP) encoding, which can then be solved using any MILP solver such as CPLEX or LPSolve to produce an o.c. plan

optimized for some objective function. Besides our intention of setting up this encoding to solve it to optimum (which is provably NP-hard [2]), we also want to use it for baseline characterization of the "greedy" partialization algorithms. The greedy algorithms that we present can themselves be seen as specific variable and value ordering strategies over the CSOP encoding. Our results show that the temporal flexibility measures, such as the makespan, of the plans produced by *Sapa* can be significantly improved while retaining its efficiency advantages. The greedy partialization algorithms were used as part of the *Sapa* implementation that took part in the 2002 International Planning Competition [27] and helped improve the quality of the plans produced by *Sapa.* We also show that at least for the competition domains, the option of solving the encodings to optimum, besides being significantly more expensive, is not particularly effective in improving the makespan further.

Extending *Sapa* to handle PSP Net Benefit problems: Many metric temporal planning problems can be characterized as over-subscription problems (c.f. [84, 85]) in that goals have different values and the planning system must choose a subset that can be achieved within the time and resource limits. Examples of the over-subscription problems include many of NASA planning problems such as planning for telescopes like Hubble[56], SIRTF[57], Landsat 7 Satellite[78]; and planning science for Mars rover [84]. Given the resource and time limits, only certain set of goals can be achieved and thus it's best to achieve the subset of goals that have highest total value given those constraints. In this dissertation, we consider a subclass of the over-subscription problem where goals have different utilities (or values) and actions incur different execution costs. The objective is to find the most *beneficial* plan, that is the plan with the best tradeoff between the total benefit of achieved goals and the total execution cost of actions in the plan. We refer to this subclass of the over-subscription problem as Partial-Satisfaction Planning (PSP) Net Benefit problem where not all the goals need to be satisfied by the final plan.

Current planning systems are not designed to solve the over-subscription or PSP problems. Most of them expect a set of conjunctive goals of equal value and the planning process does not terminate until all the goals are achieved. Extending the traditional planning techniques to solve the over-subscription problem poses several challenges:

- The termination criteria for the planning process change because there is no fixed set of conjuntive goals to satisfy.
- Heuristic guidance in the traditional planning systems are designed to guide the planners to achieve a fixed set of goals. They can not be used directly in the over-subscription problem.
- Plan quality should take into account not only action costs but also the values of goals achieved by the final plan.

In this dissertation, we discuss a new heuristic framework based on A* search for solving the PSP problem by treating the top-level goals as soft-constraints. The search framework does not concentrate on achieving a particular subset of goals, but rather decides the best solution for each node in a search tree. The evaluations of the g and h values of nodes in the A* search tree are based on the subset of goals achieved in the current search node and the best potential beneficial plan from the current state to achieve a subset of the remaining goals. We implement this technique over the *Sapa* planner and show that the resulting *Sapa*^{ps} planner can produce high quality plans compared to the greedy approach.

Organization: We start with Chapter 2 on the background on relevant planning issues. Then, in Chapter 3, we discuss the metric temporal planning representation and forward search algorithm used in *Sapa.* Next, in Chapter 4, we address the problem of (i) propagating the time and cost information over a temporal planning graph; and (ii) how the propagated information can be used to estimate the cost of achieving the goals from a given state. We also discuss in that chapter how the

mutual exclusion relations and resource information help improve the heuristic estimate. Chapter 5 shows empirical results where *Sapa* produces plans with tradeoffs between cost and makespan, and analyze its performance in the 2002 International Planning Competition (IPC 2002).

To improve the quality of the solution, Chapter 6 discusses the problem of converting the "position-constrained" plans produced by *Sapa* to more flexible "order-constrained" plans. In this chapter, the problem definition is given in Section 6.1, the overall Constraint Satisfaction Optimization Problem (CSOP) encoding that captures the partialization problem is described in Section 6.2. Next, for solving this problem, in Section 6.3 and Section 6.4, we discuss the linear-time greedy and MILP-based optimal approaches for solving this CSOP encoding.

The next chapter of the dissertation (Chapter 7) discusses the extensions of *Sapa* to handle the Partial-Satisfaction Net Benefit Planning (PSP Net Benefit) problem. This chapter contains Section 7.1 on extending the search framework in *Sapa* to build the anytime heuristic search in *Sapa*^{ps} ; and Section 7.2 the heuristic estimation for PSP Net Benefit problems. We also present some preliminary empirical results comparing *Sapa*^{ps} with other search frameworks in Section 7.3. Chapter 8 contains sections on the related work, and Chapter 9 concludes the dissertation and provide the future work that we plan to pursue.

CHAPTER 2

Background on Planning

Intelligent agency involves controlling the evolution of external environments in desirable ways. Planning provides a way in which the agent can maximize its chances of effecting this control. Informally, a plan can be seen as a course of actions that the agent decides upon based on its overall goals, information about the current state of the environment, and the dynamic of its evolution. The complexity of plan synthesis depends on a variety of properties of the environment and the agent. Perhaps the simplest case of planning occurs when: (i) the environment is static (i.e. in that it changes only in response to the agent's action); (ii) observable (i.e. the agent has a complete knowledge of the world at all times); (iii) the agent's actions have deterministic effects on the state of the environment; (iv) actions are instantaneous (no temporal constraint involvement); and (v) world states and action's preconditions and effects only involve boolean state variables. Figure 2 shows this simplest case of planning (aka "classical" planning) and other branches that diverge from the above simplest assumptions. For example, conformant and contingent planning deal with scenarios where the environment is partially-observable, and temporal planning concentrates on problems where durative actions and other types of temporal constraints are necessary. Despite its limitation and the fact that most real-world applications require one or more planning properties beyond the classical specifications (e.g. non-deterministic or durative actions), classical planning problems are still computationally hard, and have received a significant amount of attention. Work in classical

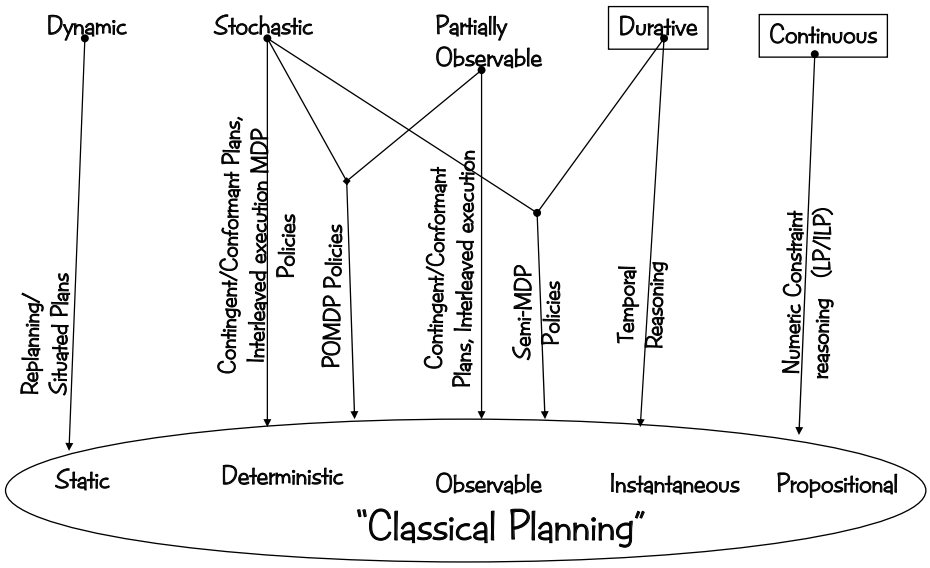


Figure 2. Planning and its branches [48].

planning historically helped out the understanding of planning under non classical assumptions. In this dissertation, we concentrate on developing scalable techniques for planning with temporal constraints and continuous quantities; many of those techniques are adaptation of recent advances in classical planning.

In this chapter, we briefly discuss the plan representation and search techniques that are most relevant to the understanding of this dissertation. They include the STRIPS representation, fixed-time vs. partial-order plan representation, forward state-space search algorithm, and the planning graph structure. For each issue, we start with the basic classical setting and then discuss the extensions to metric temporal planning.

2.1. Plan Representation

Metric temporal planning is the problem of finding a set of actions and the start times of their executions to satisfy all causal, metric, and resource constraints. Action and planning domain representation languages greatly influence on the representation of the plans and thus on the planning

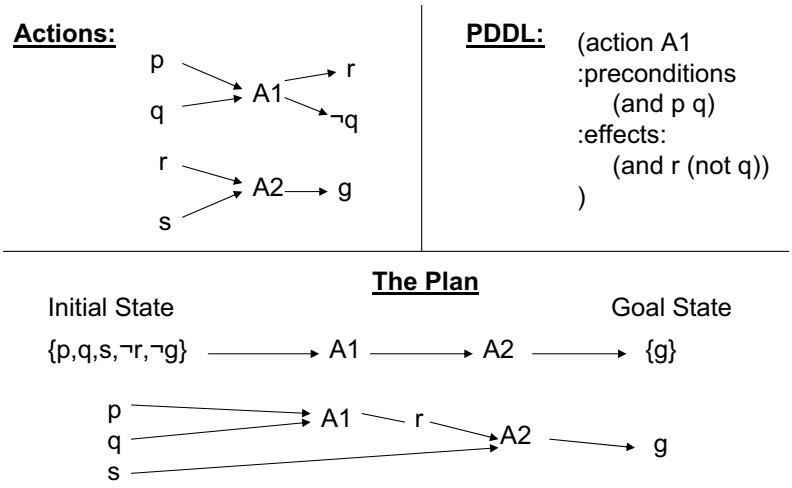


Figure 3. Example of plan in STRIPS representation.

algorithms.

Problem Representation: Until now, most work in classical planning followed the STRIPS representation [60]. In this representation, a planning problem involves:

- Planning "states" consisting of boolean state variables (aka. propositions or facts).
- Each action is specified by: (i) precondition list: the set of propositions need to be true to enable the executability of that action; (ii) effect list: consists of facts that are made true (add list) or false (delete list) after executing that action. An action a is applicable in state S if all preconditions of a are true in S. The state resulted from applying a in S is defined as: $S' = Apply(a, S) = (S \bigcup Add(a)) \setminus Delete(a)$.
- The planning problem consists of a (i) totally-specified *initial state* (e.g. values of all declared propositions are specified) and (ii) a partially-specified goal state, and (iii) a set of (ground) actions. A plan is then a sequence of actions that when executed sequentially will lead from the initial state to a state that subsumes the goal state.

Figure 3 shows a simple example of planning problem in STRIPS representation with two

actions (A_1, A_2), five facts (p, q, r, s, g), a fully-specified initial state ($S_{init} = \{p, q, \neg r, s, \neg g\}$), and a partially specified goal state $G = \{g\}$. The plan is an action sequence $P = \{A_1, A_2\}$ that when executed will lead from S_{init} to a state $S = \{p, \neg q, r, s, g\}$ that subsumes the goal state G.

To represent the planning problem following the STRIPS representation, the most common planning language is PDDL [63] (stands for Planning Domain Description Language). The first version of PDDL (PDDL1.0) was introduced at the first International Planning Competition (IPC 1998). In PDDL, the planning problem is represented using two files: a domain and a problem files. The domain file specifies object types and action templates for a particular planning domain and is used with all different problems for that domain. Problem files specify different object sets that belong to each object type declared in the domain file. Binding of the objects in the problem files with the action templates in the domain file would create the set of ground actions that can potentially be included in the final plan. Those ground actions, along with the initial and goal states, are also specified in each problem file and then used to find a plan. In Appendix A.1, we present the complete domain and problem files for the *Satellite* domain used in the last planning competition.

There are various extensions of STRIPS and PDDL to deal with different branches of planning that go beyond the classical assumptions (ref. Figure 2). Among them, most notable are ADL language [74] that extends the STRIPS representation to include conditional effects, negative preconditions, and quantifications; PDDL2.1 [28] for metric temporal planning; and more recently the extension of PDDL2.1 for probabilistic STRIPS [99].

Sapa uses PDDL2.1 and its extension. Therefore, we only elaborate on that extension in this chapter. In short, PDDL2.1 supports durative actions, for which action's preconditions and effects need to be specified at different time points during action duration. Specifically, for action A with duration D_A then A's preconditions may need to be true at the starting/ending time of A or need to be true at the starting time and remain to be true until A's end time. A's (instantaneous) effects occur

at either its start or end time points. While PDDL2.1 has limitations, and there are proposed more expressive language such as PDDL+ [29] to enable the representation of more types of temporal and continuous metric constraints, PDDL2.1 is still a language of choice for most current domain-independent temporal planning systems. We elaborate on the description of this language with an example in the next chapter (Chapter 3) (along with the search algorithm employed by *Sapa* for searching for plan using this language.) We also present examples showing the full domain and problem description in the *Satellite* domain in the Appendix A.2.

Plan Representation: For the STRIPS representation, depending on the problem specification and the involving constraints, there are many ways to represent a plan. While the most common approach is to represent plans as sequences of actions with fixed starting times, a plan can also be represented as a set of actions and the ordering relations between them (aka. order-constrained or partial order causal link - POCL plans), as a tree or graph with branching points for contingency plan, a hierarchical task network (HTN), or a "policy" that maps each possible state to a particular action. Nevertheless, for classical and metric temporal planning, the most common format are actions with fixed starting time or order-constrained plans.

Using the first approach, each action in the final plan is associated with a starting time point. For classical planning where there is no notion of time, we can use "level" to represent the position of an action in the plan. The orderings between every pair of actions in the plan are totally specified by the starting time or "level" of those actions. For example, in Figure 3, the plan consists of action A_1 at level 1 and action A_2 at level 2. In the order-constrained format, the same plan is represented by A_1, A_2 and the causal links between $S_{init} \rightarrow A_1$ (supporting p, q), $S_{init} \rightarrow A_2$ (supporting s), $A_1 \rightarrow A_2$ (supporting r) and $A_2 \rightarrow S_G$ (supporting goal g). Any action sequence that is consistent with the ordering in a POCL plan can be executed to achieve the goals. *Sapa* searches for fixed-time plans, then if desired, can convert it into a more flexible order-constrained plan. We will elaborate

more on the temporal order-constrained plan and the conversion technique in Chapter 6.

2.2. Forward State-space Search Algorithm

For planning with STRIPS representation, especially for classical setting, there are various planning algorithms including: planning as theorem proving, state space search (forward and backward), plan-space search (partial order causal link), search on the space of task networks, and planning as satisfaction (e.g. planning as SAT, CSP, and ILP). In [47], Kambhampati explained each type of planning search in detail and gave a unified view of different search algorithms as different plan refinement strategies; each utilizing different types of plan discussed in the previous sections. For example, state-space planners refine the search by adding one action along with its starting time to the partial plan until the complete action sequence can achieve the goal state from the initial state. On the other hand, partial order planner (POP) extends the partial plan by adding one action along with its causal relations to the set of actions already selected. Among different search frameworks, by adding actions to the plan tail starting from the initial state, forward state space planner has a distinct advantage of visiting "consistent states" at each search step. In a more complicated planning environment involving not only logical but also metric and temporal constraints, this advantage of not having to check for consistency at each step seems to be even more critical. We decide to employ this approach in *Sapa* for our objective of building a scalable metric temporal planner using the action representation described in the previous section.

In a forward state space planner, the search starts from the initial state. The planner consecutively picks up a state S and generates new states by applying actions A that are applicable in S (the applicability conditions and new state generation rules are described in the previous section). The newly generated states are put back into the state queue Q, which starts with a single initial state, and the planner will again select one from Q to repeat the process. The search

ends when the selected state satisfies all goals. In the example in Figure 3, assume that there is another additional action A_3 for which $Precondition(A_3) = \{p, s\}$ and $Effect(A_3) = \{\neg s\}$. Starting from $S_{init} = \{p, q, \neg r, s, \neg g\}$, the planner tries to generate new states by applying the applicable actions A_1, A_3, resulted in new states: $S_1 = Apply(A_1, S_{init}) = \{p, \neg q, r, s, \neg g\}$ and $S_2 = Apply(A_3, S_{init}) = \{p, \neg q, r\neg s, \neg g\}$. Assume that the planner picks S_1 over S_2 (using some type of *heuristic*), given that the only applicable action in S_1 is A_2, the new state is $S_3 = Apply(A_2, S_1) = \{p, \neg q, r, s, g\}$ which satisfies all the goals (only g in this case). The sequence of actions leading from the initial state S_{init} to the state S_3 that satisfies all the goal is $\{A_1, A_2\}$ is then returned as the final plan.

While the forward state space planning algorithm described above works for the classical planning, the metric temporal planning setting cause additional complications to this algorithm: (i) non-uniform durative actions make it necessary to move forward from one "time point" to another instead of from one level/step to the next; (ii) the state is necessarily to be extended to handle metric quantities. In Chapter 3, we describe the forward state space search algorithm used in *Sapa* to solve metric temporal planning problems. It extends the algorithm for classical planning discussed above.

2.3. Search Control and Reachability Analysis based on the Planning Graph

The planning-graph and the Graphplan algorithm that searches for the plans using the planning-graph structure were introduced by Blum & Furst [4]. The original algorithm for classical planning builds the planning graph by alternating between the "action" and "fact" levels. Starting from the initial state as the first fact level, the union of actions which have preconditions satisfied by the previous fact level makes up the next action level, and the union of the "add" effects of actions in the previous level makes up the next fact level. Two types of levels are alternated until all the goals appear in a fact level. Besides normal actions and facts, special "noop" actions and the

mutex reasoning and propagation are critical parts of the the planning graph building algorithm[1]. There are many extensions from the original algorithm to build the planning graph for non-classical assumptions (temporal planning [81, 35], stochastic planning [82, 10], and probabilistic planning [6]) and there are work on using the planning graph not to search for the plans but only for heuristic extraction to guide classical state-space or partial order planners [70, 71, 41]. In *Sapa*, we use a variation of the (relaxed) temporal planning graph to derive heuristic estimates to guide the state space search algorithm described in the previous section. In this section, we first describe the planning graph structure for classical planning with an example and then the extensions for handling the temporal planning specifications by Smith and Weld [81]. The algorithm that builds a variation and TGP's temporal planning graph and use it in *Sapa* for the heuristic estimation purpose is explained in detail in Chapter 4.

Planning-Graph for Classical Planning: The planning graph optimistically estimates the facts that can be achieved at each "level". It utilizes the assumption that there are no negative preconditions or negative goals in the planning problem specifications and thus we only care about the achievement of positive values of facts. Therefore, in each level, only a set of positive facts are presented with an assumption that non-presented facts are unachievable or having the false values. Projection of the set of achievable facts is done through applicable actions and their "add" (positive) effects, the "delete" (negative) effects are used for propagating and reasoning about the "mutual exclusion" (mutex) relations. We elaborate on those issues using a variation of an example shown in Figure 3.

Figure 4 shows an example of the planning graph for the planning problems with three actions A_1, A_2, A_3 and the initial state $S_{init} = \{p, q\}$ (which is a complete state and actually means $S_{init} = \{p, q, \neg r, \neg s, \neg g\}$) and the (partial) goal state $S_G = \{g\}$. The first "fact" level of the planning graph represents the initial state and the first "action" level contains:

[1] Weld [94] gives an excellent review of the Graphplan algorithm.

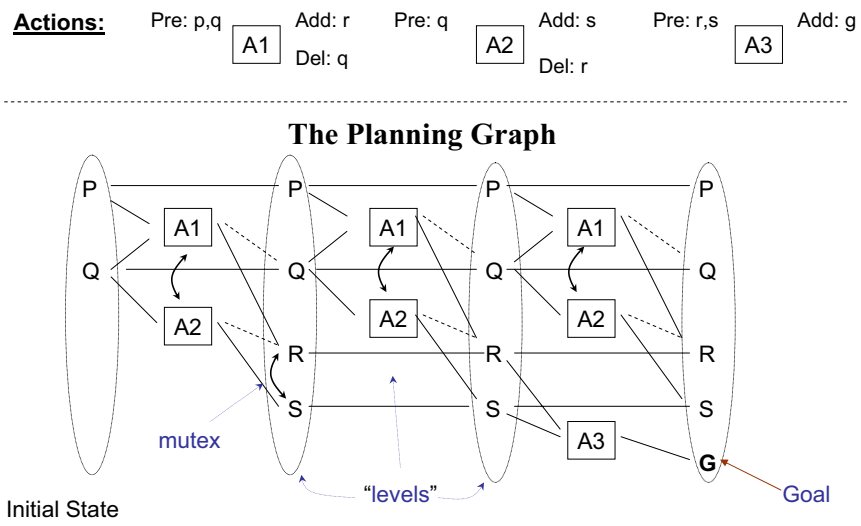


Figure 4. Example of the Planning Graph.

- All actions that are applicable in the S_{init}, which are A_1, A_2.
- Special "noop" (aka. "persistent") actions that represent the maintainance of facts through one fact level to the next. In this case, there are two noop actions $noop_p$ and $noop_q$.

There are also mutual exclusion (aka. mutex) relations stored in each levels, which indicate that two actions cannot be executed concurrently in the same level, or two facts can not be achieved in the same level. The mutex relations are defined as follows:

- *Action Mutex:* Two actions A, B are mutex if either: (i) one action deletes the other's precondition or effect; (ii) there exists a precondition p of A and q of B such that (p, q) are mutex.
- *Fact Mutex:* Two facts p, q are mutex at level l iff for all pair of actions A, B that support p, q at level $l-1$, (A, B) are mutex.

In our example, two actions A_1, A_2 are mutex because A_1 deletes q, which is a precondition of A_2 and also because A_2 deletes r, which A_1 supports. Using the mutex and noop action prop-

agation rules listed above, the planning graph grows forward from the initial state by alternating between fact and action levels. Each action level contains all applicable actions (i.e. *all* preconditions appear pair-wise non-mutex in the previous fact level). Each fact level contains the union of all effects of all actions (include noops) in the previous level. This process continues until all the goals appear pair-wise non-mutex in a given fact level. In our example, the fact level 1 contains $\{p, q, r, s\}$ with new facts r, s supported by A_1 and A_2. These two new facts r, s are mutex because A_1 and A_2 are mutex in the previous level, and thus action A_3, which has preconditions (r, s), can not be put in the action level 2. The fact level 3 contains the same facts with level 2, however, there is no longer the mutex relation between r, s because there are two actions in level 2: A_1 supporting r and $noop_s$ supporting s that are non-mutex. Finally, action A_3 can be put in the action level 3 and support the goal g at fact level 4. At this point, the planning graph building process stops. The planning graph along with the Graphplan algorithm that conduct search for the plans over the planning graph is introduced by Blum & Furst in [4]; and the more detailed discussion can be found in [5]. Due to the fact that we only build the planning graph and use it for heuristic estimation (but not for solution extracting) in *Sapa*, we do not discuss the Graphplan algorithm in this dissertation.

Extending the Planning Graph: Based on the observation that all facts and actions appear at level k will also appear at later levels $k + 1$, and mutex relations if disappearing from level k then also do not exist in level $k + 1$, the improved "bi-level" implementation of the original planning graph structure described above only uses one fact and one action level. Each fact or action is then associated with a number indicating the first level that fact/action appears in the planning graph. Each fact/action mutex relation is also associated with the first level that it disappears from the graph. This type of implementation is first used in the STAN [61] and IPP [54] planners and is utilized in most recent planners that make use of the planning graph structure. In [81], Smith & Weld argued that this bi-level planning graph structure is particularly suited for temporal planning

setting where there is no conceivable "level" but each action or fact is associated with the earliest time point that it can be achieved (fact) or executed (action). For TGP's temporal planning graph, the noop actions are removed from the planning graph building phase but its mutex relations with other actions are partially replaced by the mutex relations between actions and facts. The temporal planning graph is also built forward starting from the initial state with time stamp $t = 0$, applicable actions at time point t (with applicability condition similar to the classical planning scenario) are put in the action level. Because different actions have different durations, we move forward not by "level" but to the earliest time point that one of the activated action end. The details of the graph building and mutex propagation process for temporal planning are discussed in [81].

Planning-graph as a basis for deriving heuristics: Besides the extensions to the planning graph structure and the graphplan search algorithm to handle more expressive domains involving temporal [81, 35], contingency [82], probability[6], and sensing [93] constraints, the planning graph and its variations can also be used solely for heuristic estimate purpose to guide state-space (both backward [70, 10], and forward [41, 25, 22]), POCL planners [71, 98], and local-search planner [33]. This can be done by either: (i) using the levels at which goals appear in the planning graph to estimate how difficult to achieve the goals; or (ii) use the planning graph to extract the "relaxed" plan. For the first type of approach, in [70, 71], Nguyen et. al. discuss different frameworks to use the goal-bearing level information and the positive/negative interactions between goals to derive effective heuristics guiding backward state search and partial-order planner. The second approach of extracting the relaxed plan mimics the Graphplan algorithm but avoids any backtracking due to the mutex relations. Based on the causal structure encoded in the planning graph, the extraction process starts by selecting actions to support top-level goals. When an action is selected, its preconditions are added to the list of goals. This "backward" process stops when all the unachieved goals are supported by the initial state. The set of collected action is then returned as a "relaxed plan" and

is used to estimate the real plan that can potentially achieve all the goals from the current initial state. The name “relaxed plan” refers to the fact that mutual exclusion relations are ignored when extracting the plan and thus the relaxed-plan may contain interacting actions that can not co-exist in the non-relaxed valid plan.

To effectively extracting high-quality heuristics, there are several noteworthy variations of the traditional planning graph, each one is suitable for a different search strategy. For the backward planners (state-space regression, partial-order), where only one planning graph is needed for all generated states[2], the “serial” planning graph in which all pairs of actions (except noops) are made mutex at every action level is more effective. For the forward planners, because each node representing a different initial state and thus new planning graphs are needed, the “relaxed” planning graph where the mutex relations are ignored is a common choice. In *Sapa*, we use the relaxed version of the temporal planning graph introduced in TGP for the purpose of heuristic estimation. The details of the planning graph building and heuristic extraction procedures for the PDDL2.1 Level 3 language are described in Chapter 4.

[2]This is due to the fact that all regression states share the same initial state, the starting point of the planning graph.

CHAPTER 3

Handling concurrent actions in a forward state space planner

The *Sapa* planner, the center piece of this dissertation, addresses planning problems that involve durative actions, metric resources, and deadline goals. In this chapter, we describe how such planning problems are represented and solved in *Sapa.* We will first describe the action and problem representations in Section 3.1 and then will present the forward chaining state search algorithm used by *Sapa* in Section 3.2.

3.1. Action Representation and Constraints

In this section, we will briefly describe our representation, which is an extension of the action representation in PDDL2.1 Level 3 [28], the most expressive representation level used in the Third International Planning Competition (IPC3). PDDL2.1 planning language extended PDDL [63], which was used in the first planning competition (IPC1) in 1998 to represent the classical planning problems following the STRIPS representation. It supports durative actions and continuous value functions in several levels (with level 1 equal to PDDL1.0). For reference, we provide the sample planning domain and problem files represented in PDDL and the extended version for metric temporal planning in PDDL2.1 in the Appendix A.1 and A.2. Our extensions to PDDL2.1 Level 3 are: (i) interval preconditions; (ii) delayed effects that happen at time points other than action's start

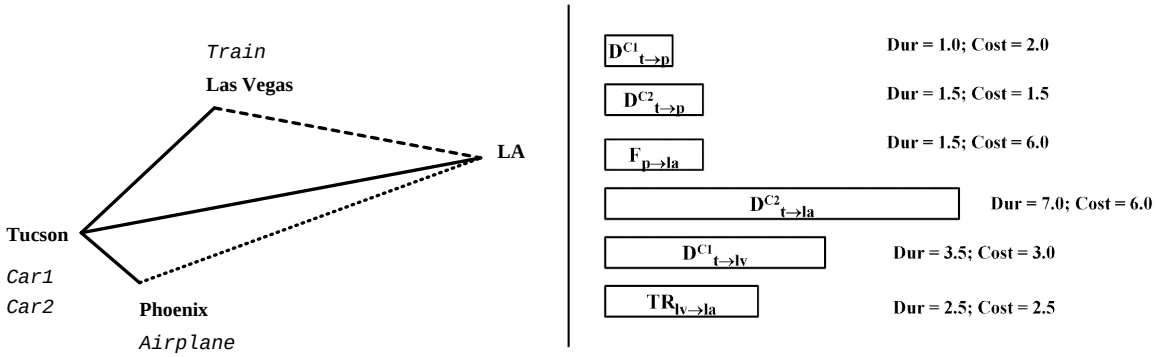


Figure 5. The travel example

and end time points; and (iii) deadline goals.

Example: We shall start with an example to illustrate the action representation in a simple temporal planning problem. This problem and its variations will be used as the running examples throughout the next several chapters of this dissertation. Figure 5 shows graphically the problem description. In this problem, a group of students in Tucson need to go to Los Angeles (LA). There are two car rental options. If the students rent a faster but more expensive car (*Car1*), they can only go to Phoenix (PHX) or Las Vegas (LV). However, if they decide to rent a slower but cheaper *Car2*, then they can use it to drive to Phoenix or directly to LA. Moreover, to reach LA, the students can also take a *train* from LV or a flight from PHX. In total, there are 6 movement actions in the domain: *drive-car1-tucson-phoenix* ($D^{c1}_{t\to p}$, *Dur = 1.0, Cost = 2.0*), *drive-car1-tucson-lv* ($D^{c1}_{t\to lv}$, *Dur = 3.5, Cost = 3.0*), *drive-car2-tucson-phoenix* ($D^{c2}_{t\to p}$, *Dur = 1.5, Cost = 1.5*), *drive-car2-tucson-la* ($D^{c2}_{t\to la}$),*Dur = 7.0, Cost = 6.0, fly-airplane-phoenix-la* ($F_{p\to la}$, *Dur = 1.5, Cost = 6.0*), and *use-train-lv-la* ($T_{lv\to la}$, *Dur = 2.5, Cost = 2.5*). Each move action A (by car/airplane/train) between two cities X and Y requires the precondition that the students be at X ($at(X)$) at the beginning of A. There are also two temporal effects: $\neg at(X)$ occurs at the starting time point of A and $at(Y)$ at the end time point of A. Driving and flying actions also consume different types of resources (e.g fuel) at different rates depending on the specific car or airplane used. In addition, there are refueling

actions for cars and airplanes. The durations of the refueling actions depend on the amount of fuel remaining in the vehicle and the refueling rate. The summaries of action specifications for this example are shown on the right side of Figure 5. In this example, the costs of moving by train or airplane are the respective ticket prices, and the costs of moving by rental cars include the rental fees and gas (resource) costs.

As illustrated in the example, unlike actions in classical planning, in planning problems with temporal and resource constraints, actions are not instantaneous but have durations. Each action *A* has a duration D_A, starting time S_A, and end time ($E_A = S_A + D_A$). The value of D_A can be statically defined for a domain, statically defined for a particular planning problem, or can be dynamically decided at the time of execution. For example, in the traveling domain discussed above, boarding a passenger always takes 10 minutes for all problems in this domain. Duration of the action of flying an airplane between two cities depends on the distance between these two cities and the speed of the airplane. Because the distance between two cities will not change over time, the duration of a particular flying action will be totally specified once we parse the planning problem. However, *refueling* an airplane has a duration that depends on the current fuel level of that airplane. We may only be able to calculate the duration of a given *refueling* action according to the fuel level at the exact time instant when the action will be executed.

An action *A* can have preconditions $Pre(A)$ that may be required either to be instantaneously true at the time point S_A or E_A, or required to be true starting at S_A and remain true for some duration $d \leq D_A$. The logical effects ***Eff(A)*** of *A* are divided into two sets $E_s(A)$, and $E_d(A)$ containing, respectively, the instantaneous effects at time points S_A, and delayed effects at $S_A + d, d \leq D_A$. In PDDL2.1, d must be equal to D_A for durative preconditions and delayed effects. Figure 6 shows the PDDL2.1 description of action driver-car for our example[1]. This action

[1]This example is similar to the description of the *drive-truck* action in the DriverLog domain used in the IPC3.

```
(:durative-action DRIVE-CAR
:parameters
     (?car - car
     ?loc-from - location
     ?loc-to - location
     ?driver - driver)
:duration (= ?duration (time-to-drive ?loc-from ?loc-to))
:condition
     (and (at start (> (fuel-level ?car)
               (/ (distance ?loc-from ?loc-to) (consume-rate ?car))))
     (at start (at ?car ?loc-from))
     (over all (driving ?driver ?car))
     (at start (link ?loc-from ?loc-to)))
:effect
     (and (at start (not (at ?car ?loc-from)))
     (at end (at ?car ?loc-to)))
     (at start (decrease (fuel-level ?car)
               (/ (distance ?loc-from ?loc-to) (consume-rate ?car)))))
```

Figure 6. Sample Drive-Car action in PDDL2.1 Level 3

has 3 (pre)conditions among which one (driving ?driver ?car) requires to be true for the whole action duration and the other two only need to be true at action's starting time.

Actions can also consume or produce metric resources and their preconditions may also depend on the values of those resources. For resource related preconditions, we allow several types of equality or inequality checking including ==, <, >, <=, >=. For resource-related effects, we allow the following types of change (update): assignment(=), increment(+=), decrement(-=), multiplication(*=), and division(/=). In essence, actions consume and produce metric resources in the same way that is specified in PDDL2.1. Action *drive-car* in Figure 6 requires the car's fuel level to be higher than it would consume for the whole trip to execute and the action decrease the fuel level by the amount equal to the trip distance divided by the fuel consume rate at its starting time. In the Appendix A.2, we provide examples of the whole domain and problem descriptions of several domains used in the planning competition.

3.2. A Forward Chaining Search Algorithm for Metric Temporal Planning

While variations of the metric temporal action representation scheme described in the last section have been used in partial order temporal planners such as IxTeT [37] and Zeno [75], Bacchus and Ady [1] were the first to propose a forward chaining algorithm capable of using this type of action representation and still allow concurrent execution of actions in the plan. We adopt and generalize their search algorithm in *Sapa.* The main idea here is to separate the decisions of "which action to apply" and "at what time point to apply the action." Regular progression search planners apply an action in the state resulting from the application of all the actions in the current prefix plan. This means that the start time of the new action is *after* the end time of the last action in the prefix, and the resulting plan will not allow concurrent execution. In contrast, *Sapa* non-deterministically considers (i) application of new actions at the current time stamp (where presumably other actions have already been applied; thus allowing concurrency) and (ii) advancement of the current time stamp.

Sapa's search is thus conducted through the space of time stamped states. We define a time stamped state S as a tuple $S = (P, M, \Pi, Q, t)$ consisting of the following structure:

- $P = (\langle p_i, t_i \rangle \mid t_i \leq t)$ is a set of predicates p_i that are true at *t* and t_i is the last time instant at which they were achieved.
- *M* is a set of values for all continuous functions, which may change over the course of planning. Functions are used to represent the metric-resources and other continuous values. Examples of functions are the fuel levels of vehicles.
- Π is a set of persistent conditions, such as durative preconditions, that need to be protected during a specific period of time.

- *Q* is an event queue containing a set of updates each scheduled to occur at a specified time in the future. An event *e* can do one of three things: (1) change the True/False value of some predicate, (2) update the value of some function representing a metric-resource, or (3) end the persistence of some condition.

- t is the time stamp of S

In this dissertation, unless noted otherwise, when we say "state" we mean a time stamped state. Note that a time stamped state with a stamp t not only describes the expected snapshot of the world at time t during execution (as done in classical progression planners), but also the delayed (but inevitable) effects of the commitments that have been made by (or before) time t.

If there is no exogenous events, the initial state S_{init} has time stamp $t = 0$ and has an empty event queue and empty set of persistent conditions. If the problem also involves a set of exogenous events (in the form of *timed initial facts* discussed in PDDL2.2), then the initial state S_{init}'s event queue is made up by the collection of those events. It is completely specified in terms of function and predicate values. The goals are represented by a set of 2-tuples $G = (\langle p_1, t_1\rangle ... \langle p_n, t_n\rangle)$ where p_i is the i^{th} goal and t_i is the time instant by which p_i needs to be achieved. Note that PDDL2.1 does not allow the specification of goal deadline constraints.

Goal Satisfaction: The state $S = (P, M, \Pi, Q, t)$ *subsumes* (entails) the goal *G* if for each $\langle p_i, t_i\rangle \in G$ either:

1. $\exists \langle p_i, t_j\rangle \in P$, $t_j < t_i$ and there is no event in *Q* that deletes p_i.

2. $\exists e \in Q$ that adds p_i at time instant $t_e < t_i$, and there is no event in *Q* that deletes p_i.[2]

Action Applicability: An action A is *applicable* in state $S = (P, M, \Pi, Q, t)$ if:

[2]In practice, conflicting events are never put on *Q*

1. All logical (pre)conditions of *A* are satisfied by *P*.

2. All metric resource (pre)conditions of A are satisfied by *M*. (For example, if the condition to execute an action $A = move(truck, A, B)$ is $fuel(truck) > 500$ then A is executable in S if the value v of $fuel(truck)$ in M satisfies $v > 500$.)

3. *A*'s effects do not interfere with any persistent condition in Π and any event in *Q*.

4. There is no event in Q that interferes with persistent preconditions of *A*.

***Interference*:** Interference is defined as the violation of any of the following conditions:

1. Action A should not add any event e that causes p if there is another event currently in Q that causes $\neg p$. Thus, there is never a state in which there are two events in the event queue that cause opposite effects.

2. If A deletes p and p is protected in Π until time point t_p, then A should not delete p before t_p.

3. If A has a persistent precondition p, and there is an event that gives $\neg p$, then that event should occur *after* A terminates.

4. A should not change the value of any function which is currently accessed by another unterminated action[3]. Moreover, A also should not access the value of any function that is currently changed by an unterminated action.

At first glance, the first interference condition seems to be overly strong. However, we argue that it is necessary to keep underlying processes that cause contradicting state changes from overlapping each other. For example, suppose that we have two actions $A_1 = build\_house$, $A_2 =$

[3]Unterminated actions are the ones that started before the time point t of the current state S but have not yet finished at t.

$destroy\_house$ and $Dur(A_1) = 10$, $Dur(A_2) = 7$. A_1 has effect has_house and A_2 has effect $\neg has\_house$ at their end time points. Assuming that A_1 is applied at time $t = 0$ and added an event $e = Add(has\_house)$ at $t = 10$. If we are allowed to apply A_2 at time $t = 0$ and add a contradicting event $e' = Delete(has\_house)$ at $t = 7$, then it is unreasonable to believe that we will still have a house at time $t = 10$ anymore. Thus, even though in our current action modeling, state changes that cause has_house and $\neg has\_house$ look as if they happen instantaneously at the actions' end time points, there are underlying processes (build/destroy house) that span the whole action durations to make them happen. To prevent those contradicting processes from overlapping with each other, we employ the conservative approach of not letting Q contain contradicting effects.[4]

When we apply an action *A* to a state $S = (P, M, \Pi, Q, t)$, all instantaneous effects of *A* will be immediately used to update the predicate list *P* and metric resources database *M* of *S*. *A*'s persistent preconditions and delayed effects will be put into the persistent condition set Π and event queue *Q* of *S*.

Besides the normal actions, we will have a special action called **advance-time** which we use to advance the time stamp of *S* to the time instant t_e of the earliest event e in the event queue *Q* of *S*. The advance-time action will be applicable in any state *S* that has a non-empty event queue. Upon applying this action, the state *S* gets updated according to all the events in the event queue that are scheduled to occur at t_e. Note that we can apply multiple non-interfering actions at a given time point before applying the special advance-time action. This allows for concurrency in the final plan.

[4]It may be argued that there are cases in which there is no process to give certain effect, or there are situations in which the contradicting processes are allowed to overlap. However, without the ability to explicitly specify the processes and their characteristics in the action representation, we currently decided to go with the conservative approach. We should also mention that the interference relations above *do not* preclude a condition from being established and deleted in the course of a plan as long as the processes involved in establishment and deletion do not overlap. In the example above, it is legal to first build the house and then destroy it.

```
State Queue: SQ={S_init}
while SQ≠{}
    S:= Dequeue(SQ)
    Nondeterministically select A applicable in S
            /* A can be advance-time action */
        S' := Apply(A,S)
        if S' satisfies G then PrintSolution
        else Enqueue(S',SQ)
end while;
```

Figure 7. Main search algorithm

Search algorithm: The basic algorithm for searching in the space of time stamped states is shown in Figure 7. We proceed by applying each applicable action to the current state and put each resulting state into the sorted queue using the $Enqueue()$ function. The $Dequeue()$ function is used to take out the first state from the state queue. Currently, *Sapa* employs the A* search. Thus, the state queue is sorted according to some heuristic function that measures the difficulty of reaching the goals from the current state. Next several sections of the paper discuss the design of these heuristic functions.

Example: To illustrate how different data structures in the search state $S = (P, M, \Pi, Q, t)$ are maintained during search, we will use a (simpler) variation of our ongoing example introduced at the end of Section 3.1. In this variation, we eliminate the route from Tucson to Los Angeles (LA) going through Las Vegas. Moreover, we assume that there are too many students to fit into one car and they had to be divided into two groups. The first group rents the first car, goes to Phoenix (Phx), and then flies to LA. The second group rents the second car and drives directly to LA. Because the trip from Tucson to LA is very long, the second car needs to be refueled before driving. To further make the problem simpler, we eliminate the boarding/un-boarding actions and assume that the students will reach a certain place (e.g. Phoenix) when their means of transportation (e.g. Car1) arrives there. Figure 8 shows graphically the plan and how the search state S's components change as we go forward. In this example, we assume the $refuel(car)$ action refuels each car to a maximum

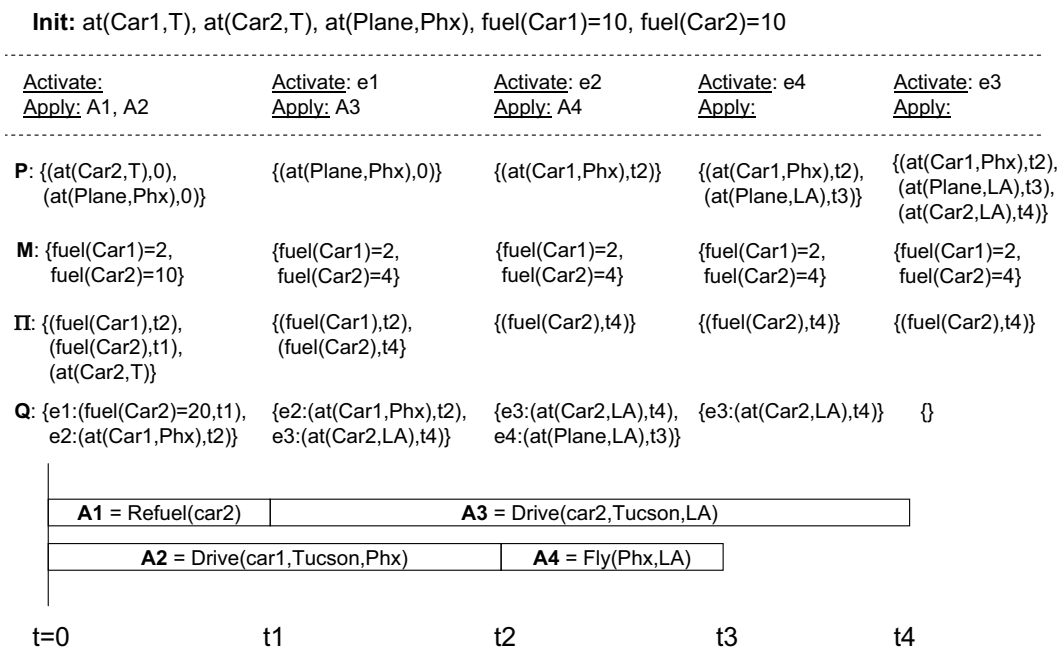


Figure 8. An example showing how different datastructures representing the search state $S = (P, M, \Pi, Q)$ change as we advance the time stamp, apply actions and activate events. The top row shows the initial state. The second row shows the events and actions that are activated and executed at each given time point. The lower rows show how the search state $S = (P, M, \Pi, Q)$ changes due to action application. Finally, we show graphically the durative actions in this plan.

of 20 gallons. $Drive(car, Tucson, Phoenix)$ takes 8 gallons of gas and $Drive(car, Tucson, LA)$ takes 16 gallons. Note that, at time point t_1, event e_1 increases the fuel level of $car2$ to 20 gallons. However, the immediately following application of action A_3 reduces $fuel(car2)$ back to the lower level of 4 gallons.

3.3. Summary and Discussion

In this chapter, we discuss the representation of metric temporal planning involving durative action, metric resource consumption, and deadline goal. It is an extension of the standard PDDL2.1

Level 3 planning language. We also describe the forward search algorithm in *Sapa* that produces fixed-time temporal parallel plans using this representation.

In the future, we want to make *Sapa* support a richer set of temporal and resource constraints such as:

- Time-dependent action duration/cost and resource consumption (e.g. driving from office to the airport takes longer time and is costlier during rush hour than at less-traffic time).
- Supporting continuous change during action duration (PDDL2.1 Level 4).

For both of those issues, due to the forward state space search algorithm where the total knowledge of the world is available at each action's starting time, unlike backward planner, it is not hard to extend the state representation and consistency checking routine to handle those additional constraints. From the technical point of view, for the first issue, we need a better time-related estimation for actions in the partial plan (g value) and in the relaxed plan (h value). For the g value, we are currently investigating an approach of "online partialization" to push every newly added action's starting time as early as possible. This is done by maintaining an additional causal structure between actions in the partial plan. For the h value, better estimation of the starting time of actions that can potentially in the relaxed plan is a plus. We will elaborate it in the later part of this chapter (dedicated for heuristic improvement). For the second issue of supporting continuous changes, we plan to explicitly keep a resource profile for each resource that is currently under change according to some functions in the partial plan.

CHAPTER 4

Heuristics based on Propagated Cost-Functions over the Relaxed Planning Graph

A critical part of any planner is its heuristic estimate component. In forward state space planners, quality of the heuristic is basically decided by the ability to select lower cost actions that lead to states closer to the goals. Without good heuristic control, it would be nearly impossible for blind search to find a plan in reasonable time. Let's assume that the branching factor of a normal planning problem is 20 and we have a very fast computer that can examine 100,000 nodes per second. Then, to find a solution of length 5, we need to search about 32 seconds, a solution of length 10 would need more than 3 years and a solution of length 20 would need about 3^{18} years to find. Nevertheless, good heuristics enable state-of-the-art planners to find solutions with hundred of actions in minutes.

In this chapter, we discuss the issue of deriving heuristics, that are sensitive to both time and cost, to guide *Sapa*'s search algorithm. An important challenge in finding heuristics to support multi-objective search, as illustrated by the example below, is that the cost and temporal aspects of a plan are often inter-dependent. Therefore, in this chapter, we introduce the approach of tracking the costs of achieving goals and executing actions in the plan as functions of time. The propagated cost functions can then be used to derive the heuristic values to guide the search in *Sapa.*

Example: Consider a simpler version of our ongoing example. Suppose that we need to go from Tucson to Los Angeles and have two transport options: (i) rent a car and drive from Tucson to Los Angeles in one day for $100 or (ii) take a shuttle to the Phoenix airport and fly to Los Angeles in 3 hours for $200. The first option takes more time (higher makespan) but less money, while the second one clearly takes less time but is more expensive. Depending on the specific weights the user gives to each criterion, she may prefer the first option over the second or *vice versa*. Moreover, the user's decision may also be influenced by other constraints on time and cost that are imposed on the final plan. For example, if she needs to be in Los Angeles in six hours, then she may be forced to choose the second option. However, if she has plenty of time but limited budget, then she may choose the first option.

The simple example above shows that makespan and execution cost, while nominally independent of each other, are nevertheless related in terms of the overall objectives of the user and the constraints on a given planning problem. More specifically, for a given makespan threshold (e.g. to be in LA within six hours), there is a certain estimated solution cost tied to it (shuttle fee and ticket price to LA) and analogously for a given cost threshold there is a certain estimated time tied to it. Thus, in order to find plans that are good with respect to both cost and makespan, we need to develop heuristics that track cost of a set of (sub)goals as a function of time.

Given that the planning graph is an excellent structure to represent the relation between facts and actions [70], we will use a temporal version of the planning graph structure, such as that introduced in TGP [81], as a substrate for propagating the cost information. We starts with Section 4.1 containing a brief discussion of the data structures used for the cost propagation process. We then continue with the details of the propagation process in Section 4.2, and the criteria used to terminate the propagation in Section 4.3. Section 4.4 discusses how the cost functions are used to extract heuristic values. We finish with Section 4.5 on adjustment techniques to improve the

heuristic quality.

4.1. The Temporal Planning Graph Structure

We now adapt the notion of temporal planning graphs, introduced by Smith & Weld in [81], to our action representation. The temporal planning graph for a given problem is a bi-level graph, with one level containing all *facts*, and the other containing all *actions* in the planning problem. Each fact has links to all actions supporting it, and each action has links to all facts that belong to its precondition and effect lists.[1] Actions are durative and their effects are represented as events that occur at some time between the action's start and end time points. As we will see in more detail in the later parts of this section, we build the temporal planning graph by incrementally increasing the time (makespan value) of the graph. At a given time point t, an action A is activated if all preconditions of A can be achieved at t. To support the *delayed effects* of the activated actions (i.e., effects that occur at the *future* time points beyond t), we also maintain a global event queue for the entire graph, $\mathcal{Q} = \{e_1, e_2, ...e_n\}$ sorted in the increasing order of event time. The event queue for the temporal graph differs from the event queue for the search state (discussed in the previous section) in the following ways:

- It is associated with the whole planning graph (rather than with each single state).
- It only contains the *positive* events. Specifically, the negative effects and the resource-related effects of the actions are not entered in to the graph's queue.
- All the events in $\mathcal{Q}$ have *event costs* associated with each individual event (see below).

[1] The bi-level representation has been used in classical planning to save time and space [61], but as Smith & Weld [81] show, it makes even more sense in temporal planning domains because there is actually no notion of level. All we have are a set of fact/action nodes, each one encoding information such as the *earliest time point* at which the fact/action can be achieved/executed, and the *lowest cost* incurred to achieve them.

Each event in $\mathcal{Q}$ is a 4-tuple $e = \langle f, t, c, A \rangle$ in which: (1) f is the fact that e will add; (2) t is the time point at which the event will occur; and (3) c is the cost incurred to enable the execution of action A which causes e. For each action A, we introduce a cost function $C(A, t) = v$ to specify the estimated cost v that we incur to enable A's execution at time point t. In other words, $C(A, t)$ is the estimate of the cost incurred to achieve all of A's preconditions at time point t. Moreover, each action will also have an *execution cost* ($C_{exec}(A)$), which is the cost incurred in executing A (e.g. ticket price for the *fly* action, gas cost for driving a car). For each fact f, a similar cost function $C(f, t) = v$ specifies the estimated cost v incurred to achieve f at time point t (e.g. cost incurred to be in Los Angeles in 6 hours). We also need an additional function $SA(f, t) = A_f$ to specify the action A_f that can be used to *support* f with cost v at time point t.

Since we are using a "relaxed" planning graph that is constructed ignoring delete effects, and resource effects, the derived heuristics will not be sensitive to negative interactions and resource restrictions[2]. In Sections 4.5 we discuss how the heuristic measures are adjusted to take these interactions into account.

4.2. Cost Propagation Procedure

As mentioned above, our general approach is to propagate the estimated costs incurred to achieve facts and actions from the initial state. As a first step, we need to initialize the cost functions $C(A, t)$ and $C(f, t)$ for all facts and actions. For a given initial state S_{init}, let $F = \{f_1, f_2 ... f_n\}$ be the set of facts that are true at time point t_{init} and $\{(f'_1, t_1), ...(f'_m, t_m)\}$, be a set of outstanding positive events which specify the addition of facts f'_i at time points $t_i > t_{init}$. We introduce a dummy action A_{init} to represent S_{init} where A_{init} (i) requires no preconditions; (ii) has

[2] In the original Graphplan algorithm [4], there is a process of propagating mutex information, which captures the negative interactions between different propositions and actions occurring at the same time (level). To reduce the heuristic computation cost, we will neglect the mutex propagation and will discuss the propagation process in the context of the relaxed problem in which the *delete effects* of actions, which cause the mutex relations, are ignored.

Function *Propagate Cost*
  Current time: $t_c = 0$;
  $Apply(A_{init}, 0)$;
  while *Termination-Criteria* $\neq$ *true*
    Get earliest event $e = \langle f_e, t_e, c_e, A_e \rangle$ from $\mathcal{Q}$;
    $t_c = t_e$;
    if $c_e < C(f, t_c)$ **then**
    Update: $C(f, t) = c_e$
      for all action A: $f \in Precondition(A)$
        $NewCost_A = CostAggregate(A, t_c)$;
        if $NewCost_A < C(A, t_c)$ **then**
          Update: $C(A, t) = NewCost(A), t_c \leq t < \infty$;
          $Apply(A, t_c)$;
End *Propagate Cost*;

Function $Apply(A, t)$
  For all A's effect that add f at $S_A + d$ **do**
    $\mathcal{Q} = \mathcal{Q} \bigcup \{e = \langle f, t + d, C(A, t) + C_{exec}(A), A \rangle\}$;
End $Apply(A, t)$;

Figure 9. Main cost propagation algorithm

cost $C_{exec}(A_{init}) = 0$ and (iii) causes the events of adding all f_i at t_{init} and f_i' at time points t_i. At the beginning ($t = 0$), the event queue $\mathcal{Q}$ is empty, the cost functions for all facts and actions are initialized as: $C(A, t) = \infty, C(f, t) = \infty, \ \forall 0 \leq t < \infty$, and A_{init} is the only action that is applicable.

Figure 9 summarizes the steps in the cost propagation algorithm. The main algorithm contains two interleaved parts: one for applying an action and the other for activating an event representing the action's effect.

Action Introduction: When an action A is introduced into the planning graph, we (1) augment the event queue $\mathcal{Q}$ with events corresponding to all of A's effects, and (2) update the cost function $C(A, t)$ of A.

Event Activation: When an event $e = \langle f_e, t_e, C_e, A_e \rangle \in \mathcal{Q}$, which represents an effect of A_e occurring at time point t_e and adding a fact f_e with cost C_e is activated, the cost function of the fact

f_e is updated if $C_e < C(f_e, t_e)$. Moreover, if the newly improved cost of f_e leads to a reduction in the cost function of any action A that f_e supports (as decided by function $CostAggregate(A, t)$ in line 11 of Figure 9) then we will *(re)apply* A in the graph to propagate f_e's new cost of achievement to the cost functions of A and its effects.

At any given time point t, $C(A, t)$ is an aggregated cost (returned by function $CostAggregate(A, t)$) to achieve all of its preconditions. The aggregation can be done in different ways:

1. **Max-propagation:**

$$C(A, t) = Max\{C(f, t) : f \in Precond(A)\} \tag{4.1}$$

2. **Sum-propagation:**

$$C(A, t) = \sum\{C(f, t) : f \in Precond(A)\} \tag{4.2}$$

The first method assumes that all preconditions of an action depend on each other and the cost to achieve all of them is equal to the cost to achieve the costliest one. This rule leads to the underestimation of $C(A, t)$ and the value of $C(A, t)$ is admissible. The second method (*sum-propagation*) assumes that all facts are independent and is thus inadmissible when subgoals have positive interactions. In classical planning scenarios, sum combination has proved to be more effective than the admissible but much less informed max combination [70, 7].

When the cost function of one of the preconditions of a given action is updated (lowered), the $CostAggregate(A, t)$ function is called and it uses one of the methods described above to calculate if the cost required to execute an action has improved (been reduced).[3] If $C(A, t)$ has

[3]Propagation rule (2) and (3) will improve (lower) the value of $C(A, t)$ when the cost function of one of A's preconditions is improved. However, for rule (1), the value of $C(A, t)$ is improved only when the cost function of its costliest precondition is updated.

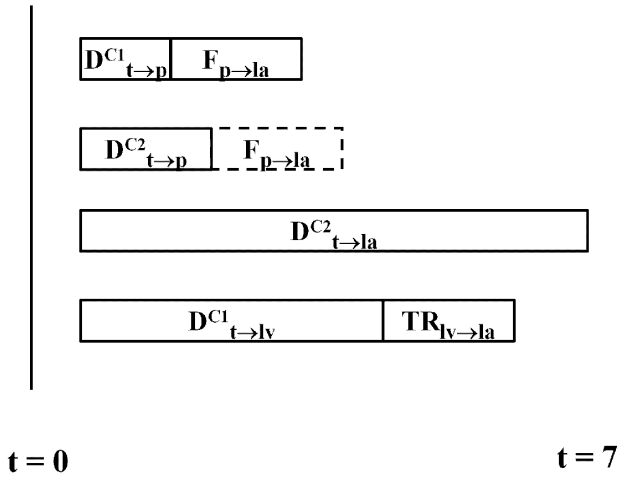


Figure 10. Timeline to represent actions at their earliest possible execution times in the relaxed temporal planning graph.

improved, then we will *re-apply* A (line 12-14 in Figure 9) to propagate the improved cost $C(A,t)$ to the cost functions $C(f,t)$ of its effects.

The only remaining issue in the main algorithm illustrated in Figure 9 is the *termination criteria* for the propagation, which will be discussed in details in Section 4.3. Notice that the way we update the cost functions of facts and actions in the planning domains described above shows the challenges in heuristic estimation in temporal planning domains. Because an action's effects do not occur instantaneously at the action's starting time, concurrent actions overlap in many possible ways and thus the cost functions, which represent the difficulty of achieving facts and actions are *time-sensitive*.

Before demonstrating the cost propagation process in our ongoing example, we make two observations about our propagated cost function:

Observation 1: *The propagated cost functions of facts and actions are non-increasing over time.*

Observation 2: *Because we increase time in* steps *by going through events in the event queue, the cost functions for all facts and actions will be step-functions, even though time is measured*

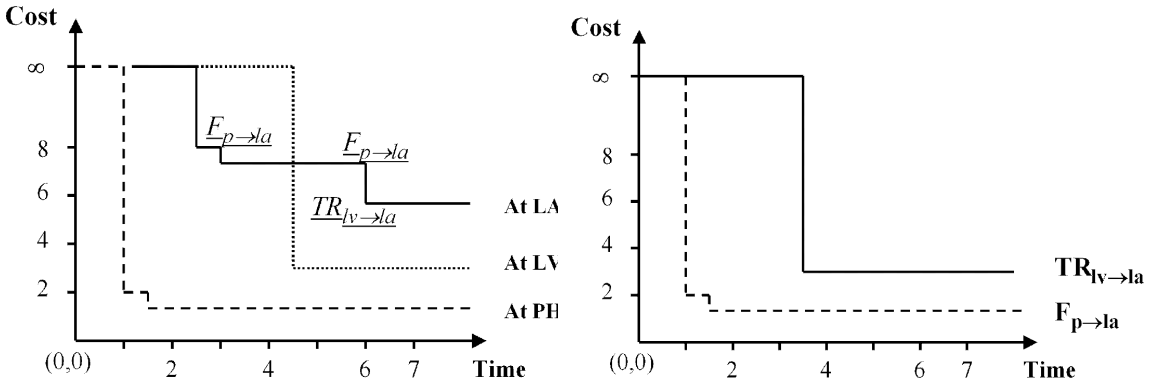


Figure 11. Cost functions for facts and actions in the travel example.

continuously.

From the first observation, the estimated cheapest cost of achieving a given goal g at time point t_g is $C(g, t_g)$. We do not need to look at the value of $C(g, t)$ at time point $t < t_g$. The second observation helps us in efficiently evaluating the heuristic value for an objective function f involving both time and cost. Specifically, we need compute f at only the (finite number of)time points where the cost function of some fact or action changes. We will come back to the details of the heuristic estimation routines in Section 4.4.

Returning to our running example, Figure 10 shows graphically the earliest time point at which each action can be applied ($C(A, t) < \infty$) and Figure 11 shows how the cost function of facts/actions change as the time increases. Here is an outline of the update process in this example: at time point $t = 0$, four actions can be applied. They are $D^{c_1}_{t\to p}$, $D^{c_2}_{t\to p}$, $D^{c_1}_{t\to lv}$, $D^{c_2}_{t\to la}$. These actions add 4 events into the event queue $\mathcal{Q} = \{e_1 = \langle at\_phx, t = 1.0, c = 2.0, D^{c_1}_{t\to p}\rangle$, $e_2 = \langle at\_phx, 1.5, 1.5, D^{c_2}_{t\to p}\rangle$, $e_3 = \langle at\_lv, 3.5, 3.0, D^{c_1}_{t\to lv}\rangle$, $e_4 = \langle at\_la, 7.0, 6.0, D^{c_2}_{t\to la}\rangle\}$. After we advance the time to $t = 1.0$, the first event e_1 is activated and $C(at\_phx, t)$ is updated. Moreover, because at_phx is a precondition of $F_{p\to la}$, we also update $C(F_{p\to la}, t)$ at $t_e = 1.0$ from ∞ to 2.0 and put an event $e = \langle at\_la, 2.5, 8.0, F_{p\to la}\rangle$, which represents $F_{p\to la}$'s effect, into $\mathcal{Q}$. We then go

on with the second event $\langle at\_phx, 1.5, 1.5, D^{c2}_{t\rightarrow p}\rangle$ and lower the cost of the fact at_phx and action $F_{p\rightarrow la}$. Event $e = \langle at\_la, 3.0, 7.5, F_{p\rightarrow la}\rangle$ is added as a result of the newly improved cost of $F_{p\rightarrow la}$. Continuing the process, we update the cost function of at_la once at time point $t = 2.5$, and again at $t = 3.0$ as the delayed effects of actions $F_{p\rightarrow la}$ occur. At time point $t = 3.5$, we update the cost value of at_lv and action $T_{lv\rightarrow la}$ and introduce the event $e = \langle at\_la, 6.0, 5.5, T_{lv\rightarrow la}\rangle$. Notice that the final event $e' = \langle at\_la, 7.0, 6.0, D^{c2}_{t\rightarrow la}\rangle$ representing a delayed effect of the action $D^{c2}_{t\rightarrow la}$ applied at $t = 0$ will not cause any cost update. This is because the cost function of at_la has been updated to value $c = 5.5 < c_{e'}$ at time $t = 6.0 < t_{e'} = 7.0$.

Besides the values of the cost functions, Figure 11 also shows the supporting actions ($SA(f, t)$, defined in Section 4.1) for the fact (goal) at_la. We can see that action $T_{lv\rightarrow la}$ gives the best cost of $C(at\_la, t) = 5.5$ for $t \geq 6.0$ and action $F_{p\rightarrow la}$ gives best cost $C(at\_la, t) = 7.5$ for $3.0 \leq t < 5.5$ and $C(at\_la, t) = 8.0$ for $2.5 \leq t < 3.0$. The right most graph in Figure 11 shows similar cost functions for the actions in this example. We only show the cost functions of actions $T_{lv\rightarrow la}$ and $F_{p\rightarrow la}$ because the other four actions are already applicable at time point $t_{init} = 0$ and thus their cost functions stabilize at 0.

4.3. Termination Criteria for the Cost Propagation Process

In this section, we discuss the issue of when we should terminate the cost propagation process. The first thing to note is that cost propagation is in some ways inherently more complex than makespan propagation. For example, once a set of literals enter the planning graph (and are not mutually exclusive), the estimate of the makespan of the shortest plan for achieving them does not change as we continue to expand the planning graph. In contrast, the estimate of the cost of the cheapest plan for achieving them can change until the planning graph levels off. This is why we need to carefully consider the effect of different criteria for stopping the expansion of the planning graph

on the accuracy of the cost estimates. The first intuition is that we should not stop the propagation when there exist top level goals for which the cost of achievement is still infinite (unreached goal). On the other hand, given our objective function of finding the cheapest way to achieve the goals, we need not continue the propagation when there is no chance that we can improve the cost of achieving the goals. From those intuitions, following are several rules that can be used to determine when to terminate propagation:

Deadline termination: *The propagation should stop at a time point* t *if: (1)* $\forall\ goal\ G\ :\ Deadline(G) \leq t$*, or (2)* $\exists\ goal\ G : (Deadline(G) < t) \wedge (C(G,t) = \infty)$.

The first rule governs the hard constraints on the goal deadlines. It implies that we should not propagate beyond the latest goal deadline (because any cost estimation beyond that point is useless), or we can not achieve some goal by its deadline.

With the observation that the propagated costs can change only if we still have some events left in the queue that can possibly change the cost functions of a specific propositions, we have the second general termination rule regarding the propagation:

Fix-point termination: *The propagation should stop when there are no more events that can decrease the cost of any proposition.*

The second rule is a qualification for reaching the fix-point in which there is no gain on the cost function of any fact or action. It is analogous to the idea of growing the planning graph until it *levels-off* in classical planning.

Stopping the propagation according to the two general rules above leads us to the best (lowest value) achievable cost estimation for all propositions given a specific initial state. However, there are several situations in which we may want to stop the propagation process earlier. First, propagation until the fix-point, where there is no gain on the cost function of any fact or action, would be too costly [70]. Second, the cost functions of the goals may reach the fix-point long before the full

propagation process is terminated according to the general rules discussed above, where the costs of *all* propositions and actions stabilize.

Given the above motivations, we introduce several different criteria to stop the propagation earlier than is entailed by the fix-point computation:

Zero-lookahead approximation: *Stop the propagation at the earliest time point t where all the goals are reachable ($C(G,t) < \infty$).*

One-lookahead approximation: *At the earliest time point t where all the goals are reachable, execute all the remaining events in the event queue and stop the propagation.*

One-lookahead approximation looks ahead one step in the (future) event queues when one path to achieve all the goals under the relaxed assumption is guaranteed and hopes that executing all those events would explicate some cheaper path to achieve all goals.[4]

Zero and one-lookahead are examples of a more general k-lookahead approximation, in which extracting the heuristic value as soon as all the goals are reachable corresponds to *zero-lookahead* and continuing to propagate until the fix-point corresponds to the *infinite (full) lookahead*. The rationale behind the k-lookahead approximation is that when all the goals appear, which is an indication that there exists at least one (relaxed) solution, then we will look ahead one or more steps to see if we can achieve some extra improvement in the cost of achieving the goals (and thus lead to a lower cost solution).[5]

Coming back to our travel example, zero-lookahead stops the propagation process at the time point $t = 2.5$ and the goal cost is $C(in\_la, 2.5) = 8.0$. The action chain giving that cost is $\{D^{c_1}_{t\rightarrow p}, F_{p\rightarrow la}\}$. With one-lookahead, we find the lowest cost for achieving the goal in_la is

[4]Note that even if none of those events is directly related to the goals, their executions can still indirectly lead to better (cheaper) path to reach all the goals.

[5]For backward planners where we only need to run the propagation one time, infi nite-lookahead or higher levels of lookahead may pay off, while in forward planners where we need to evaluate the cost of goals for each single search state, lower values of k may be more appropriate.

$C(in\_la, 7.0) = 6.0$ and it is given by the action $(D^{c_2}_{t \rightarrow la})$. With two-lookahead approximation, the lowest cost for in_la is $C(in\_la, 6.0) = 5.5$ and it is achieved by cost propagation through the action set $\{(D^{c_1}_{t \rightarrow lv}, T_{lv \rightarrow la})\}$. In this example, two-lookahead has the same effect as the fix-point propagation (infinite lookahead) if the deadline to achieve in_la is later than $t = 6.0$. If it is earlier, say $Deadline(in\_la) = 5.5$, then the one-lookahead will have the same effect as the infinite-lookahead option and gives the cost of $C(in\_la, 3.0) = 7.5$ for the action chain $\{D^{c_2}_{t \rightarrow phx}, F_{phx \rightarrow la}\}$.

4.4. Heuristics based on Propagated Cost Functions

Once the propagation process terminates, the time-sensitive cost functions contain sufficient information to estimate any makespan and cost-based heuristic value of a given state. Specifically, suppose the planning graph is grown from a state S. Then the cost functions for the set of goals $G = \{(g_1, t_1), (g_2, t_2)...(g_n, t_n)\}, t_i = Deadline(g_i)$ can be used to derive the following estimates:

- The minimum makespan estimate $T(P_S)$ for a plan starting from S is given by the earliest time point τ_0 at which all goals are reached with finite cost $C(g, t) < \infty$.
- The minimum/maximum/summation estimate of slack $Slack(P_S)$ for a plan starting from S is given by the minimum/maximum/summation of the distances between the time point at which each goal first appears in the temporal planning graph and the deadline of that goal.
- The minimum cost estimate, ($C(g, deadline(g))$), of a plan starting from a state S and achieving a set of goals G, $C(P_S, \tau_\infty)$, can be computed by aggregating the cost estimates for achieving each of the individual goals at their respective deadlines.[6] Notice that we use τ_∞ to

[6] If we consider G as the set of preconditions for a dummy action that represents the goal state, then we can use any of the propagation rules (max/sum) discussed in Section 4.2 to directly estimate the total cost of achieving the goals from the given initial state.

denote the time point at which the cost propagation process stops. Thus, τ_∞ is the time point at which the cost functions for all individual goals $C(f, \tau_\infty)$ have their lowest value.

- For each value $t : \tau_0 < t < \tau_\infty$, the cost estimate of a plan $C(P_S, t)$, which can achieve goals within a given makespan limit of t, is the aggregation of the values $C(g_i, t)$ of goals g_i.

The makespan and the cost estimates of a state can be used as the basis for deriving heuristics. The specific way these estimates are combined to compute the heuristic values does of course depend on what the user's ultimate objective function is. In the general case, the objective would be a function $f(C(P_S), T(P_S))$ involving both the cost ($C(P_S)$) and makespan ($T(P_S)$) values of the plan. Suppose that the objective function is a linear combination of cost and makespan:

$$h(S) = f(C(P_S), T(P_S)) = \alpha.C(P_S) + (1 - \alpha).T(P_S)$$

If the user only cares about the makespan value ($\alpha = 0$), then $h(S) = T(P_S) = \tau_0$. Similarly, if the user only cares about the plan cost ($\alpha = 1$), then $h(S) = C(P_S, \tau_\infty)$. In the more general case, where $0 < \alpha < 1$, then we have to find the time point t, $\tau_0 \leq t \leq \tau_\infty$, such that $h_t(S) = f(C(P_S, t), t) = \alpha.C(P_S, t) + (1 - \alpha).t$ has minimum value.[7]

In our ongoing example, given our goal of being in Los Angeles (*at_la*), if $\alpha = 0$, the heuristic value is $h(S) = \tau_0 = 2.5$ which is the earliest time point at which $C(at\_a, t) < \infty$. The heuristic value corresponds to the propagation through action chain $(D^{c_1}_{t \to p}, F_{p \to la})$. If $\alpha = 1$ and $Deadline(At_{LA}) \geq 6.0$, then $h(S) = 5.5$, which is the cheapest cost we can get at time point $\tau_\infty = 6.0$. This heuristic value represents another solution $(D^{c_1}_{t \to lv}, T_{lv \to la})$. Finally, if $0 < \alpha < 1$, say $\alpha = 0.55$, then the lowest heuristic value $h(S) = \alpha.C(P_S, t) + (1 - \alpha).t$ is $h(S) = 0.55 * 7.5 +$

[7] Because $f(C(P_S, t), t)$ estimates the cost of the (cheapest) plan that achieves all goals with the makespan value $T(P_S) = t$, the minimum of $f(C(P_S, t), t)$ ($\tau_0 \leq t \leq \tau_\infty$) estimates the plan P that achieves the goals from state S and P has a smallest value of $f(C(P_S), T(P_S))$. That value would be the heuristic estimation for our objective function of minimizing $f(C(P_S), T(P_S))$.

$0.45*3.0 = 5.47$ at time point $2.5 < t = 3.0 < 6.0$. For $\alpha = 0.55$, this heuristic value $h(S) = 5.47$ corresponds to yet another solution involving driving part way and flying the rest: $(D^{c_2}_{t\rightarrow p}, F_{p\rightarrow la})$.

Notice that in the general case where $0 < \alpha < 1$, even though time is measured continuously, we do not need to check every time point t: $\tau_0 < t < \tau_\infty$ to find the value where $h(S) = f(C(P_S, t), t)$ is minimal. This is due to the fact that the cost functions for all facts (including goals) are *step functions*. Thus, we only need to compute $h(S)$ at the time points where one of the cost functions $C(g_i, t)$ changes value. In our example above, we only need to calculate values of $h(S)$ at $\tau_0 = 2.5$, $t = 3.0$ and $\tau_\infty = 6.0$ to realize that $h(S)$ has minimum value at time point $t = 3.0$ for $\alpha = 0.55$.

Before we end this section, we note that when there are multiple goals there are several possible ways of computing $C(P_S)$ from the cost functions of the individual goals. This is a consequence of the fact that there are multiple rules to propagate the cost, and there are also interactions between the subgoals. Broadly, there are two different ways to extract the plan costs. We can either directly use the cost functions of the goals to compute $C(P_S)$, or first extract a relaxed plan from the temporal planning graph using the cost functions, and then measure $C(P_S)$ based on the relaxed plan. We discuss these two approaches below.

4.4.1. Directly Using Cost Functions to Estimate $C(P_S)$: After we terminate the propagation using any of the criteria discussed in Section 4.3, let $G = \{(g_1, t_1), (g_2, t_2)...(g_n, t_n)\}$, $t_i = Deadline(g_i)$ be a set of goals and $C_G = \{c_1, ...c_n | c_i = C(g_i, Deadline(g_i)\}$ be their best possible achievement costs. If we consider G as the set of preconditions for a dummy action that represents the goal state, then we can use any of the propagation rules (max/sum) discussed in Section 4.2 to directly estimate the total cost of achieving the goals from the given initial state. Among all the different combinations of the propagation rules and the aggregation rules to compute the

Goals: $G = \{(g_1, t_1), (g_2, t_2)...(g_n, t_n)\}$
Actions in the relaxed-plan: $RP = \{\}$
Supported facts: $SF = \{f : \ f \in InitialStateS\}$
While $G \neq \emptyset$
    Select the best action A that support g_1 at t_1
    $RP = RP + A$
    $t_A = t_1 - Dur(A)$
    Update makespan value $T(RP)$ if $t_A < T(RP)$
    For all $f \in Effect(A)$ added by A after
        duration t_f from starting point of A **do**
        $SF = SF \bigcup \{(f, t_A + t_f)\}$
    For all $f \in Precondition(A)$ s.t $C(f, t_A) > 0$ **do**
        $G = G \bigcup \{(f, t_A)\}$
    If $\exists (g_i, t_i) \in G, (g_i, t_j) \in SF : t_j < t_i$ **Then**
        $G = G \setminus \{(g_i, t_i)\}$
End while;

Figure 12. Procedure to extract the relaxed plan

total cost of the set of goals G, only the *max-max* (max-propagation to update $C(g_i, t)$, and cost of G is the maximum of the values of $C(g_i, Deadline(g_i))$ is admissible. The *sum-sum* rule, which assumes the total independence between all facts, and the other combinations are different options to reflect the dependencies between facts in the planning problem. The tradeoffs between them can only be evaluated empirically.

4.4.2. Computing Cost from the Relaxed Plan: To take into account the positive interactions between facts in planning problems, we can do a backtrack-free search from the goals to find a relaxed plan. Then, the total execution cost of actions in the relaxed plan and its makespan can be used for the heuristic estimation. Besides providing a possibly better heuristic estimate, work on FF [41] shows that actions in the relaxed plan can also be used to effectively focus the search on the branches surrounding the relaxed solution. Moreover, extracting the relaxed solution allows us to use the resource adjustment techniques (to be discussed in Section 4.5) to improve the heuristic estimations. The challenge here is how to use the cost functions to guide the search for the best

relaxed plan and we address this below.

The basic idea is to work backwards, finding actions to achieve the goals. When an action is selected, we add its preconditions to the goal list and remove the goals that are achieved by that action. The partial relaxed plan is the plan containing the selected actions and the causal structure between them. When all the remaining goals are satisfied by the initial state S, we have the complete relaxed plan and the extraction process is finished. At each stage, an action is selected so that the complete relaxed plan that contains the selected actions is likely to have the lowest estimated objective value $f(P_S, T_S)$. For a given initial state S and the objective function $h(S) = f(C(P_S), T(P_S))$, Figure 12 describes a greedy procedure to find a relaxed plan given the temporal planning graph. First, let RP be the set of actions in the relaxed plan, SF be the set of time-stamped facts (f_i, t_i) that are currently supported , and G be the set of current goals. Thus, SF is the collection of facts supported by the initial state S and the effects of actions in RP, and G is the conjunction of top level goals and the set of preconditions of actions in RP that are not currently supported by facts in SF. The estimated heuristic value for the current (partial) relaxed plan and the current goal set is computed as follows: $h(S) = h(RP) + h(G)$ in which $h(RP) = f(C(RP), T(RP))$. For the given set of goals G, $h(G) = min_{\tau_0 < t < \tau_\infty} f(C(G,t), t)$ is calculated according to the approach discussed in the previous section (Section 4.4). Finally, $C(RP) = \sum_{A \in RP} C_{exec}(A)$ and $T(RP)$ is the makespan of RP, where actions in RP are aligned according to their causal relationship (see below). We will elaborate on this in the example shown later in this section.

At the start, G is the set of top level goals, RP is empty and SF contains facts in the initial state. Thus $C(RP) = 0$, $T(RP) = 0$ and $h(S) = h(G)$. We start the extraction process by backward search for the *least expensive* action A supporting the first goal g_1. By least expensive, we mean that A contributes the smallest amount to the objective function $h(S) = h(RP) + h(G)$ if

A is added to the current relaxed plan. Specifically, for each action A that supports g_1, we calculate the value $h_A(S) = h(RP+A)+h((G\backslash Effect(A)) \bigcup Precond(A))$ which estimates the heuristic value if we add A to the relaxed plan. We then choose the action A that has the smallest $h_A(S)$ value.

When an action A is chosen, we put its preconditions into the current goal list G, and its effects into the set of supported facts SF. Moreover, we add a precedence constraint between A and the action A_1 that has g_1 as its precondition so that A gives g_1 before the time point at which A_1 needs it. Using these ordering relations between actions in RP and the mutex orderings discussed in Section 4.5, we can update the makespan value $T(RP)$ of the current (partial) relaxed plan.

In our ongoing example, suppose that our objective function is $h(S) = f(C(P_S), T(P_S)) = \alpha.C(P_S)+(1-\alpha).T(P_S)$, with $\alpha = 0.55$ and the infinite-lookahead criterion is used to stop the cost propagation process. When we start extracting the relaxed plan, the initial setting is $G = \{at\_la\}$, $RP = \emptyset$ and $SF = \{at\_tucson\}$. Among the three actions $D^{c2}_{t\rightarrow la}$, $T_{lv\rightarrow la}$ and $F_{p\rightarrow la}$ that support the goal at_la, we choose action $A = F_{p\rightarrow la}$ because if we add it to the relaxed plan RP, then the estimated value $h_A(S) = h(RP + A) + h((G \setminus at\_la) \bigcup at\_phx)$ = $(\alpha * C_{exec}(F_{p\rightarrow la}) + (1 - \alpha) * Dur(F_{p\rightarrow la})) + min_t(f(C(at\_phx), t))$ = (0.55*6.0 + 0.45*1.5) + (0.55*1.5 + 0.45*1.5) = 5.475. This turns out to be the smallest among the three actions. After we add $F_{p\rightarrow la}$ to the relaxed plan, we update the goal set to $G = \{at\_phx\}$. It is then easy to compare between the two actions $D^{c2}_{t\rightarrow phx}$ and $D^{c1}_{t\rightarrow phx}$ to see that $D^{c2}_{t\rightarrow phx}$ is cheaper for achieving *at-phx* given the value $\alpha = 0.55$. The final cost $C(P_S) = 6.0 + 1.5 = 7.5$ and makespan of $T(P_S) = 1.5 + 1.5 = 3$ of the final relaxed plan can be used as the final heuristic estimation $h(S) = 0.55 * 7.5 + 0.45 * 3 = 5.475$ for the given state.

Notice that in the relaxed-plan extraction procedure, we set the time points for the goal set to be the goal deadlines, instead of the latest time points where the cost functions for the goals

stabilized. The reason is that the cost values of facts and actions *monotonically decrease* and the costs are *time-sensitive*. Therefore, the later we set the time points for goals to start searching for the relaxed plan, the better chance we have of getting the low-cost plan, especially when we use the k-lookahead approximation approach with $k \neq \infty$. In our ongoing example, if we use the zero-lookahead option to stop the propagation, we find that the smallest cost is $C(in\_la) = 8.0$ at $t = 2.5$. If we search back for the relaxed plan with the combination $(in\_la, 2.5)$ then we would find a plan $P_1 = (D^{c_1}_{t\rightarrow p}, F_{p\rightarrow la})$. However, if we search from the goal deadline, say $t = 7.0$, then we would realize that the lowest cost for the precondition in_phx of $F_{p\rightarrow la}$ at $t = 7.0 - 1.5 = 5.5$ is $C(in\_phx, 5.5) = 1.5$ (caused by $D^{c_2}_{t\rightarrow p}$ at time point $t = 2.0$) and thus the final plan is $P_2 = (D^{c_2}_{t\rightarrow p}, F_{p\rightarrow la})$ which is cheaper than P_1.

4.4.3. Origin of Action Costs: In all our preceding discussion of cost-based heuristics, we have implicitly assumed that the individual action costs are specified directly as part of the problem specification. While this is a reasonable assumption, it can also be argued that unlike the duration, the cost of an action is implicitly dependent on what the user is interested in optimizing. For example, suppose, in a transportation domain, the user declares the objective function to be optimized as:[8]

$$4 * TotalTime + 0.005 * TotalFuelUsed$$

without providing any additional explicit information about action costs. It is possible to use the objective function to assess the costs of individual actions (in terms of how much they contribute to the cost portion of the objective). Specifically, the cost each action can be set equal to the amount of fuel used by that action. The α value (for combining cost and makespan) can be set based on the

[8] In fact, this was the metric specified for the first problem in the Zeno-Travel domain in IPC 2003.

coefficients in the objective function. Of course, this type of "de-compilation" of the objective function into action costs is only possible if the objective function is a linear combination of makespan and resource consumption.

4.5. Adjustments to the Relaxed Plan Heuristic

Until now, the heuristic estimates have been calculated by relaxing certain types of constraints such as negative effects and metric resource consumptions. In this section, we discuss how those constraints can then be used to adjust and improve the final heuristic values.

4.5.1. Improving the Relaxed Plan Heuristic Estimation with Static Mutex Relations.

When building the relaxed temporal planning graph (RTPG), we ignored the negative interactions between concurrent actions. We now discuss a way of using the static mutex relations to help improve the heuristic estimation when extracting the relaxed plan. Specifically, our approach involves the following steps:

1. Find the set of static mutex relations between the ground actions in the planning problem based on their negative interactions.[9]

2. When extracting the relaxed plan, besides the orderings between actions that have causal relationships (i.e one action gives the effect that supports the other action's preconditions), we also post precedence constraints to avoid concurrent execution of actions that are mutex. Specifically, when a new action is added to the relaxed plan, we use the pre-calculated static mutexes to establish ordering between mutually exclusive action pairs so that they can not be executed concurrently. The orderings are selected in such a way that they violate the least number of existing causal links in the relaxed plan.

[9]Two actions are static mutex if the delete effects of one action intersect with the preconditions or add effects of the other.

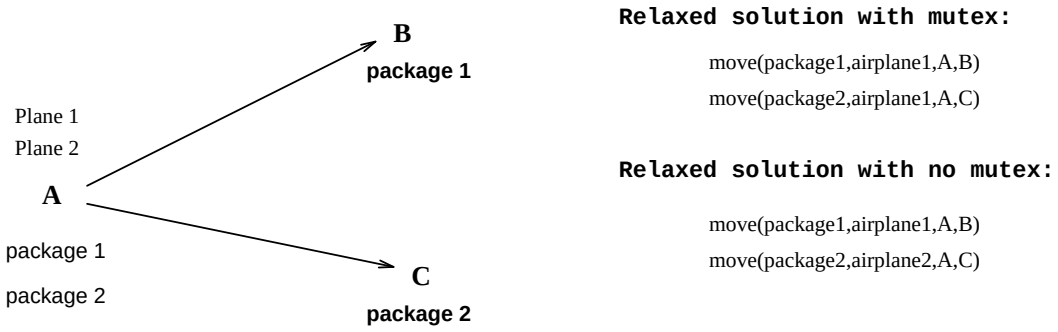


Figure 13. Example of mutex in the relaxed plan

By using the mutex relations in this way, we can improve the makespan estimation of the relaxed plan, and thus the heuristic estimation. Moreover, in some cases, the mutex relations can also help us detect that the relaxed plan is in fact a valid plan, and thus can lead to the early termination of the search. Consider the example of the Logistics domain illustrated in Figure 13. In this example, we need to move two packages from $cityA$ to $cityB$ and $cityC$ and there are two airplanes ($plane_1, plane_2$) at $cityA$ that can be used to move them. Moreover, we assume that $plane_1$ is 1.5 times faster than $plane_2$ and uses the same amount of resources to fly between two cities. There are two relaxed plans

$$P_1 = \{move(package_1, plane_1, cityA, cityB), move(package_2, plane_1, cityA, cityC)\}$$

$$P_2 = \{move(package_1, plane_1, cityA, cityB), move(package_2, plane_2, cityA, cityC)\}$$

that both contain two actions. The first one uses the same plane to carry both packages, while the second one uses two different planes. The first one has a shorter makespan if mutexes are ignored. However, if we consider the mutex constraints, then we know that two actions in P_1 can not be executed concurrently and thus the makespan of P_1 is actually longer than P_2. Moreover, the static mutex relations also show that even if we order the two actions in P_1, there is a violation because the first action cuts off the causal link between the initial state and the second one. Thus, the mutex information helps us in this simple case to find a better (consistent)

relaxed plan to use as a heuristic estimate. Here is a sketch of how the relaxed plan P_2 can be found. After the first action $A_1 = move(package_1, plane_1, cityA, cityB)$ is selected to support the goal $at(package_1, cityB)$, the relaxed plan is $RP = A_1$ and the two potential actions to support the second goal $at(package_2, cityC)$ are $A_2 = move(package_2, plane_1, cityA, cityC)$ and $A_2' = move(package_2, plane_2, cityA, cityC)$. With mutex information, we will be able to choose A_2' over A_2 to include in the final relaxed plan.

4.5.2. Using Resource Information to Adjust the Cost Estimates. The heuristics discussed in Section 4.4 have used the knowledge about durations of actions and deadline goals but not resource consumption. By ignoring the resource related effects when building the relaxed plan, we may miss counting actions whose only purpose is to provide sufficient resource-related conditions to other actions. In our ongoing example, if we want to drive a car from Tucson to LA and the gas level is low, by totally ignoring the resource related conditions, we will not realize that we need to *refuel* the car before *drive*. Consequently, ignoring resource constraints may reduce the quality of the heuristic estimate based on the relaxed plan. We are thus interested in adjusting the heuristic values discussed in the last two sections to account for the resource constraints.

In many real-world problems, most actions consume resources, while there are special actions that increase the levels of resources. Since checking whether the level of a resource is sufficient for allowing the execution of an action is similar to checking the predicate preconditions, one obvious approach is to adjust the relaxed plan by including actions that provide that resource-related condition to the relaxed plan. However, for many reasons, it turns out to be too difficult to decide which actions should be added to the relaxed plan to satisfy the given resource conditions (In [19], we give a more detailed discussion of these difficulties). Therefore, we introduce an indirect way of adjusting the cost of the relaxed plan to take into account the resource constraints. We first pre-

process the problem specifications and find for each resource *R* an action A_R that can increase the amount of *R* maximally. Let Δ_R be the amount by which A_R increases *R*, and let $C(A_R)$ be the cost value of A_R. Let $Init(R)$ be the level of resource *R* at the state *S* for which we want to compute the relaxed plan, and $Con(R)$, $Pro(R)$ be the total consumption and production of *R* by all actions in the relaxed plan. If $Con(R) > Init(R) + Pro(R)$, then we increase the cost by the number of production actions necessary to make up the difference. More precisely:

$$C \leftarrow C + \sum_R \left\lceil \frac{(Con(R) - (Init(R) + Pro(R)))}{\Delta_R} \right\rceil * C(A_R)$$

We shall call this the adjusted cost heuristic. The basic idea is that even though we do not know if an individual resource-consuming action in the relaxed plan needs another action to support its resource-related preconditions, we can still adjust the number of actions in the relaxed plan by reasoning about the total resource consumption of *all* the actions in the plan. If we know the resources R consumed by the relaxed plan and the maximum production of those resources possible by any individual action in the domain, then we can infer the minimum number of resource-increasing actions that we need to add to the relaxed plan to balance the resource consumption. In our ongoing example, if the car rented by the students at *Tucson* does not have enough fuel in the initial state to make the trip to Phoenix, LA, or Las Vegas, then this approach will discover that the planner needs to add a *refuel* action to the relaxed plan.

Currently, our resource-adjustment technique discussed above is limited to simple consumption and production of resources using addition and subtraction. These are the most common forms, as evidenced by the fact that in all metric temporal planning domains used in the competition, actions consume and produce resources solely using addition (increase) and subtraction (decrease). Modifications are needed to extend our current approach to deal with other types of resource consumption such as using multiplication or division.

4.6. Summary and Discussion

In this chapter, we discuss the issue of deriving heuristics, which are sensitive to both time and cost, from the temporal planning graph. We also introduce an approach of tracking costs of achieving goals and other facts as functions of time to guide the multi-objective search. We plan on extending and improving this current multi-objective heuristic search framework in several directions:

Multi-Objective Search: While we considered cost of a plan in terms of a single monetary cost associated with each action, in more complex domains, the cost may be better defined as a vector comprising different types of resource consumption. Further, in addition to cost and makespan, we may also be interested in other measures of plan quality such as robustness and execution flexibility of the plan. To this end, we plan to extend our methodology to derive heuristics sensitive to a larger variety of quality measures. Besides heuristic estimates, we also intend to investigate different multi-objective search frameworks such as priotizing different criteria or pareto-set optimization. In multi-objective planning scenario, it's important to have the ability to find a decent quality plan and later improve it as given more time or finding multiple non-dominated plans. In this sense, work in anytime search algorithm for $Sapa^{ps}$ in Chapter 7, which gradually returns better quality plans given a single objective function, can help in multi-objective search.

Heuristic and Scalability: In our current framework of propagating the cost functions over the planning graph, while the cost estimation using relaxed-plan extraction over the cost functions seems to be reasonably good heuristic, the time-estimation using the first time point at which the goal appears in the relaxed planning graph seems to underestimate the real time needed to achieve that given goal. The evidence is that TGP and TP4 perform much better than *Sapa* using this heuristic for finding optimal makespan plan. Because time-related plan qualities are important and we are

also looking at extending the *Sapa* and *Sapa*^{ps} planners to deal with more plan metrics depending on time, improving goal achievement and action starting time estimation over the planning graph is an important issue. One option would be to use the mutex relations more aggressively. Nevertheless, due to the current framework of having to build a separated planning graph for each generated state, the traditional approach of mutex propagation seems to be too costly. One cheaper alternative would be to use only pre-collected static mutexes when building the planning graph but ignore the dynamic propagation. However, this approach still suffers from having to explicitly reason about mutex relations between every pair of facts and actions at each (important) time point. Currently, we believe that the best approach would be to use the pre-processing tool such as the one used in the "fast-downward" planner [40] to convert PDDL into the multi-valued SAS+ representation. The mutex relations are implicitly embedded in different values of the same variable and thus we do not need to explicitly reason about them when building the graph[10]. Besides heuristic quality, we also plan on improving the time to extract the heuristic by exploiting ways to reuse the planning graph between related search nodes. This approach was used in the Optop planner [64], which also does forward search. However, keeping the planning graph for every search node with hope to use it later (if that node is selected) may be too expensive in terms of memory usage. Therefore, we plan to use it only for (enforced) "hill-climbing" style search where all search nodes belong to one branch from the root node and thus consecutively explored nodes are similar to each other (which maximize the possibility of reusing most of the previous planning graph).

Exogenous event, in the name of *timed-initial-literal*, is one of two recent important extensions to PDDL2.1 planning language (along with *domain axiom*). In the previous chapter, we discussed how exogenous events can be handled in the current forward search framework of *Sapa* by representing them as events in the event queue of the initial state. In fact, *Sapa* can solve the

[10]The other advantage of this approach is the reduced set of variables which can lead to a signifi cantly smaller graph structure

sample problem involving timed-initial-literal in the IPC4 in a quite short time. Even though extending the search framework to take exogenous event into account is easy, modifying the heuristic estimation process to adapt to the additional constraints caused by exogenous events is not easy. On one hand, exogenous events appear like normal instantaneous actions occurring at fixed time-points; on the other hand, they are different from normal actions in the sense that planners can not choose whether or not to include them in the final plan. Therefore, in the current planning graph building process, even though normal actions are put in even when there are mutex relations with other actions at the same time point (because there is no guarantee that the mutexed actions would be selected in the final plan), treating exogenous events the same way would lower the heuristic quality. This is because exogenous events are guaranteed to be in any valid plan and thus any action that conflicts with any of the exogenous events would definitely not be in the final plan. Given this observation, we are investigating several modifications to the current planning graph building process when there exist exogenous events. They are: (i) an approach to de-activate (remove) actions from the planning graph if their preconditions are no longer hold true due to the conflicts with exogenous events; (ii) a technique of maitaining multiple noop actions with different costs; and (iii) maintaining non-monotonic cost functions for facts and actions affected by exogenous events.

For the cost estimation in the current framework, even though the sum-propagation rule tends to over-estimate the achievement cost badly, the later phase of relaxed plan extraction tends to correct this and give good estimation in term of total planning cost. However, the relaxed-plan extraction phase is still dependent on the propagated cost function. Therefore, improvement in the cost-propagation phase can potentially improve the overall heuristic quality. Currently, we are implementing a new “union” propagation rule that take into account the duplications in the “max” propagation rule and thus improve the quality of the cost function[11]. More specifically, while con-

[11]This technique was hinted by David Smith at the proposal defense time.

ducting cost-propagation, for each fact, we keep a estimated lowest total cost set of actions (equals to a relaxed plan) that supports each fact. The estimated cost to execute an action is then calculated by taking the total cost of the union of action sets that supporting its preconditions. This is potentially a better estimation than simply taking the sum or max of the values to support individual preconditions.

Some of the resource and temporal constraints (e.g. exogenous events, discrete resources) has been extensively investigated in the scheduling community. Therefore, we plan to look at: (i) how to use scheduling techniques to improve the heuristic quality to guide the metric temporal planner; and (ii) an effective framework to separate the set of logical, temporal, and resource constraints between two different modules: a planner and a scheduler. For the first direction, our preliminary investigation in [23] is a starting point in integrating scheduling techniques into metric temporal planning. For the second direction, our previous work in the RealPlan system [86] showed that in many planning scenarios, decoupling and integrating a planner and scheduler can significantly scale up the overall system's performance. Nevertheless, RealPlan was designed for classical scenario so extending the framework to metric temporal planning is very promising.

CHAPTER 5

Implementation & Empirical Evaluation

The *Sapa* system with all the techniques described in this paper has been implemented in Java. The implementation includes:

1. The forward chaining algorithm (Section 3).
2. The cost sensitive temporal planning graph and the routines to propagate the cost information and extract the heuristic value from it (Section 4.1 and 4.2).
3. The routines to extract and adjust the relaxed plan using static mutex and resource information (Section 4.4).

By default *Sapa* uses the sum-propagation rule, infinite lookahead termination, resource-adjusted heuristics, and converts the solutions into o.c. plans. Besides the techniques described in this paper, we also wrote a JAVA-based parser for PDDL2.1 Level 3, which is the highest level used in the Third International Planning Competition (IPC3).

To visualize the plans returned by *Sapa* and the relations between actions in the plan (such as causal links, mutual exclusions, and resource relations), we have developed a Graphical User Interface (GUI)[1] for *Sapa*. Figure 14 and 15 shows the screen shots of the current GUI. It displays the time line of the final plan with each action shown with its actual duration and starting time in the

[1]The GUI was developed by Dan Bryce

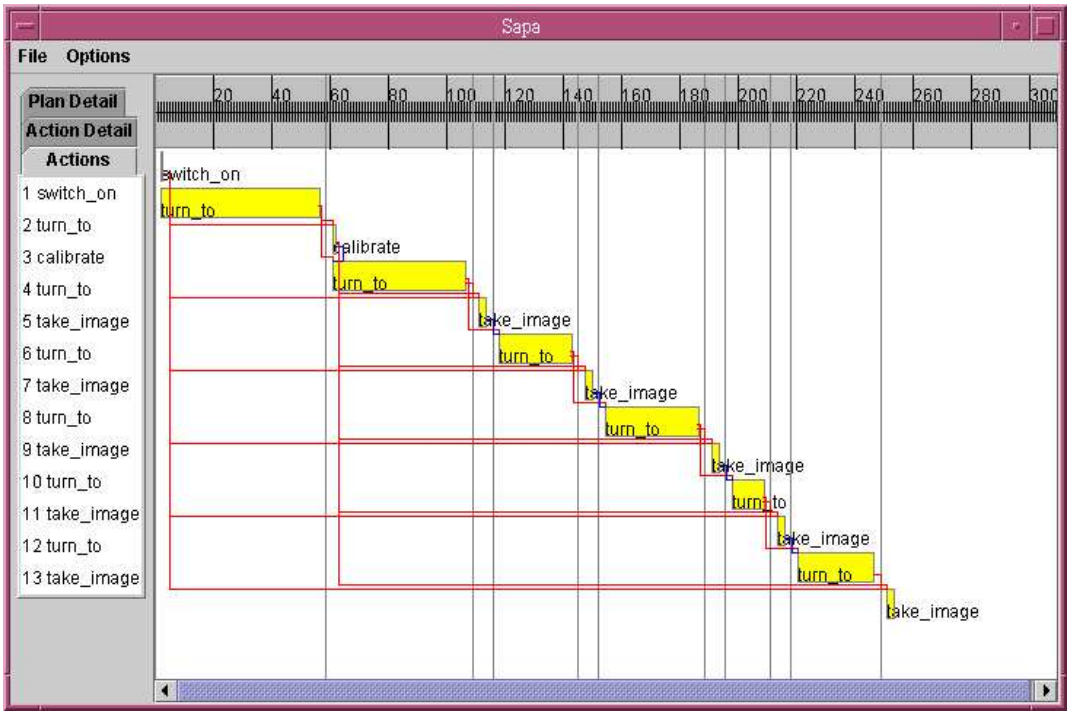


Figure 14. Screen shot of *Sapa*'s GUI: PERT chart showing the actions' starting times and the precedence orderings between them.

final plan. There are options to display the causal relations between actions (found using the greedy approach discussed in Section 6.3), and logical and resource mutexes between actions. The specific times at which individual goals are achieved are also displayed.

Our implementation is publicly available through the *Sapa* homepage[2]. Since the planner as well as the GUI are in JAVA, we also provide web-based interactive access to the planner.

We have subjected the individual components of the *Sapa* implementation to systematic empirical evaluation [19, 20, 21]. In this section, we will describe the experiments that we conducted [19] to show that *Sapa* is capable of satisfying a variety of cost/makespan tradeoffs. Moreover, we also provide results to show the effectiveness of the heuristic adjustment techniques, the utility of different termination criteria, and the utility of the post-processing. Comparison of *Sapa* with other

[2]http://rakaposhi.eas.asu.edu/sapa.html

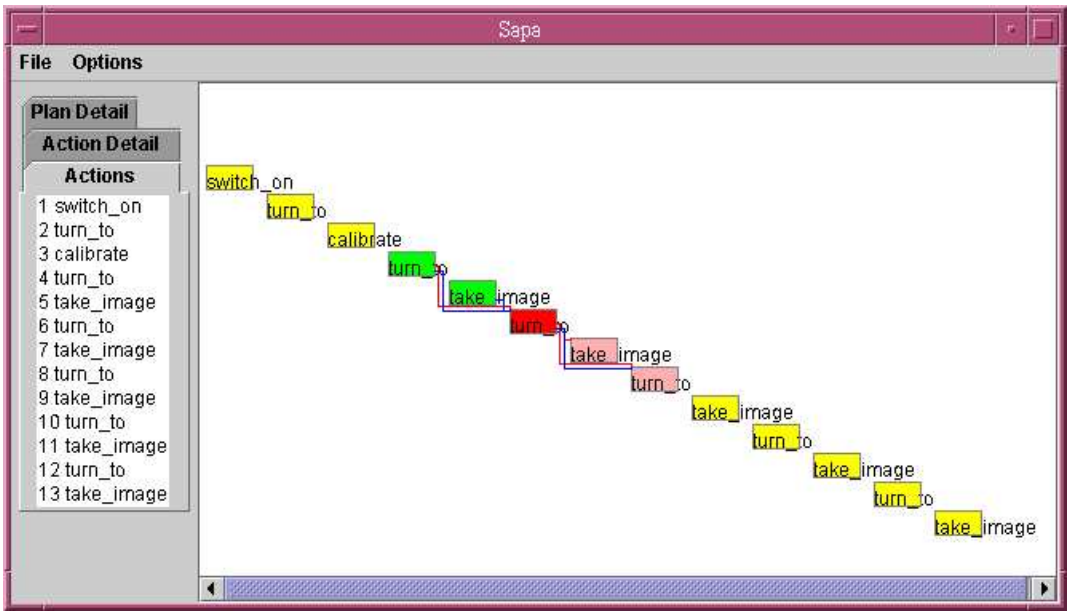


Figure 15. Screen shots of *Sapa*'s GUI: Gant chart showing different logical relations between a given action and other actions in the plan.

systems in the International Planning Competition is provided in the next section.

5.1. Component Evaluation

Our first test suite for the experiments, used to test *Sapa*'s ability to produce solutions with tradeoffs between time and cost quality, consisted of a set of randomly generated temporal logistics problems provided by Haslum and Geffner [39]. In this set of problems, we need to move packages between locations in different cities. There are multiple ways to move packages, and each option has different time and cost requirements. Airplanes are used to move packages between airports in different cities. Moving by airplanes takes only 3.0 time units, but is expensive, and costs 15.0 cost units. Moving packages by trucks between locations in different cities costs only 4.0 cost units, but takes a longer time of 12.0 time units. We can also move packages between locations inside the same city (e.g. between offices and airports). Driving between locations in the same city costs 2.0

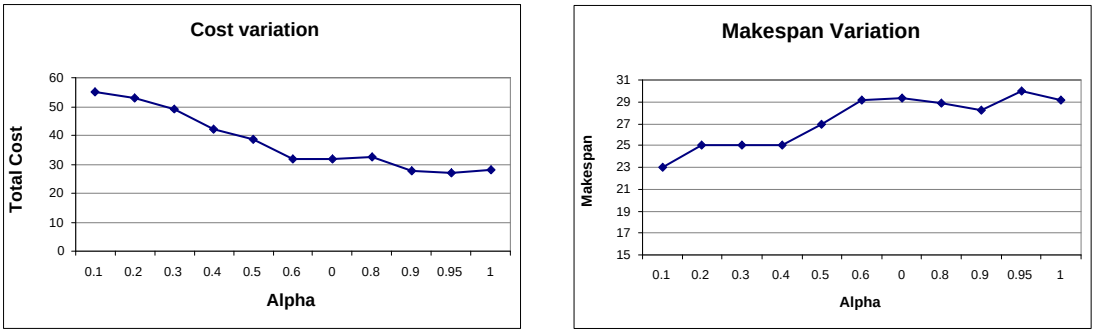


Figure 16. Cost and makespan variations according to different weights given to them in the objective function. Each point in the graph corresponds to an average value over 20 problems.

units and takes 2.0 time units. Loading/unloading packages into a truck or airplane takes 1.0 unit of time and costs 1.0 unit.

We tested the first 20 problems in the set with the objective function specified as a linear combination of both total execution cost and makespan values of the plan. Specifically, the objective function was set to

$$O = \alpha.C(Plan) + (1 - \alpha).T(Plan)$$

We tested with different values of $\alpha : 0 \leq \alpha \leq 1$. Among the techniques discussed in this paper, we used the sum-propagation rule, infinite look-ahead, and relax-plan extraction using static mutex relations. Figure 16 shows how the average cost and makespan values of the solution change according to the variation of the α value. The results show that the total execution cost of the solution decreases as we increase the α value (thus, giving more weight to the execution cost in the overall objective function). In contrast, when α decreases, giving more weight to makespan, the final cost of the solution increases and the makespan value decreases. The results show that our approach indeed produces solutions that are sensitive to an objective function that involves both time and cost. For all the combinations of $\{problem, \alpha\}$, 79% (173/220) are solvable within our cutoff time limit of 300 seconds. The average solution time is 19.99 seconds and 78.61% of the

instances can be solved within 10 seconds.

Evaluation of Different Termination Criteria: Figure 17 shows the comparison results for zero, one, and infinite lookahead for the set of metric temporal planning problems in the competition. We take the first 12 problems in each of the four temporal domains: ZenoTravel-Time, DriverLog-Time, Satellite-Time, and RoversTime. We set $\alpha = 1$ in the objective function, making it entirely cost-based. The action costs are set to 1 unit. As discussed in Section 4.3, zero-lookahead stops the cost propagation process at the time point where there is a solution under the relaxed condition. K-lookahead spends extra effort to go beyond that time point in hope of finding better quality (relaxed) solution to use as heuristic values to guide the search. The running condition is specified in the caption of the figure.

For most of the problems in the three domains ZenoTravel-Time, DriverLog-Time, and Satellite-Time, infinite-lookahead returns better quality solutions in shorter time than one-lookahead, which in turn is generally better than zero-lookahead. The exception is the Rovers-Time domain, in which there is virtually no difference in running time or solution quality between the different look-ahead options.

The following is a more elaborate summary of the results in Figure 17. The top three figures show the running time, cost, and makespan comparisons in the ZenoTravel domain (*Time* setting). In this domain, within the time and memory limit, infinite-lookahead helps to solve 3 more problems than one-lookahead and 2 more than zero-lookahead. In all but one problem (problem 10), infinite-lookahead returns equal (three) or better (eight) cost solution than zero-lookahead. Compared to one-lookahead, it's better in five problems and equal in six others. For the makespan value, infinite-lookahead is generally better, but not as consistent as other criteria. The next three lower figures show the comparison results for the DriverLog-Time domain. In this domain, infinite and one-lookahead solve one more problem than zero-lookahead, infinite-lookahead is also faster than the

other two options in all but one problem. The costs (number of actions) of solutions returned by infinite-lookahead are also better than all but two of the problems (in which all three solutions are the same). One-lookahead is also equal to or better than zero-lookahead in all but two problems. In the Satellite-Time domain, while infinite and one-lookahead solve three more (of twelve) problems than zero-lookahead, there is no option that consistently solves problems faster than the other. However, the solution quality (cost) of infinite and one-lookahead is consistently better than zero-lookahead. Moreover, the solution cost of plans returned by infinite-lookahead is worse than one-lookahead in only one problem while being slightly better in 6 problems. In this domain, it seems that there is big improvement from zero to one look-ahead, while infinite-lookahead is a slight improvement over one-lookahead. (The plots for the Rovers domain are not shown in the figure as all the different look-ahead options seem to lead to near identical results in that domain.) Finally, since the heuristic is based completely on cost (α =1), we do not, in theory, expect to see any conclusive patterns in the makespan values of the solutions produced for the different lookahead options.

Utility of the Resource Adjustment Technique: In our previous work [19], we show that the resource adjustment technique can lead to significant quality and search speed improvements in problems such as the metric temporal logistics domain in which there are several types of resource consumption objects like trucks and airplanes.

In the competition, there are two domains in which we can test the utility of the resource adjustment technique discussed in Section 4.5. The ZenoTravel domain and the Rovers domain have actions consuming resources and other (refueling) actions to renew them. Of these, the resource adjustment technique gives mixed results in the ZenoTravel domain and has no effect in the Rovers domain. Therefore, we only show the comparison for the ZenoTravel domain in Figure 18. In the ZenoTravel domain, *Sapa* with the resource adjustment runs slightly faster in 10 of 14 problems, returns shorter solutions in 5 problems and longer solutions in 3 problems. The solution

makespan with the resource adjustment technique is also generally better than without the adjustment technique. In conclusion, the resource adjustment technique indeed helps *Sapa* in this domain. In contrast, in the Rovers domain, this technique is of virtually no help. Actually, in the Rovers domain, the number of search nodes with and without the resource adjustment is the same for all solved problems. One reason maybe that in the Rovers domain, there are additional constraints on the *recharge* action so that it can only be carried out at a certain location. Therefore, even if we know that we need to add a recharge action to the current relaxed plan, we may not be able to add it because the plan does not visit the right location.

5.2. *Sapa* in the 2002 International Planning Competition

We entered an implementation of *Sapa*, using several of the techniques discussed in this paper, in the recent International Planning Competition. The specific techniques used in the competition version of *Sapa* are infinite look-ahead termination of cost propagation (Section 4.3), resource adjustment (Section 4.5). In the competition, we focused solely on the metric/temporal domains.

The sophisticated support for multi-objective search provided by *Sapa* was not fully exploited in the competition, since action cost is not part of the standard PDDL2.1 language used in the competition.[3] The competition did evaluate the quality of solution plans both in terms of number of actions and in terms of the overall makespan. Given this state of affairs, we assumed unit cost for all actions, and ran *Sapa* with $\alpha = 1$, thus making the search sensitive only to the action costs. Infinite-lookahead was used for cost propagation. This strategy biased *Sapa* to produce low cost plans (in terms of number of actions). Although the search was not sensitive to makespan optimization, the greedy post processing of p.c. plans to o.c. plans improved the makespan of the solutions

[3] Some of the competition problems did have explicit objective functions, and in theory, we could have inferred the action costs from these objective functions. We have not yet done this, given that the "plan metric" field of PDDL2.1 had not been fully standardized at the time of the competition.

enough to make *Sapa* one of the best planners in terms of the overall quality of solutions produced.[4]

The competition results were collected and distributed by the IPC3's organizers and can be found at the competition website [27]. Detailed descriptions of domains used in the competition are also available at the same place. The temporal planning domains in the competition came in two sets, one containing two domains, Satellite and Rovers (adapted from NASA domains), and the other containing three domains: *Depots*, *DriverLogistics* and *Zeno Travel*. In the planning competition, each domain had multiple versions–depending on whether or not the actions had durations and whether actions use continuous resources. *Sapa* participated in the highest levels of PDDL2.1 (in terms of the complexity of temporal and metric constraints) for the five domains listed above.

Figures 19 and 20 show that five planners (*Sapa*, LPG, MIPS, TP4, and TPSYS) submitted results for the *timed* setting and only three (*Sapa*, MIPS, and TP4) were able to handle the *complex* setting of the Satellite domain. In the *timed* setting, action durations depend on the setting of instruments aboard a particular satellite and the direction it needs to turn to. The "*complex*" setting is further complicated by the fact that each satellite has a different capacity limitation so that it can only store a certain amount of image data. Goals involve taking images of different planets and stars located at different coordinate directions. To achieve the goals, the satellite equipped with the right set of instruments should turn to the right direction, calibrate and take the image.

For the *timed* setting of this Satellite domain, Figure 19 shows that among the five planners, *Sapa*, LPG and MIPS were able to solve 19 of 20 problems while TP4 and TPSYS were able to solve 2 and 3 problems respectively. For quality comparison, LPG with the *quality* setting was able to return solutions with the best quality, *Sapa* was slightly better than LPG with the *speed* setting and was much better than MIPS. LPG with the *speed* setting is generally the fastest, followed by MIPS and then *Sapa* and LPG with the *quality* setting. For the *complex* setting, Figure 20 shows

[4]To be sure, makespan optimal planners such as TP4 can produce much shorter plans–but their search was so inefficient that they were unable to solve most problems.

that, among the three planners, *Sapa* was able to solve the most problems (16), and generated plans of higher quality than MIPS. TP4 produced the highest quality solutions, but was able to solve only the three smallest problems. The solving times of *Sapa* are slightly higher than MIPS, but are much better than TP4.

The "timed" version of the Rover domain requires that a set of scientific analyses be done using a number of rovers. Each rover carries different equipment, and has a different energy capacity. Moreover, each rover can only recharge its battery at certain points that are under the sun (which may be unreachable). Figure 21 shows that only *Sapa* and MIPS were able to handle the constraints in this problem set. *Sapa* again solved more problems (11 vs. 9) than MIPS and also returned better or equal quality solutions in all but one case. The solving time of MIPS is better than *Sapa* in 6 of 9 problems where it returns the solutions.

In the second set of problems, which come with temporal constraints, there are three domains: *Depots*, *DriverLogistics* and *Zeno Travel*. *Sapa* participated at the highest level, which is the *"timed"* settings for these three domains. Figure 22 shows the comparison between *Sapa* and three other planners (LPG, MIPS, and TP4) that submitted results in the *Depots* domain. In this domain, we need to move crates (packages) between different places. The loading actions that place the crates into each truck are complicated by the fact that they need an *empty* hoist. Thus, the *Depot* domain looks like a combination of the original logistics and blockworlds domains. Drive action durations depend on the distances between locations and the speed of the trucks. Time for loading the crates depends on the power of the hoist that we use. There is no resource consumption in this highest level. In this domain, *Sapa* was only able to solve five problems, compared to 11 by MIPS and 18 by LPG. TP4 solved only one problem. For the five problems that *Sapa* was able to solve, the solution quality is as good as other planners. For the speed comparison, LPG with *speed* setting is clearly faster than the other planners. We speculate that the poor performance of *Sapa* in this do-

main is related to two factors: (i) negative interactions between subgoals, largely ignored by *Sapa*, are an important consideration in this domain and (ii) the number of ground actions in this domain is particularly high, making the computation of the planning graph quite costly.

Figure 23 shows how *Sapa* performance compares with other planners in the competition on the *time* setting of the *DriveLog* domain. This is a variation of the original *Logistics* domain in which trucks rather than airplanes move packages between different cities. However, each truck requires a driver, so a driver must walk to and board a truck before it can move. Like the *Depot* domain, there is no resource consumption. The durations for walking and driving depend on the specified *time-to-walk* and *time-to-drive*. In this domain, *Sapa* solved 14 problems compared to 20 by LPG, 16 by MIPS and 1 by TP4. The quality of the solutions by different planners are very similar. For the speed comparison, LPG with *speed* setting is fastest, then MIPS, then *Sapa* and LPG with *quality* setting.

Finally, Figure 24 shows the performance of *Sapa* in the ZenoTravel domain with *time* setting. In this domain, passengers travel between different cities by airplanes. The airplanes can choose to fly with different speeds (fast/slow), which consume different amounts of fuel. Airplanes have different fuel capacity and need to refuel if they do not have enough for each trip. In this domain, *Sapa* and LPG solved 16 problems while MIPS solved 20. The solution quality of *Sapa* and MIPS are similar and in general better than LPG with either *speed* or *quality* setting. LPG with *speed* setting and MIPS solved problems in this domain faster than *Sapa* which is in turn faster than LPG with *quality* setting.

In summary, for problems involving both metric and temporal constraints in IPC3, *Sapa* is competitive with other planners such as LPG or MIPS[5]. In particular, *Sapa* solved the most problems and returned the plans with best solution quality in the highest setting for the two domains *Satellite*

[5]We are improving the implementation of *Sapa* and the current version at the time of writing this thesis is order of magnitude faster than the competition in many domains.

and *Rovers*, which are adapted from NASA domains. A more detailed analysis of the competition results is presented by [62].

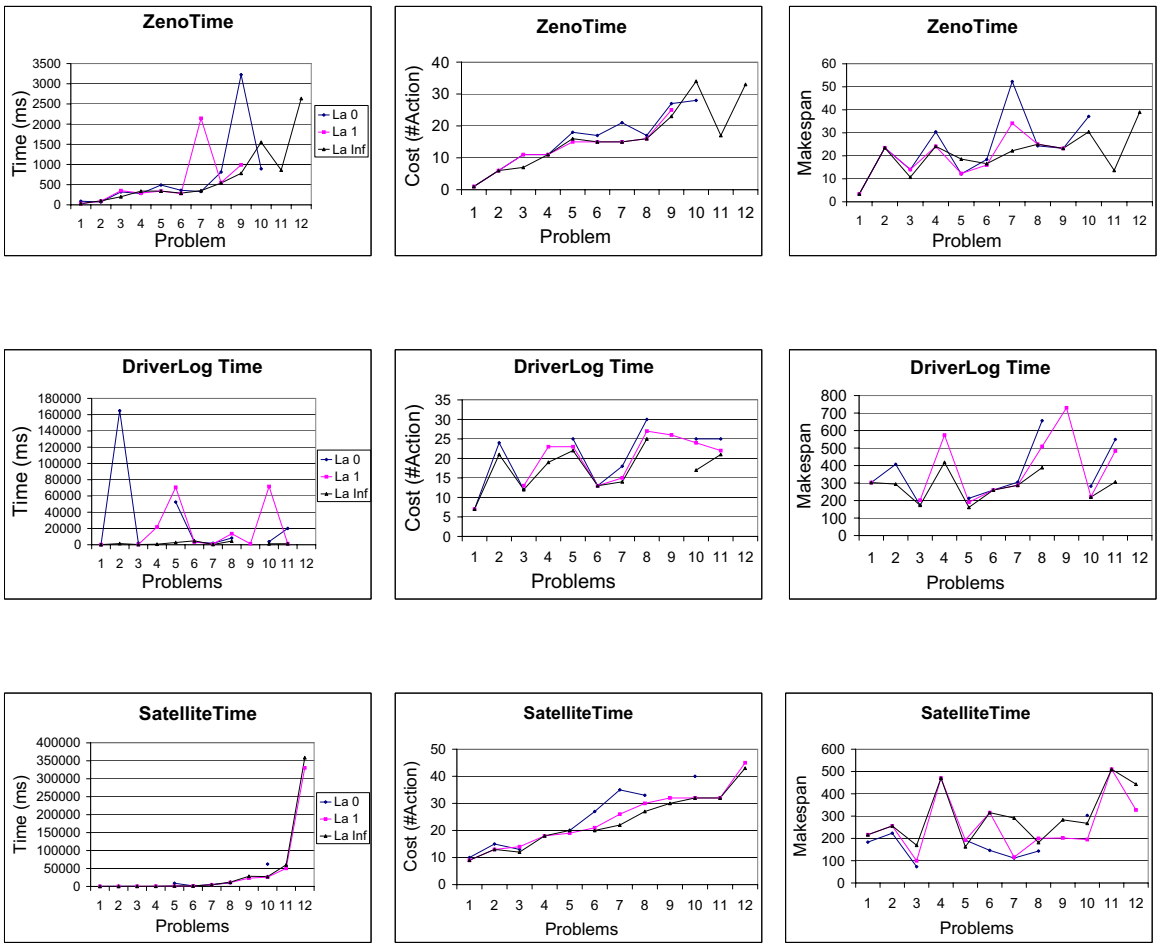


Figure 17. Comparison of the different lookahead options in the competition domains. These experiments were run on a Pentium III-750 WindowsXP machine with 256MB of RAM. The time cutoff is 600 seconds.

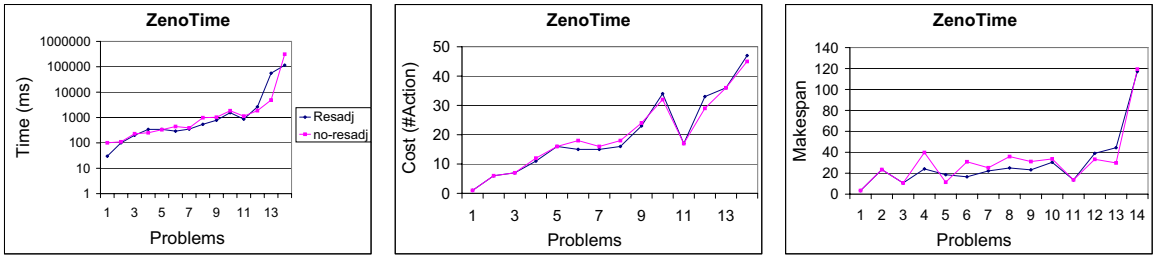


Figure 18. Utility of the resource adjustment technique on ZenoTravel (time setting) domain in the competition. Experiments were run on a WindowsXP Pentium III 750MHz with 256MB of RAM. Time cutoff is 600 seconds.

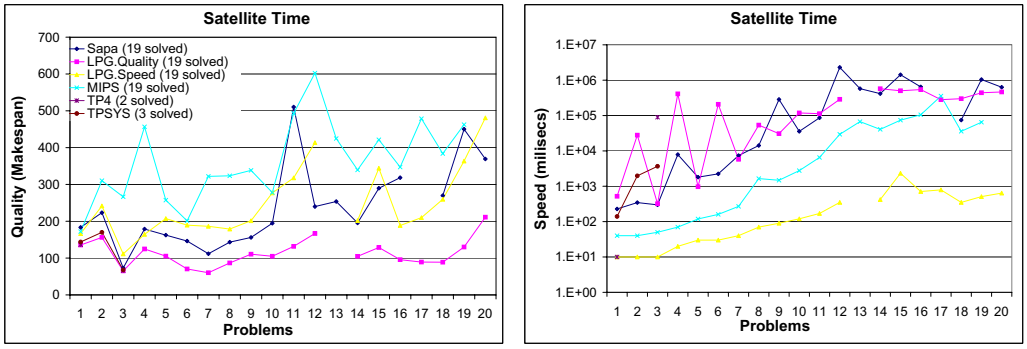


Figure 19. Results for the *time* setting of the Satellite domain (from IPC3 results).

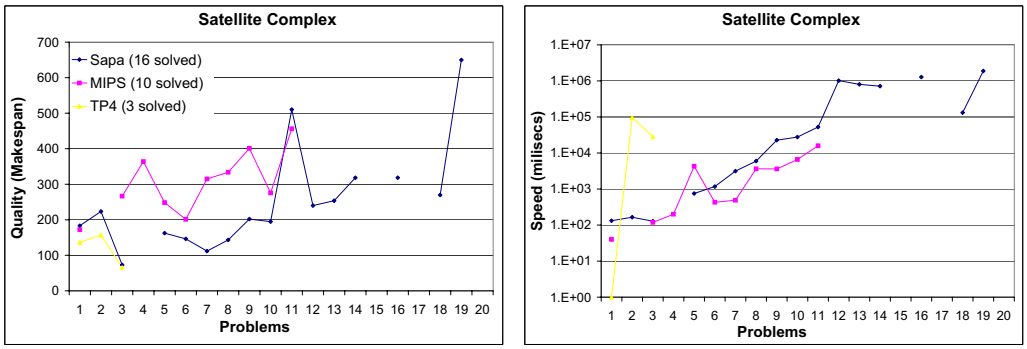


Figure 20. Results for the *complex* setting of the Satellite domain (from IPC3 results).

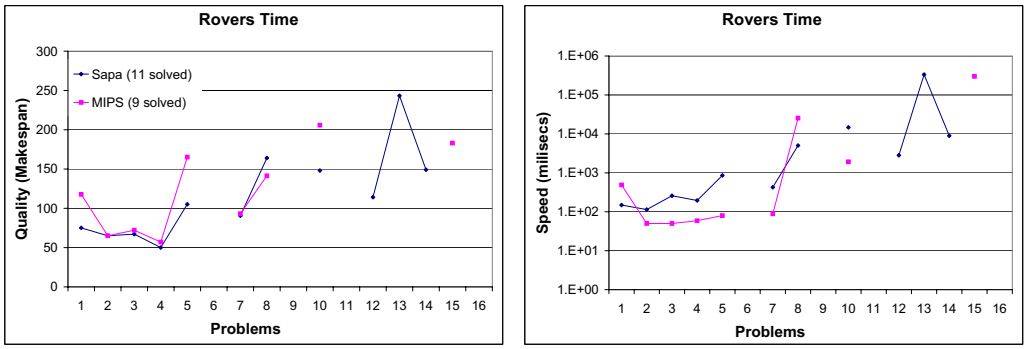


Figure 21. Results for the *time* setting of the Rover domain (from IPC3 results).

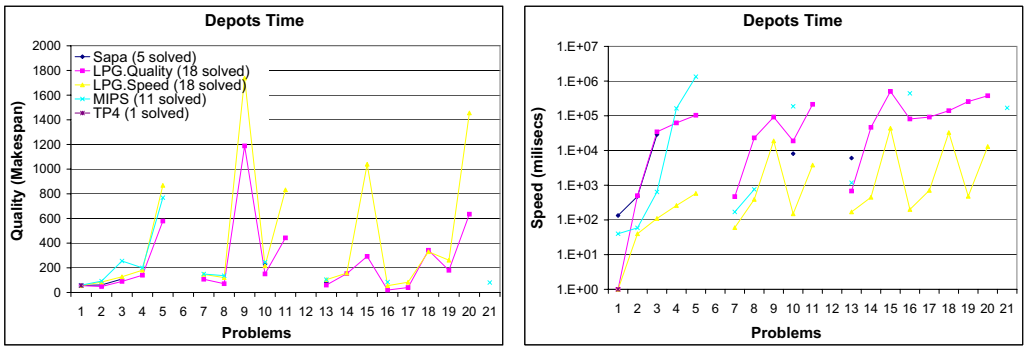


Figure 22. Results for the *time* setting of the Depots domain (from IPC3 results).

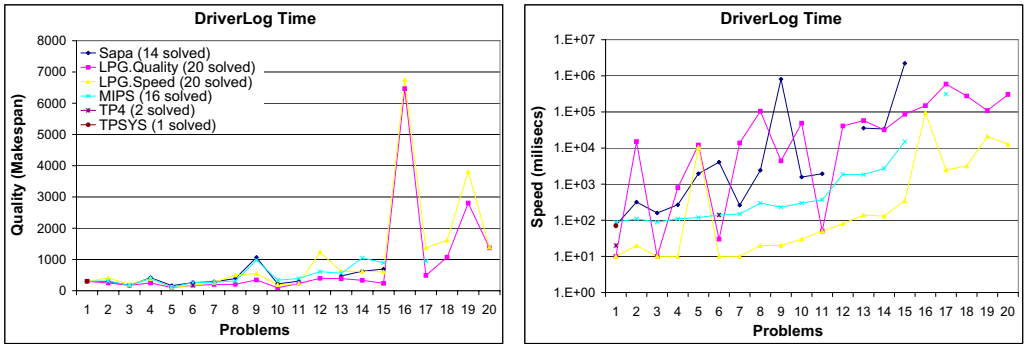


Figure 23. Results for the *time* setting of the DriverLog domain (from IPC3 results).

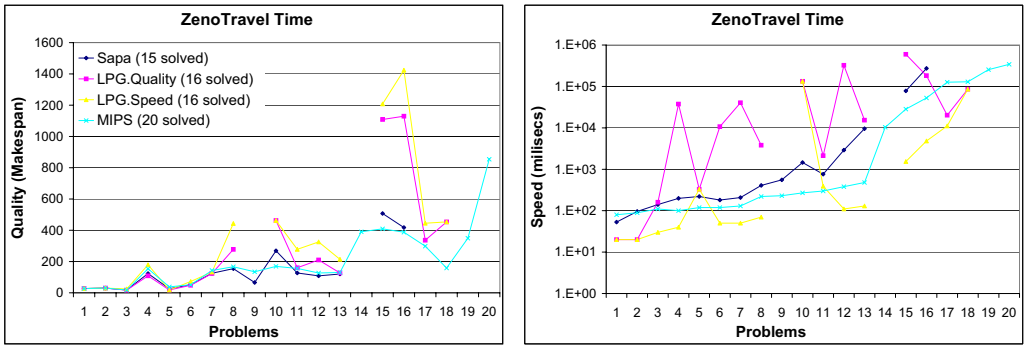


Figure 24. Results for the *time* setting of the ZenoTravel domain (from IPC3 results).

CHAPTER 6

Improving Solution Quality by Partialization

As mentioned in Chapter 2 on background on planning, plans can be classified broadly into two categories–"position constrained" (p.c.) and "order constrained" (o.c.). The former specifies the exact start time for each of the actions in the plan, while the latter only specifies the relative orderings between different actions (Figure 25 shows the examples of these two types of plans). The two types of plans offer complementary tradeoffs *vis a vis* search and execution. Specifically, constraining the positions gives complete state information about the partial plan, making it easier to control the search (viz., it is easy to compute the resource levels and check for the consistency of temporal constraints at every point in a partial plan). Not surprisingly, several of the more effective methods for plan synthesis in metric temporal domains search for and generate p.c. plans (c.f. TLPlan[1], Sapa[19], TGP [81], MIPS[24]). Position constrained plans are however less desirable from the point of view of execution flexibility and human comprehension (e.g. no causal relations between actions in the plan are shown). At the same time, from an execution point of view, o.c. plans are more advantageous than p.c. plans –they provide better execution flexibility both in terms of makespan and in terms of "scheduling flexibility" (which measures the possible execution traces supported by the plan [87, 71]). They are also more effective in interfacing the planner to other modules such as schedulers (c.f. [86, 59]), and in supporting replanning and plan reuse [90, 45].[1]

[1]Precedence constrained plan or order constrained plan (o.c plan) is also the preferred choice for lifted planning.

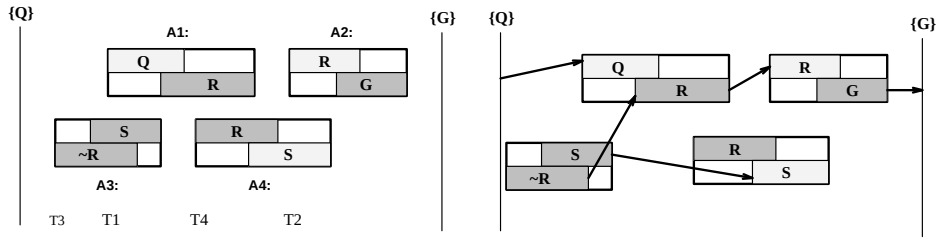


Figure 25. Examples of p.c. and o.c. plans

A solution to the dilemma presented by these complementary tradeoffs of those two types of plan is to search in the space of p.c. plans, but post-process the resulting p.c. plan by *partializing* it into an o.c. plan. Although such post-processing approaches have been considered in classical planning ([49, 90, 2]), the problem is considerably more complex in the case of metric temporal planning. The complications include the need to handle the more expressive action representation and the need to handle a variety of objective functions for partialization (in the case of classical planning, we just consider the least number of orderings). In this chapter, the conversion problem is introduced in Section 6.1, the Constraint Satisfaction Optimization Problem (CSOP) encoding that captures this partialization process is discussed in Section 6.2. To solve this CSOP encoding, we present the linear-time greedy approach in Section 6.3 and the optimal approach based on solving the MILP encoding in Section 6.4.

6.1. Problem Definition

Position and Order constrained plans: *A position constrained plan (p.c.) is a plan where the execution time of each action is fixed to a specific time point. An order constrained (o.c.) plan is a plan where only the relative orderings between the actions are specified.*

There are two types of position constrained plans: *serial* and *parallel*. In a serial position constrained plan, no concurrency is allowed. In a parallel position constrained plan, actions are allowed to execute concurrently. Examples of the serial p.c. plans are the ones returned by classical

planners such as AltAlt[70], HSP[7], FF[44], GRT [79]. The parallel p.c. plans are the ones returned by Graphplan-based planners and the temporal planners such as *Sapa* [19], TGP[81], TP4[39]. Examples of planners that output order constrained (o.c.) plans are Zeno[75], HSTS[68], IxTeT[59].

Figure 25 shows, on the left, a valid p.c. parallel plan consisting of four actions A_1, A_2, A_3, A_4 with their starting time points fixed to T_1, T_2, T_3, T_4, and on the right, an o.c plan consisting of the same set of actions and achieving the same goals. For each action, the marked rectangular regions show the durations in which each precondition or effect should hold during each action's execution time. The shaded rectangles represent the effects and the white ones represent preconditions. For example, action A_1 has a precondition Q and effect R and action A_3 has no preconditions and two effects $\neg R$ and S.

It should be easy to see that o.c. plans provide more execution flexibility than p.c. plans. In particular, an o.c. plan can be "dispatched" for execution in any way consistent with the relative orderings among the actions. In other words, for each valid o.c. plan P_{oc}, there may be multiple valid p.c. plans that satisfy the orderings in P_{oc}, which can be seen as different ways of dispatching the o.c. plan.

While generating a p.c. plan consistent with an o.c. plan is easy enough, in this dissertation, we are interested in the reverse problem–that of generating an o.c. plan given a p.c. plan.

Partialization: *Partialization is the process of generating a valid order constrained plan P_{oc} from a set of actions in a given position constrained plan P_{pc}.*

We can use different criteria to measure the quality of the o.c. plan resulting from the partialization process (e.g. makespan, slack, number of orderings). One important criterion is a plan's "makespan." The *makespan* of a plan is the minimum time needed to execute that plan. For a p.c. plan, the makespan is the duration between the earliest starting time and the latest ending time among all actions. In the case of serial p.c. plans, it is easy to see that the makespan will be greater

than or equal to the sum of the durations of all the actions in the plan. For an o.c. plan, the makespan is the minimum makespan of any of the p.c. plans that are consistent with its orderings. Given an o.c. plan P_{oc}, there is a polynomial time algorithm based on topological sort of the orderings in P_{oc}, which outputs a p.c. plan P_{pc} where all the actions are assigned earliest possible start time point according to the orderings in P_{oc}. The makespan of that p.c. plan P_{pc} is then used as the makespan of the original o.c. plan P_{oc}.

Thus, for a given p.c. plan P_{pc}, we want to find the optimal o.c. plan according to some criterion of temporal/execution flexibility such as smallest makespan or smallest number of orderings. In the next section, we shall provide a general CSP encoding for this "partialization problem." Finding optimal solution for this encoding turns out to be NP-hard even for classical planning (i.e., non-durative actions)[2]. Consequently, we shall develop value ordering strategies that are able to find a reasonable solution for the encoding in polynomial time.

6.2. Formulating a CSOP encoding for the Partialization Problem

In this section, we develop a general CSOP encoding for the partialization problem. The encoding contains both continuous and discrete variables. The constraints in the encoding guarantee that the final o.c plan is consistent, executable, and achieves all the goals. Moreover, by imposing different user's objective functions, we can get the optimal o.c plan by solving the encoding.

Preliminaries:

Let P_{pc}, containing a set of actions $\mathcal{A}$ and their fixed starting times $st^{pc}_{\mathcal{A}}$, be a valid p.c. plan for some temporal planning problem $\mathcal{P}$. We assume that each action A in P_{pc} is in the standard PDDL2.1 Level 3 representation [28].[2] To facilitate the discussion on the CSOP encoding in the

[2] PDDL2.1 Level 3 is the highest level used in the Third International Planning Competition.

following sections, we will briefly discuss the action representation and the notation used in this paper:

- For each (pre)condition p of action A, we use $[st_A^p, et_A^p]$ to represent the duration in which p should hold ($st_A^p = et_A^p$ if p is an instantaneous precondition).
- For each effect e of action A, we use et_A^e to represent the time point at which e occurs.
- For each resource r that is checked for preconditions or used by some action A, we use $[st_A^r, et_A^r]$ to represent the duration over which r is accessed by A.
- The initial and goal states are represented by two new actions A_I and A_G. A_I starts before all other actions in the P_{pc}, it has no preconditions and has effects representing the initial state. A_G starts after all other actions in P_{pc}, has no effects, and has top-level goals as its preconditions.
- The symbol "$\prec$" is used through out this section to denote the relative precedence orderings between two time points.

Note that the values of $st_A^p, et_A^p, et_A^e, st_A^r, et_A^r$ are fixed in the p.c plan but are only partially ordered in the o.c plan.

The CSOP Encoding:

Let P_{oc} be a partialization of P_{pc} for the problem $\mathcal{P}$. P_{oc} must then satisfy the following conditions:

1. P_{oc} contains the same actions $\mathcal{A}$ as P_{pc}.
2. P_{oc} is executable. This requires that the (pre)conditions of all actions are satisfied, and no pair of interfering actions are allowed to execute concurrently.

3. P_{oc} is a valid plan for $\mathcal{P}$. This requires that P_{oc} satisfies all the top level goals (including deadline goals) of $\mathcal{P}$.

4. (Optional) The orderings on P_{oc} are such that P_{pc} is a legal dispatch (execution) of P_{oc}.

5. (Optional) The set of orderings in P_{oc} is minimal (i.e., all ordering constraints are non-redundant, in that they cannot be removed without making the plan incorrect).

Given that P_{oc} is an order constrained plan, ensuring goal and precondition satisfaction involves ensuring that (a) there is a causal support for the condition and that (b) the condition, once supported, is not violated by any possibly intervening action. The fourth constraint ensures that P_{oc} is in some sense an *order generalization* of P_{pc} [49]. In the terminology of [2], the presence of fourth constraint ensures that P_{oc} is a de-ordering of P_{pc}, while in its absence P_{oc} can either be a de-ordering or a re-ordering. This is not strictly needed if our interest is only to improve temporal flexibility. Finally, the fifth constraint above is optional in the sense that any objective function defined in terms of the orderings anyway ensures that P_{oc} contains no redundant orderings.

In the following, we will develop a CSP encoding for finding P_{oc} that captures the constraints above. This involves specifying the variables, their domains, and the inter-variable constraints.

Variables: The encoding will consist of both continuous and discrete variables. The continuous variables represent the temporal and resource aspects of the actions in the plan, and the discrete variables represent the logical causal structure and orderings between the actions. Specifically, for the set of actions in the p.c. plan P_{pc} and two additional dummy actions A_i and A_g representing the initial and goal states,[3] the set of variables are as follows:

Temporal variables: For each action A, the encoding has one variable st_A to represent the time

[3] A_i has no preconditions and has effects that add the facts in the initial state. A_g has no effect and has preconditions representing the goals.

point at which we can start executing A. The domain for this variable is $Dom(st_A) = [0, +\infty)$.

Resource variables: For each action A and the resource $r \in R(A)$, we use a pseudo variable. We call V a pseudo variable because the constraints involving V are represented not directly, but rather indirectly by the constraints involving U_A^r; see below. V_A^r to represent the value of r (resource level) at the time point st_A^r.

Discrete variables: There are several different types of discrete variables representing the causal structure and qualitative orderings between actions:

- *Causal effect:* We need variables to specify the causal link relationships between actions. Specifically, for each condition $p \in P(A)$ and a set of actions $\{B_1, B_2.....B_n\}$ such that $p \in E(B_i)$, we set up one variable: S_A^p where $Dom(S_A^p) = \{B_1, B_2....B_n\}$. This variable along with its domain capture the requirement that all actions' preconditions are supported (satisfied) when each action is executed. Sometimes we will use the notation $B_i \rightarrow^p A$ to represent the relation $S_A^p = B_i$.

- *Interference:* An important issue in converting a p.c. plan into an o.c. plan is to ensure that actions that are not ordered with respect to each other are free of any interference. Two actions A and A' are in logical interference on account of p if $p \in Precond(A) \cup Effect(A)$ and $\neg p \in Effect(A')$. Thus, the temporal relations between two interfering actions A and A' depend on the exact proposition p that relates them and it is possible to have more than one interference relation between two actions, each one enforcing different set of temporal constraints.For each such pair, we introduce one variable $I_{AA'}^p$: $Dom(I_{AA'}^p) = \{\prec, \succ\}$ ($A\ before_p\ A'$, or $A\ after_p\ A'$). For the plan in Figure 25, the interference variables are: $I_{A_1A_3}^R$ and $I_{A_2A_3}^R$. Sometimes, we will use the notation $A \prec_p A'$ to represent $I_{AA'}^p = \prec$.

- *Resource ordering:* For each pair of actions A and A' that use the same resource r, we

introduce one variable $R^r_{AA'}$ to represent the resource-enforced ordering between them. If A and A' can not use the same resource concurrently, then $Dom(R^r_{AA'}) = \{\prec, \succ\}$, otherwise $Dom(R^r_{AA'}) = \{\prec, \succ, \perp\}$. Sometimes, we will use the notation $A \prec_r A'$ to represent $R^p_{AA'} = \prec$.

Following are the necessary constraints to represent the relations between different variables:

1. Causal link protections: If B supports p to A, then every other action A' that has an effect $\neg p$ must be prevented from coming between B and A:

   $S^p_A = B \Rightarrow \forall A',\ \neg p \in E(A') : (I^p_{A'B} = \prec) \vee (I^p_{A'A} = \succ)$

2. Constraints between ordering variables and action start time variables: Unlike classical planning, the temporal concurrency between A and A' depends on the exact temporal constraints (values of st^p, et^p in A and A'). Each causal-effect or interference relation constrains the temporal orders between A and A' .We want to enforce that if $A \prec_p A'$ then $et^p_A < st^p_{A'}$. However, because we only maintain one continuous variable st_A in the encoding for each action, the constraints need to be posed as follows:

   $I^p_{AA'} = \prec \Leftrightarrow\ st_A + (et^{\neg p}_A - st_A) < st_{A'} + (st^p_{A'} - st_{A'})$.

   $I^p_{AA'} = \succ \Leftrightarrow\ st_{A'} + (et^p_{A'} - st_{A'}) < st_A + (st^{\neg p}_A - st_A)$.

   $R^p_{AA'} = \prec \Leftrightarrow\ st_A + (et^r_A - st_A) < st_{A'} + (st^r_{A'} - st_{A'})$.

   $R^r_{AA'} = \succ \Leftrightarrow\ st_{A'} + (et^r_{A'} - st_{A'}) < st_A + (st^r_A - st_A)$.

   Notice that all values $(st^{p/r}_A - st_A)$, $(et^{p/r}_A - st_A)$ are constants for all actions A, propositions p, and resource r. In PDDL2.1 Level 3 language, they are equal to either the duration of action A or zero.

3. Constraints to guarantee the resource consistency for all actions: Specifically, for a given action A that has a resource constraint $V^r_{st^r_A} > K$, let U^r_A be an amount of resource r that A produces/consumes ($U^r_A > 0$ if A produces r and $U^r_A < 0$ if A consumes r). Suppose that $\{A_1, A_2, ...A_n\}$ is the set of actions that also use r and $Init_r$ be the value of r at the initial state, we set up a constraint that involves all variables $R^r_{A_iA}$ as follows:

$$Init_r + \sum_{A_i \prec_r A} U^r_{A_i} + \sum_{A_i \perp_r A, U^r_{A_i} < 0} U^r_{A_i} > K \tag{6.1}$$

(where $A_i \prec_r A$ is a shorthanded notation for $R^r_{A_iA} = \prec$).

The constraint above ensures that regardless of how the actions A_i that have no ordering relations with A ($R^r_{A_iA} = \perp$) are aligned temporally with A, the orderings between A and other actions guarantee that A has enough resource ($V^r_{st^r_A} > K$) to execute.

Note that in the constraint 6.1 above, the values of $U^r_{A_i}$ can be static or dynamic (i.e. depending on the relative orderings between actions in P_{oc}). Let's take the actions in the IPC3's *Zeno-Travel* domain for example. The amount of fuel consumed by the action $fly(cityA, cityB)$ only depends on the fixed distance between $cityA$ and $cityB$ and thus is static for a given problem. However, the amount of fuel $U^{fuel}_{refuel} = capacity(plane) - fuel(plane)$ produced by the action $A = refuel(plane)$ depends on the fuel level just before executing A. The fuel level in turn depends on the partial order between A and other actions in the plan that also consume/produce $fuel(plane)$. In general, let

$$U^r_A = f(f_1, f_2, ...f_n) \tag{6.2}$$

where f_i are functions that have values modified by some actions $\{A^i_1, A^i_2 ... A^i_m\}$ in the plan. Because all A^i_k are mutex with A according to the PDDL2.1 specification, there is a resource ordering variable $R^{f_i}_{AA_i}$ with $Dom(R^{f_i}_{AA_i}) = \{\prec, \succ\}$ and the value $V^{f_i}_{st_A}$ can be computed as:

$$V_{st_A}^{f_i} = Init_r + \sum_{A_i \prec_{f_i} A} U_{A_i}^{f_i} \tag{6.3}$$

Then, we can substitute the value of $V_{st_A}^{f_i}$ in equation 6.3 for each variable f_i in 6.2. Solving the set of equations 6.2 for all action A and resource r, we will find the value of U_A^r. Finally, that value of U_A^r can be used to justify the consistency of the CSP constraint 6.1 for each resource-related precondition $V_{st_A^r}^r > K$. Other constraints $V_{st_A^r}^r \star K$ ($\star = \leq, \geq, <$) are handled similarly.

4. Deadlines and other temporal constraints: These model any deadline type constraints in terms of the temporal variables. For example, if all the goals need to be achieved before time t_g, then we need to add a constraint: $st_{A_g} \leq t_g$. Other temporal constraints, such as those that specify that certain actions should be executed before/after certain time points, can also be handled by adding similar temporal constraints to the encoding (e.g $L \leq st_A \leq U$).

5. Constraints to make the orderings on P_{oc} consistent with P_{pc} (optional): Let T_A be the fixed starting time point of action A in the original p.c plan P_{pc}. To guarantee that P_{pc} is consistent with the set of orderings in the resulting o.c plan P_{oc}, we add a constraint to ensure that the value T_A is always present in the live domain of the temporal variable st_A.

Objective Function:

Each satisficing assignment for the encoding above will correspond to a possible partialization of P_{pc}, i.e., an o.c. plan that contains all the actions of P_{pc}. However, some of these assignments (o.c. plans) may have better execution properties than the others. We can handle this by specifying an objective function to be optimized, and treating the encoding as a Constraint Satisfaction Optimization (CSOP) encoding. The only requirement on the objective function is that it is specifiable in terms of the variables of the encodings. Objective functions such as makespan minimization and

order minimization readily satisfy this requirement. Following are several objective functions that worth investigating:

Temporal Quality:

- Minimum Makespan: $minimize\ Max_A(st_A + dur_A)$
- Maximize summation of slacks: $Maximize\ \sum_{g \in Goals}(st^g_{A_g} - et^g_A)\ :\ S^g_{A_g} = A$
- Maximize average flexibility: $Maximize\ Average(Domain(st_A))$

Ordering Quality:

- Fewest orderings: $minimize\ \#(st_A \prec st_{A'})$

6.3. Greedy Approach for Solving the partialization encoding

Solving the CSOP encoding to optimum, whether by MILP encoding (discussed in the next section) or otherwise, will be NP-hard problem (this follows from [2]). Moreover, our motivation in developing the encoding was not limited to solve it to optimum, we are also interested in developing greedy variable and value ordering strategies for the encoding which can ensure that the very first satisficing solution found will have a high quality in terms of the objective function. The optimal solutions can be used to characterize how good the solution found by greedy variable/value ordering procedure.

Clearly, the best greedy variable/value ordering strategies will depend on the specific objective function. In this section, we will develop strategies that are suited to objective functions based on minimizing the makespan. Specifically, we discuss a value ordering strategy that finds an assignment to the CSOP encoding such that the corresponding o.c plan P_{oc} is biased to have a reasonably good makespan. The strategy depends heavily on the positions of all the actions in the

original p.c. plan. Thus, it works based on the fact that the alignment of actions in the original p.c. plan guarantees that causality and preservation constraints are satisfied. Specifically, all CSP variables are assigned values as follows:

Supporting Variables: For each variable S_A^p representing the action that is used to support precondition p of action A, we choose action A' such that:

1. $p \in E(A')$ and $et_{A'}^p < st_A^p$ in the p.c. plan P_{pc}.
2. There is no action B s.t: $\neg p \in E(B)$ and $et_{A'}^p < et_B^{\neg p} < st_A^p$ in P_{pc}.
3. There is no other action C that also satisfies the two conditions above and $et_C^p < et_{A'}^p$.

Interference ordering variables: For each variable $I_{AA'}^p$, we assign values based on the fixed starting times of A and A' in the original p.c plan P_{pc} as follows:

1. $I_{AA'}^p = \prec$ if $et_A^p < st_{A'}^p$ in P_{pc}.
2. $I_{AA'}^p = \succ$ if $et_{A'}^p < st_A^p$ in P_{pc}.

Resource variables: For each variables $R_{AA'}^r$, we assign values based on the fixed starting times of A and A' in the original p.c plan P_{pc} as follows:

- $R_{AA'}^r = \prec$ if $et_A^r < st_{A'}^r$ in P_{pc}.
- $R_{AA'}^r = \succ$ if $et_{A'}^r < st_A^r$ in P_{pc}.
- $R_{AA'}^r = \perp$ otherwise.

This strategy is backtrack-free due to the fact that the original p.c. plan is correct. Thus, all (pre)conditions of all actions are satisfied and for all *supporting variables* we can always find an action A' that satisfies the three constraints listed above to support a precondition p of action

A. Moreover, one of the temporal constraints that lead to the consistent ordering between two interfering actions (logical or resource interference) will always be satisfied because the p.c. plan is consistent and no pair of interfering actions overlap each other in P_{pc}. Thus, the search is backtrack-free and we are guaranteed to find an o.c. plan due to the existence of one legal dispatch of the final o.c. plan P_{oc} (which is the starting p.c. plan P_{pc}).

The final o.c. plan is valid because there is a causal-link for every action's precondition, all causal links are safe, no interfering actions can overlap, and all the resource-related (pre)conditions are satisfied. Moreover, this strategy ensures that the orderings on P_{oc} are consistent with the original P_{pc}. Therefore, because the p.c plan P_{pc} is one among multiple p.c plans that are consistent with the o.c plan P_{oc}, the makespan of P_{oc} is guaranteed to be equal or better than the makespan of P_{pc}.
Complexity: It is also easy to see that the complexity of the greedy algorithm is $O(S * A + I + O)$ where S is the number of supporting relations, A is the number of actions in the plan, I is the number of interference relations and O is the number of ordering variables. In turn $S \leq A * P$, $I \leq A^2$ and $O \leq P * A^2$ where P is the number of preconditions of an action. Thus, the complexity of the algorithm is $O(P * A^2)$.

6.4. Solving the CSOP Encoding by Converting it to MILP Encoding

In the previous section, we discussed the encoding that captures the problem of generating order-constrained (o.c) plans from position-constrained (p.c) plans returned by *Sapa.* We also discussed the implemented greedy approach that runs in linear time. Even though the greedy algorithm finishes very fast, it only guarantees that the o.c plan we get has better or equal makespan value compared to the original p.c plan. To get the optimal solutions for a given user-defined objective function F, we need different ways to solve the encoding. In this section, we concentrate on the approach of compiling it into the Mixed Integer Linear Programming (MILP) encoding and

solve it using off-the-shelf MILP solvers. After discussing the MILP approach in details, we will also briefly discuss the other techniques for the same conversion problem.

Given the CSOP encoding discussed in Section 6.2 we can convert it into a Mixed Integer Linear Program (MILP) encoding and use any standard solver to find an optimal solution. The final solution can then be interpreted to get back the o.c plan. In this section, we will first discuss the set of MILP variables and constraints needed for the encoding, then, we concentrate on the problem of how to setup the objective functions using this approach.

MILP Variables and Constraints:

For the corresponding CSOP problem, the set of variables and constraints for the MILP encoding is as follows:

Variables: We will use the binary integer variables (0,1) to represent the logical orderings between actions and linear variables to represent the starting times of actions in the CSOP encoding (Section 6.3).

- *Binary (0,1) Variables:*

  1. Causal effect variables: $X^p_{AB} = 1$ if $S^p_A = B$, $X^p_{AB} = 0$ otherwise.
  2. Mutual exclusion (mutex) variables: $Y^p_{AB} = 1$ if $I^p_{AB} = \prec$, $Y^p_{BA} = 1$ if $I^p_{AB} = \succ$,
  3. Resource interference variables: $X^r_{AA'} = 1$ if $A \prec_r A'$ (i.e. $et^r_A < st^r_{A'}$). $N^r_{AA'} = 1$ if there is no order between two actions A and A' (they can access resource r at the same time).[4]

- *Continuous Variable:* one variable st_A for each action A and one variable st_{A_g} for each goal g.

[4] In PDDL 2.1, two actions A and B are allowed to access the same function (resource) overlappingly if: (1) A do not change any function that B is checking as its precondition; (2) A and B using the functions to change the value of r in a *commute* way (increase/decrease only).

Constraints: The CSP constraints discussed in Section 6.3 can be directly converted to the MILP constraints as follows:

- Mutual exclusion:

$$Y^p_{AB} + Y^p_{BA} = 1 \tag{6.4}$$

- Only one supporter:

$$\forall p \in Precond(A) : \Sigma X^p_{BA} = 1 \tag{6.5}$$

- Causal-link protection:

$$\forall A', \neg p \in Effect(A') : (1 - X^p_{AB}) + (Y^p_{A'A} + Y^p_{BA'}) \geq 1 \tag{6.6}$$

- Ordering and temporal variables relation:

$$M.(1 - X^p_{AB}) + (st^p_B - et^p_A) > 0 \tag{6.7}$$

  where M is a very big constant. The big constant M enforces the logical constraint: $X^p_{AB} = 1 \Rightarrow et^p_A < st^p_B$. Notice that if $X^p_{AB} = 0$ then there is no particular relation between et^p_A and st^p_B. In this case, the objective function would take care of the actual value of et^p_A and st^p_B. The big M value can be any value which is bigger than the summation of the durations of all actions in the plan.

- Mutex and temporal variables relation:

$$M.(1 - Y^p_{AB}) + (st^p_B - et^p_A) > 0 \tag{6.8}$$

- Resource-related constraints: Let U^r_A be the amount of resource r that action A uses. $U^r_A < 0$ if A consumes (reduces) r and $U^r_A > 0$ if A produces (increases) r. By now, we assume that

U^r_A are constants for all actions A in the original p.c plan returned by *Sapa* and will elaborate on this matter in the later part of this section.

– Only one legal ordering between two actions:

$$X^r_{AA'} + X^r_{A'A} + N^r_{AA'} = 1 \tag{6.9}$$

– Resource ordering and temporal ordering relations:

$$M.(X^r_{AA'}) + (st^r_{A'} - et^r_A) > 0 \tag{6.10}$$

– Constraint for satisficing resource-related preconditions:

$$Init_r + \sum X^r_{A'A}.U^r_{A_i} + \sum_{U^r_B<0} N^r_{AB}.U^r_B > K \tag{6.11}$$

if the condition to execute action A is that the resource level of r when A starts executing is higher than K.[5]

Note that in the equation 6.11 listed above, we assume that U^r_A are all constants for all resource-related functions r and actions A. The reason is that if U^r_A are also variables (non-constant), then equation 6.11 is no longer a linear equation (and thus can not be handled by a MILP solver). In Section 6.2, however, we discussed the cases in which the values of U^r_A are not constants and depend on the relative orders between A and other actions in the plan. Therefore, to use the MILP approach, we need to add additional constraints to ensure that the values of U^r_A are all constants and equal to the U^r_A values in the original p.c plan. By doing so, we in some sense enforce that the actions in P_{oc} and P_{pc} are physically identical.

[5]This constraint basically means that even if the actions that has no ordering with A ($N^r_{AA'} = 1$) align with A in the worst possible way, the A has enough r at its starting time. Notice also that the initial level of r can be considered as the production of the initial state action A_{init}, which is constrained to execute before all other actions in the plan.

To ensure that U_A^r are constants and consistent with the orderings in the final o.c plan P_{oc}, we have to do some pre-processing and add additional linear constraints to the MILP encoding. First, we pre-process P_{pc} and for each action A and function f which A accesses/changes the value of, we record the value $V^f_{st^f_A}$ and U^f_A. Let's call those fixed values $VPC^f_{st^f_A}$ and UPC^f_A. Then, for each action A and function f which A access the value, we add the following MILP constraint to the encoding:

$$V^r_{st^r_A} = Init_r + \sum X^f_{A_iA}.UPC^f_{A_i} = VPC^f_{st^f_A} \tag{6.12}$$

The linear constraint 6.12 means that the orderings between A and other actions that change the value of f ensure that the value of f when we execute A is $V^f_{st^f_A} = VPC^f_{st^f_A}$. Then, using equation (3.1) (Section 6.2), the value of U^r_A can be calculated as:

$$U^r_A = f(f_1, ...f_n) = f(VPC^{f_1}_{st^{f_1}_A}, ...VPC^{f_1}_{st^{f_n}_A}) = UPC^r_A \tag{6.13}$$

and is fixed for every pair of action A and resource r regardless of the orderings in the final o.c plan P_{oc}.

- Constraints to enforce that all actions start after A_{init} and finish before A_{goal}:

$$\forall A : st_A - st_{A_{init}} \geq 0, st_{A_{goal}} - (st_A + dur_A) \geq 0 \tag{6.14}$$

- Goal deadline constraints:

$$st_{A_g} \leq Deadline(g) \tag{6.15}$$

MILP Objective Functions:

Starting from the base encoding above, we can model a variety of objective functions to get the optimal o.c. plans upon solving MILP encoding as follows:

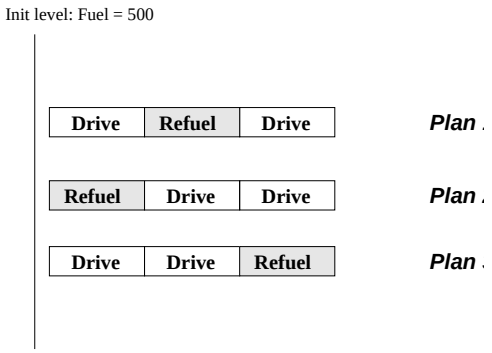


Figure 26. Example of plans with different action orderings.

Minimum Makespan:

- An additional (continuous) variable to represent the plan makespan value: V_{ms}
- Additional constraints for all actions in the plan:

$$\forall A: \ st_A + dur_A \leq V_{ms} \tag{6.16}$$

- MILP Objective function: $minimize\, V_{ms}$

Maximize minimum slack[6] *value:*

- An additional (continuous) variable to represent the minimum slack value: V_{ms}
- Additional constraints for all goals:

$$\forall g \forall A: \ V_{ms} - (M.X^g_{AA_g} + (st_{A_g} - et^g_A)) \geq 0 \tag{6.17}$$

M is a very big constant. This constraint contains two parts. The first part: $M.X^g_{AA_g} + (st_{A_g} - et^g_A)$ guarantees that among all actions that add g (cause g for A_g), the real supporting action A ($X^g_{AA_g} = 1$) is the one that is used to measure the slack value (i.e. among all actions that can potentially support goal g, the value $M.X^g_{AA_g} + (st_{A_g} - et^g_A)$ is biggest for A chosen to

[6] *The objective function of* maximize maximum slack *and* maximize summation of slack *can be handled similarly.*

support g). The whole equation with V_{ms} involved would then guarantee that the slack value is measured correctly. The same big M value is used across all the constraints for different goals and would be subtracted from the final V_{ms} value to get the correct *minimum slack* value.

- MILP objective function: $minimize\, V_{ms}$

Minimum number of orderings:

- Additional binary ordering variables for every pair of actions: O_{AB}
- Additional constraints:

$$\forall A, B, p : O_{AB} - X^p_{BA} \geq 0, O_{AB} - Y^p_{AB} \geq 0 \tag{6.18}$$

- MILP objective function: $minimize\, \Sigma O_{AB}$

6.5. Partialization: Implementation

We have implemented the greedy variable and value ordering discussed in Section 6.3 and have also implemented the MILP encoding discussed in Section 6.4. We tested our implementation as the post-processor in the *Sapa* planner. While *Sapa* is quite efficient, it often generates plans with inferior makespan values. Our aim is to see how much of an improvement the partialization algorithm provides for the plans produced by *Sapa.*

Given a p.c plan P_{pc}, the greedy partialization (GP) and optimal partialization (OP) routines return three different plans. The first is what we call a *logical order constrained (logical o.c)* plan. It consists of a set of logical relations between actions (e.g. causal link from the end point of A_1 to the start point of A_2). The logical relations include (i) causal link, (ii) logical mutex, and (iii) resource mutex. The second is a *temporal order constrained (temporal o.c)* plan in which the temporal o.c

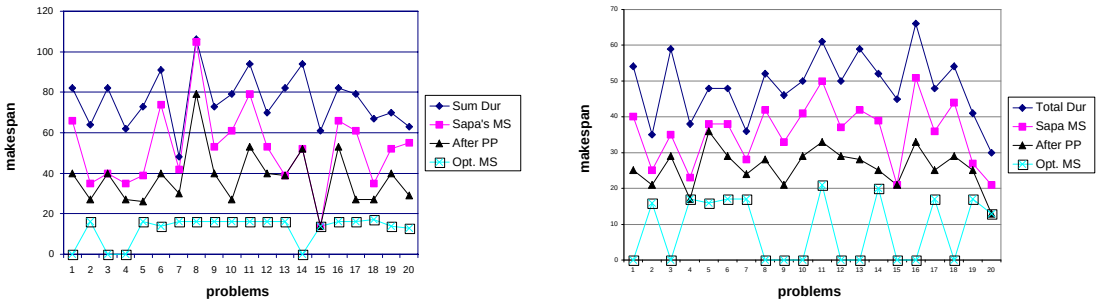
plan is represented by the temporal relations between the starting time points of actions. In short, we collapse multiple logical relations (in a logical o.c plan) between a pair of actions (A_1, A_2) into a single temporal relation between A_1 and A_2. The temporal o.c plan is actually a Simple Temporal Network (STN) [18]. While the logical o.c plan gives more information, the temporal o.c plan is simpler and more compact. Moreover, from the flexibility execution point of view, temporal o.c plan may be just enough[7]. The third plan is the p.c plan sorted from a logical or temporal o.c plan in which each action is given an earliest starting time allowed by the logical/temporal ordering in P_{oc}. The makespan of the resulted o.c plan P_{oc} that we report in this section is the makespan of this p.c plan.

We report the results for the greedy partialization approach in Section 6.5.1 and Section 6.5.2. The current empirical results for the optimal partialization using MILP approach are discussed in Section 6.5.3. The MILP solver that we used is the Java version of the lp_solve package, which can be downloaded from http://www.cs.wustl.edu/~javagrp/help/LinearProgramming.html. The reason that we choose this solve is that it's also implemented in Java and can thus be integrated into the *Sapa* package[8].

6.5.1. Greedy Partialization Approach. The first test suite is the 80 random temporal logistics provided with the TP4 planner. In this planning domain, trucks move packages between locations inside a city and airplanes move them between cities. Figure 27 shows the comparison results for only the 20 largest problems, in terms of number of cities and packages, among 80 of that suite. In the left graph of Figure 27, trucks are allowed to move packages between different locations in different cities, while in the right graph of the same figure, trucks are not allowed to do

[7] The temporal o.c plan can be built from a logical o.c plan by sorting the logical relations between each pair of actions. It's not clear how to build a logical o.c plan from a temporal o.c plan, though.

[8] In the stand-alone partialization software separated from *Sapa*, we also allow option to use the external lp_solve code implemented in C.



(a) With *drive inter-city* action. (b) Without *drive inter-city* action.

Figure 27. Compare different makespan values for random generated temporal logistics problems

so.

The graphs show the comparison between four different makespan values: (1) the optimal makespan (as returned by TGP [81]); (2) the makespan of the plan returned by Sapa; (3) the makespan of the o.c. resulting from the greedy algorithm for partialization discussed in the last section; and (4) the total duration of all actions, which would be the makespan value returned by several serial temporal planners such as GRT [79], or MIPS [24] if they produce the same solution as Sapa. Notice that the makespan value of *zero* for the optimal makespan indicates that the problem is not solvable by TGP.

For the first test which allows driving between cities action, compared to the optimal makespan, on the average, the makespan of the serial p.c. plans (i.e, cumulative action duration) is about 4.34 times larger, the makespan of the plans output by Sapa is about 3.23 times larger and the Sapa plans after post processing are about 2.61 times longer (over the set of 75 solvable problems; TGP failed to solve the other 5). For the second test, without the driving inter-city actions. The comparison results with regard to optimal solutions are: 2.39 times longer for serial plans, 1.75 times longer for the plans output by Sapa, and 1.31 times longer after partialization. These results are averaged over the set of 69 out of the 80 problems that were solvable by TGP.[9]

[9]While TGP could not solve several problems in this test suite, Sapa is able to solve all 80 of them.

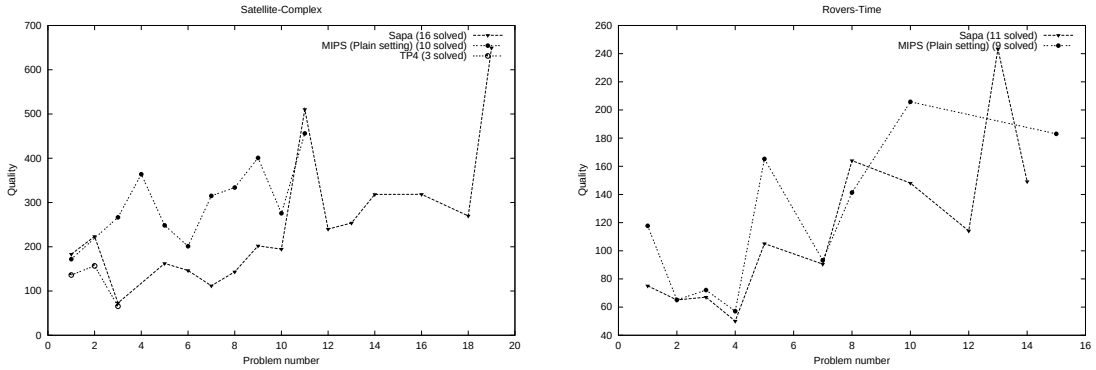


Figure 28. Comparing the quality (in terms of makespan) of the plan returned by *Sapa* to MIPS and TP4 in "Satellite" and "Rover" domains–two of the most expressive domains motivated by NASA applications.

Thus, the partialization algorithm improves the makespan values of the plans output by Sapa by an average of 20% in the first set and 25% in the second set. Notice also that the same technique can be used by GRT [79] or MIPS [24] and in this case, the improvement would be 40% and 45% respectively for the two problem sets.

6.5.2. Use of Greedy Partialization at IPC-2002. The greedy partialization procedures described in this paper were part of the implementation of *Sapa* with which we took part in the International Planning Competition (IPC-2002). *Sapa* was one of the best planners in the most expressive metric temporal domains, both in terms of planning time, and in terms of plan quality (measured in makespan). The credit for the plan quality goes in large part to the partialization algorithms described in this paper. In Figure 28, we show the comparison results on the quality of plans returned by *Sapa* and its nearest competitors from the Satellite (complex setting) and Rovers domains–two of the most expressive domains at IPC, motivated by NASA applications.[10] It is interesting to note that although TP4 [39] guarantees optimal makespan, it was unable to solve more than 3 problems in Satellite domain. *Sapa* was able to leverage its search in the space of

[10]The competition results were collected and distributed by the IPC3's organizers and can be found at [27]. Detailed descriptions of domains used in the competition are also available at the same place.

domains	orig/tt-dur	gpp/tt-dur	gpp/orig
zeno simpletime	0.8763	0.7056	0.8020
zeno time	0.9335	0.6376	0.6758
driverlog simpletime	0.8685	0.5779	0.6634
driverlog time	0.8947	0.6431	0.7226
satellite time	0.7718	0.6200	0.7991
satellite complex	0.7641	0.6109	0.7969
rovers simpletime	0.8204	0.6780	0.8342
rovers time	0.8143	0.7570	0.9227

Table 1. Compare different makespan values in the IPC's domains

position-constrained plans to improve search time, while at the same time using post-processing to provide good quality plans.

Figures 29, 30, 31, and 32 show in more details the comparisons of the makespan values before/after greedily and optimally post-processed. We use problems of the four domains used in the competition, which are: ZenoTravel, DriverLog, Satellite, and Rovers (the problem descriptions are discussed in Section 5.2). For each domain, we use two sets of problems of highest levels, and take the first 15 (among the total of 20) problems for testing. The *simple-time* sets involving durative actions without metric resource consumption and *time/complex* sets (except the DriverLog domain) involving durative actions using resources. In the four figures, we show the comparison between the makespans of a (i) serial plan, (ii) a parallel p.c plan returned by Sapa, (iii) an o.c plan built by greedy partialization, and (iv) an o.c plan returned by solving the MILP encoding. Because the two optimal-makespan planners participated in the competition, TP4 and TPSYS, can only solve the first few problems in each domain, we do not include the optimal makespan values in each graph. For this set of problems, we discuss the effect of greedy partialization here and leave the comparison regarding the results of optimal post-processing until the next section (Section 6.5.3). Table 1 summarizes the comparison between different makespan values for 8 sets of problems in those 4 domains. The three columns show the fractions between the makespans of greedily partialized o.c plan (gp), the original

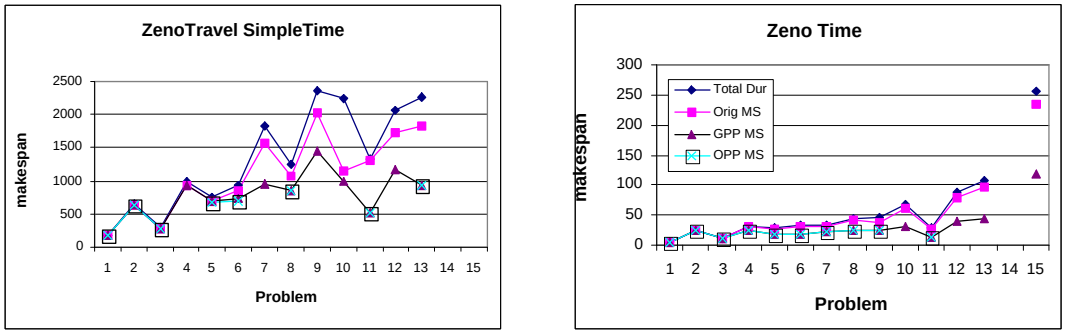


Figure 29. Compare different makespan values for problems in ZenoSimpletime and ZenoTime domains

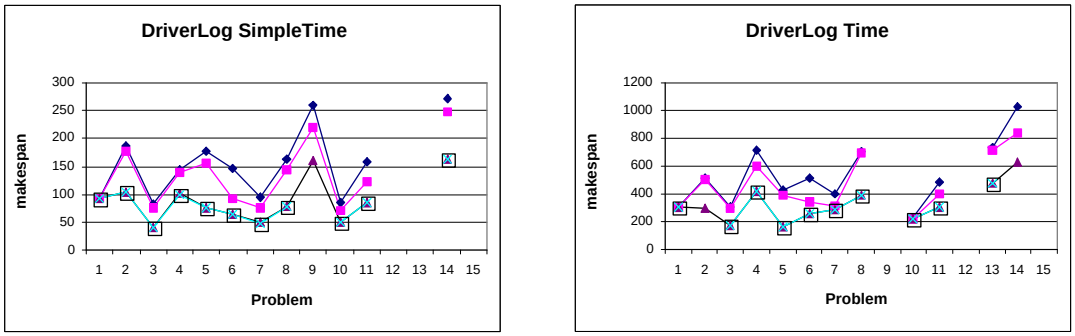


Figure 30. Compare different makespan values for problems in DriverlogSimpletime and DriverlogTime domains

parallel p.c plan (orig), and the total duration of actions in the plan (tt-dur), which is equal to the makespan of a serial plan. Of particular interest is the last column which shows that the greedy partialization approach improves the makespan values of the original plans by the least of 8.7% in the RoversTime domain to as much as 33.7% in the DriverLog Simpletime domain. Compare with the serial plans, the greedily partialized o.c plans improved the makespan values 24.7%-42.2%.

The greedy partialization and topological sort times are extremely short. Specifically, they are less than 0.1 seconds for all problems with the number of actions ranging from 1 to 68. Thus, using our partialization algorithm as a post-processing stage essentially preserves the significant efficiency advantages of planners such as Sapa, GRT and MIPS, that search in the space of p.c.

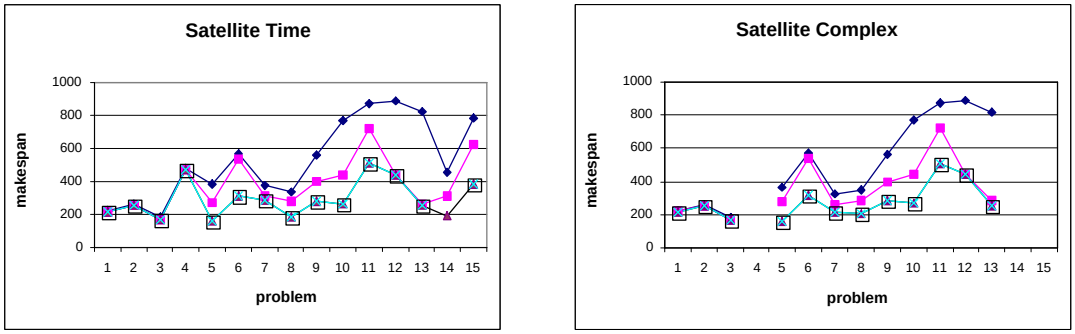


Figure 31. Compare different makespan values for problems in SatelliteTime and SatelliteComplex domains

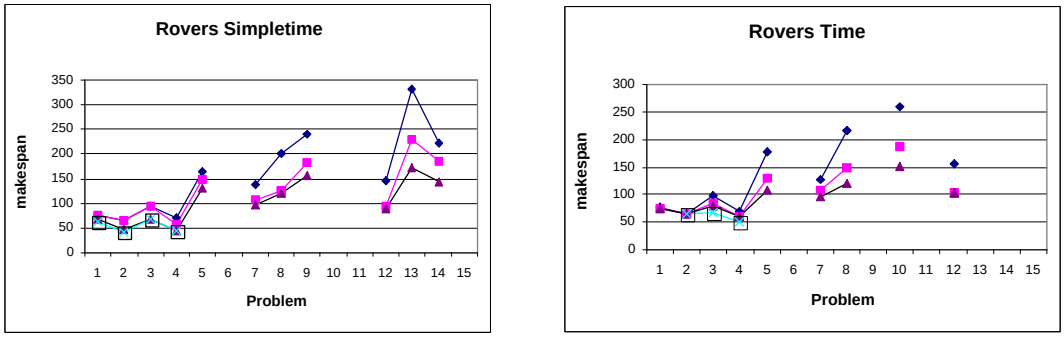


Figure 32. Compare different makespan values for problems in RoversSimpletime and RoversTime domains

plans, while improving the temporal flexibility of the plans generated by those planners.

Finally, it should be noted that partialization improves not only makespan but also other temporal flexibility measures. For example, the "scheduling flexibility" of a plan defined in [71], which measures the number of actions that do not have any ordering relations among them, is significantly higher for the partialized plans, compared even to the parallel p.c. plans generated by TGP. In fact, our partialization routine can be applied to the plans produced by TGP to improve their scheduling flexibility.

6.5.3. Optimal Makespan Partialization. One limitation of the evaluation of the greedy strategies that we have presented in this section is that we have not characterized how far from the

domains	#Solved	Diff GP	Aveg. Diff
zeno simpletime	8/13	2/2	0.9723
zeno time	10/10	0/0	1.0
driverlog simpletime	11/12	2/2	0.9748
driverlog time	10/12	1/2	0.9928
satellite time	14/15	0/3	1.0
satellite complex	12/12	0/1	1.0
rovers simpletime	4/11	2/2	0.9276
rovers time	3/9	2/3	0.8355

Table 2. Compare optimal and greedy partializations

optimum the quality of the plans found by the greedy strategies are. Our intention was to compute the optimal solution to the MILP encoding discussed in Section 6.4 and compare it to that obtained through greedy strategies. To this end, we built the MILP encodings and use the Java version of LP_SOLVE, a public domain LP solver, to find the solution.

Table 2 shows the statistic of solving the 8 sets of problems listed in Figures 29, 30, 31, and 32. The objective function is to minimize the makespan value. The first column shows the number of problem that can be solved by lp_solve (it crashed when solving the other encodings). For example, for ZenoSimpletime domains, lp_solve can solve 8 of 13 encodings. In the second column, we show the number of problems, among the ones solvable by lp_solve, that the optimal o.c plan is different from the greedily partialized o.c plan. For example, in the RoversTime domains, there are 3 problems in which the two o.c plans are different and in 2 of them, the optimal makespans are smaller than the greedily partialized makespans. The third column shows the average ratios between the optimal and greedy makespans (in only problems that they are different). The table shows that in the ZenoTime domain, for all 10 problems, the optimal o.c plans and greedy o.c plans are identical. For the two Satellite domains (time and complex) there are 4 problems in which the two o.c plans are different, but in all the cases, the makespan values are not improved. In the ZenoSimpletime and two Driverlog domains, there are few problems in which the two o.c plans are different but the

makespan improvements are very small (0.7-2.8%). The most promising domains for the optimal partialization approach is the Rovers domains in which 2 of 4 solved problems in RoversSimpletime and 2 of 3 solved problems in RoversTime have better optimal o.c plans than greedy o.c plans. The improvements are from 7.3% in RoversSimpletime to 16.4% in RoversTime. Unfortunately, the encodings for the Rovers domain seems to be more complicate than other domains and lp_solve crashed in solving most of them. We are planning to use more powerful solvers such as CPLEX to find the solutions for the remaining unsolved encodings.

While investigating the reason why the optimally partialized o.c plans tend to be equal to the greedy partialized o.c plans in domains other than Rovers, we looked at the causal structure of the MILP encodings for different domains. We found that the size of the causal link constraints (i.e. number of supporters for a given action's precondition) are small for domains other than Rovers. In fact, for those domains, most of the causal links are of size 1 (only one supporter). For example, in the Satellite domains, the biggest causal link size is 2 and on average, the percentage of size-1 causal links is around 93%. In the ZenoTravel and DriverLog domains, the number of size-1 causal links is less dominant but the biggest causal link size is still only 4 with most of the problems still only have causal links of size 1 and 2. Because of the dominant of size-1 causal links, there are only few candidate o.c plans and thus it is more likely that the greedy and optimal partialization routines will output the same o.c plans. In the Rovers domain, there are causal links of size up to 12 and there is no problem in which the causal link constraints involving only size-1 and size-2 constraints. The percentage of size-1 constraints are only 77.8% for RoversSimpletime and 81.3% for RoversTime domains. Because there are more causal link constraints of bigger sizes, there are more potential o.c plans for a given set of actions. Thus, there are more chance that the optimal partialization will find a better o.c plan than the greedy partialization approach. Currently, we are implementing the pre-processing phase to simplify the encoding using the unit-propagation technique.

6.6. Summary and Discussion

In this chapter, we present an approach of encoding the partialization problem as Constraint Satisfaction Optimization Problem (CSOP). We also implemented two different ways of solving this CSOP encoding, either greedily in linear time or optimally by converting it into a MILP encoding. Those techniques can be used in *Sapa* and other state-space search planners to generate more flexible order-constrained plans, or to improve the makespan values of the final plan.

To extend the work on partialization in this chapter, we are currently focusing on:

- Improving the optimal solving of the CSOP encodings (Section 6.4): the first idea in mind is to use a more powerful MILP solver (e.g. CPLEX). Given that a large portion of the encoding involving binary variables, other types of solvers besides the pure MILP solver can potentially be the better fits. The first approach is to follow the LPSAT [97] approach and separate the use the SAT solver (which is specifically designed for boolean variables) to handle the binary MILP variables and constraints involving them. The continuous value variables representing action starting times are then managed using a LP encoding. Besides this coupled framework, using CSOP solver to directly solve our CSOP encoding, which involves both discrete and continuous variables is also promising. Previously, we could not find a suitable CSOP solver for this task. However, the CSOP solver used in the recently-developed CPT [91] planner appears to be a good candidate. Given that the CPT's encoding seems to be much bigger than our encoding (in terms of involving variables) and its good performance. To use this solver, we may need to make some adjustments: (i) while metric resource related constraints also involve continuous variables like temporal constraints, they are different and thus the base solver may need extensions to handle them; (ii) the variable and value orderings are aimed toward the objective function of minimizing plan's makespan value. Therefore, different

heuristics are needed for other objective functions discussed in Section 6.2.

- Based on the observation that there is a large portion of the supporting constraints (i.e. specifying the supporter for a given action precondition) involving only a single supporter, we can significantly reduce the number of variables and constraints by pre-assigning values to those variables and simplifying the other constraints. Therefore, we are implementing a preprocessing routine based on unit propagation and hope that it can speedup the solver by significantly simplifying the encoding.

CHAPTER 7

Adapting Best-First Search to Partial-Satisfaction Planning

Many metric temporal planning problems can be characterized as over-subscription problems (c.f. Smith([84, 85])) in that goals have different values and the planning system must choose a subset that can be achieved within the time and resource limits. This type of problem is more general than the ones we have been concentrated on so far in this dissertation where all the goals need to be achieved for the plan to be valid. Examples of the over-subscription problems include many of NASA planning problems such as planning for telescopes like Hubble[56], SIRTF[57], Landsat 7 Satellite[78]; and planning science for Mars rover [84]. Given the resource and time limits, only certain set of goals can be achieved and thus it is best to achieve the subset of goals that have highest total value given those constraints. In this dissertation, we consider a subclass of the over-subscription problem where goals have different utility (or values) and actions incur different execution costs, which are generally defined by the amount of resource (e.g. money, fuel) consumption and the temporal aspect of that action (e.g how much time spent executing that action). The objective is then to find the most *beneficial* plan, that is the plan with the best tradeoff between the total benefit of achieved goals and the total execution cost of actions in the plan. We refer to this subclass of the over-subscription problem as Partial-Satisfaction Planning (PSP) Net Benefit problem where not all the goals need to be satisfied by the final plan. In this chapter, we present the extensions to the *Sapa*'s search algorithm to solve PSP Net Benefit problems. Later, we also discuss

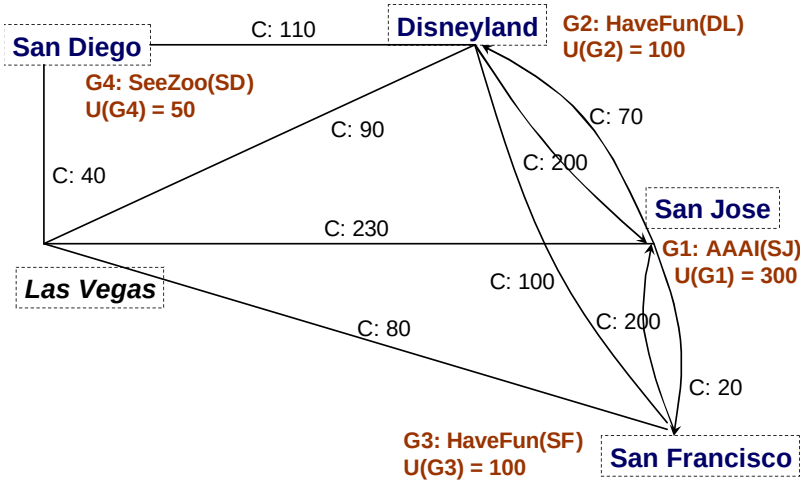


Figure 33. The travel example

the potential extensions to deal with other types of PSP planning problems in the future work in Section 9.2.

Definition PSP NET BENEFIT: Given a planning problem $P = (F, A, I, G)$ and, for each action a "cost" $C_a \geq 0$ and, for each goal specification $g \in G$ a "utility" $U_g \geq 0$ and the logical relation $h(g) = True/False$ represents the "hard/soft" property of g. Finding a plan $P = \langle a_1, ..., a_n \rangle$ starting from I leads to a state S that satisfies all goals g such that $h(g) = True$ with the maximum net benefit value $\sum_{f \in (S \cap G)} U_f - \sum_{a \in \Delta} C_a$?

Example: In Figure 33, we show the travel example that we will use throughout this chapter. In this example, a student living in Las Vegas (LV) needs to go to San Jose (SJ) to present a AAAI paper. The cost for traveling is $C(travel(LV, SJ)) = 230$ (airfare + hotel). To simplify the problem, we assume that if the student arrives at San Jose, he automatically achieves the goal $g_1 = Attended\_AAAI$ with utility $U(g_1) = 300$ (equals to the AAAI's student scholarship). The student also wants to go to Disneyland (DL) and San Francisco (SF) to have some fun and to San Diego (SD) to see the zoo. The utilities of having fun in those three places ($U(g_2 = HaveFun(DL))$, $U(g_3 = HaveFun(SF))$, $U(g_4 = SeeZoo(SD))$) and the cost of

```
(:durative-action TRAVEL
:parameters
     (?person - person
     ?loc-from - location
     ?loc-to - location)
:duration (= ?duration ( + (time-to-fly ?loc-from ?loc-to)
          (time-to-stay ?loc-to)))
:cost (+ (air-ticket-price ?loc-from ?loc-to)
          (* (time-to-stay ?loc-to) (hotel-rate ?loc-to)))
:condition
     (and (at start (have-ticket ?loc-from ?loc-to))
     (at start (hotel-booked ?loc-to))
     (at start (at ?person ?loc-from)))
:effect
     (and (at start (not (at ?person ?loc-from)))
     (at end (at ?person ?loc-to))
     (at end (have-fun ?person ?loc-to))))
```

Figure 34. Sample *Travel action in the extended PDDL2.1 Level 3 with* cost field.

traveling between different places are shown in Figure 33. The student needs to find a traveling plan that gives him the best tradeoff between the utilities of being at different places and the traveling cost (transportation, hotel, entrance ticket etc.). Among all the goals, only g_1 is a "hard" goal in the sense that any valid plan should satisfy g_1. The other are "soft", which means that we prefer achieving them only if the costs of achievement are lower than their utilities. In this example, the best plan is $P = \{travel(LV, DL), travel(DL, SJ), travel(SJ, SF)\}$ that achieves the first three goals g_1, g_2, g_3 and ignores the last goal $g_4 = SeeZoo(SD)$. Figure 34 shows the *Travel* action in this example in the extended PDDL2.1 Level 3 language with an additional *cost* field. We decided to represent the cost field similar to the way action duration and action's metric conditions/effects are described in PDDL2.1. Thus, action cost is represented as a mathematical formula and is calculated using the values of the other metric functions associated with temporal and metric resources consumed/produced by that action. In Figure 34, the cost of action *travel* depends on the price of the air-ticket between the two locations, the duration of stay in the new location, and the hotel rate

at that locations. In Section 7.3, we discuss in more details how to generate the PSP problems for benchmark domains and the full description of several domains are presented in the Appendix A.3.

Sapa and most of the current planning systems are not designed to solve the over-subscription or PSP problems. Most of them expect a set of conjunctive goals of equal value and the planning process does not terminate until all the goals are achieved. Extending the traditional planning techniques to solve the PSP Net Benefit problem poses several challenges:

- The termination criteria for the planning process change because there are no fixed set of conjunctive goals to satisfy.
- Heuristic guidance in the traditional planning systems are designed to guide the planners to achieve a fixed set of goals. They can not be used directly in the over-subscription problem.
- Plan quality should take into account not only action costs but also the values of goals achieved by the final plan.

Over-subscription problems have received some attention in scheduling, using the "greedy" approaches. Straight forward adaptation to planning would involve considering goals in the decreasing order of their values. However, goals with higher values may also be more expensive to achieve and thus may give the cost vs. benefit tradeoff that is far from optimal. Moreover, interactions between goals may make the cost/benefit to achieve a set of goals quite different from the value of individual goals. Recently, Smith ([85]) and van den Briel et. al ([89]) discuss two approaches for solving partial satisfaction planning problems by heuristically selecting a subset S of goals that appear to be the most beneficial and then use the normal planning search to find the least cost solution that achieves all goals in S. If there are n goals then this approach would essentially involve selecting the most beneficial subset of goals among a total of 2^n choices. While this type of approach is less susceptible to inoptimal plans compared to the naive greedy approach, it too is

overly dependent on the informedness of the initial goal-set selection heuristic. If the heuristic is not informed, then there can be beneficial goals left out and S may contain unbeneficial goals.

In this chapter, we investigate heuristic algorithms based on best-first search for solving PSP NET BENEFIT. *Sapa*^{ps} , an extension of *Sapa* for solving PSP Net Benefit, uses an anytime heuristic search framework in which goals are treated as a mixture of "soft" and "hard" constraints. Thus, among all the goals in G, only a subset G_H contains "hard goals" that need to be satisfied for the plan to be valid. The remaining goals in $G_S = G \setminus G_H$ are "soft" and achieving them only affects the quality of the final plan but not the validity of the plan. The search framework does not concentrate on achieving a particular subset of goals, but rather decides what is the best solution for each node in the search tree. Any executable plan that achieves all "hard" goals is considered a potential solution, with the quality of the plan measured in terms of its net benefit. The objective of the search is to find the plan with the highest net benefit. *Sapa*^{ps} uses novel ways of estimating the g and h values of partial solutions, and uses them to guide an anytime A* search. In particular, the evaluations of the g and h values of nodes in the A* search tree are based on the subset of goals achieved in the current search node and the best potential beneficial plan from the current state to achieve a subset of the remaining goals. We show that *Sapa*^{ps} can produce high quality plans compared to the greedy approach.

For the remaining of this chapter, we will first present the any-time algorithm in Section 7.1. This algorithm and the heuristic guiding it are extended from the forward search algorithm and planning graph based heuristics discussed in Chapter 3 and 4. The heuristic used in *Sapa*^{ps} is discussed in Section 7.2 and the empirical results are presented in Section 7.3. For reference, the examples for the extended version of PDDL2.1 representing the PSP Net Benefit problem are provided in the Appendix A.3.

7.1. Anytime Search Algorithm for PSP Net Benefit

Most of the current successful heuristic planners [7, 41, 70, 22, 25], including *Sapa*, use weighted A* search with heuristic guidances extracted from solving the relaxed problem ignoring the delete list. In the heuristic formula $f = g + w * h$ guiding the weighted A* search, the g value is measured by the total cost of actions leading to the current state and the h value is the estimated total action cost to achieve all goals from the current state (forward planner) or to reach the current state from the initial state (backward planner). Compared to the traditional planning problem, the PSP problem has new requirements: (i) goals have different utility values; (ii) not all the goals need to be accomplished in the final plan; (iii) the plan quality is not measured by the total action cost but the tradeoff between the total achieved goals' utilities and the total action cost. Therefore, in order to employ the A* search, we need to modify the way each search node is evaluated as well as the criteria used to terminate the search process.[1]

In this section, we discuss a method which models the top-level goals G as "soft" and "hard" constraints ($G = G_S \bigcup G_H$). All executable plans that achieve all goals in G_H are considered potential solutions, or *valid plans*. The quality of a valid plan is then measured in terms of its net benefit and the objective of the search is then to find a valid plan with the highest net benefit. To model this search problem in an A* framework, we need to first define the g and h values of a partial plan. The g value will need to capture the current net benefit of the plan, while the h value needs to estimate the net benefit that can be potentially accrued by extending the plan to cover more goals. Once we have these definitions, we need methods for efficiently estimating the the h value. We will detail this process in the context of *Sapa*^{ps} , which is an extension of *Sapa* and does forward (progression) search in the space of states.

[1] To avoid confusion, we will concentrate the discussion on the new A* search framework in the context of a forward planner. It can also be used in regression planners by reversing the search direction.

g value: In forward planners, applicable actions are executed in the current state to generate new states. Generated nodes are sorted in the queue by their f values. The search stops when the first node taken from the queue satisfies all the pre-defined conjunctive goals. In our ongoing example, at the initial state $S_{init} = \{at(LV)\}$, there are four applicable actions $A_1 = travel(LV, DL)$, $A_2 = travel(LV, SJ)$, $A_3 = travel(LV, SF)$ and $A_4 = travel(LV, SD)$ that lead to four states $S_1 = \{at(DL), g_2\}$, $S_2 = \{at(SJ), g_1\}$, $S_3 = \{at(SF), g_3\}$, and $S_4 = \{at(SD), g_4\}$. Assume that we pick state S_1 from the queue, then applying action $A_5 = travel(DL, SF)$ to S_1 would lead to state $S_5 = \{at(SF), g_2, g_3\}$.

For a given state S, let partial plan $P_P(S)$ be the plan leading from the initial state S_{init} to S, and the goal set $G(S)$ be the set of goals accomplished in S. The overall quality of the state S depends on the total utility of the goals in $G(S)$ and the costs of actions in $P_P(S)$. The g value is thus defined as :

$$g(S) = \mathrm{U}(G(S)) - \mathrm{C}(P_P(S)) \tag{7.1}$$

Where $\mathrm{U}(G(S)) = \sum_{g \in G(S)} \mathrm{U}_g$ is the total utility of the goals in $G(S)$, and $\mathrm{C}(P_P(S)) = \sum_{a \in P_P(S)} \mathrm{C}_a$ is the total cost of actions in $P_P(S)$. In our ongoing example, at the initial state $S_{init} = \{at(LV)\}$. Applying action $a_1 = travel(LV, DL)$ would leads to the state $S_1 = \{at(DL), g_2\}$ and applying action $a_2 = travel(DL, SF)$ to S_1 would lead to state $S_2 = \{at(SF), g_2, g_3\}$. Thus, for state S_2, the total utility and cost values are: $\mathrm{U}(G(S_2)) = \mathrm{U}_{g_2} + \mathrm{U}_{g_3} = 100 + 100 = 200$, and $\mathrm{C}(P_P(S_2)) = \mathrm{C}_{a_1} + \mathrm{C}_{a_2} = 90 + 100 = 190$.

h value: The h value of a state S should estimate how much additional net benefit can be accrued by extending the partial plan P_S to achieve additional goals beyond $G(S)$. The perfect heuristic function h^* would give the maximum net benefit that can be accrued. Any h function that is an upper bound on h^* will be admissible (notice that we are considering the maximizing variant of

A*). Before we go about investigating efficient h functions, it is instructive to pin down the notion of the h^* value of a state S.

For a given state S, let P_R be a valid plan segment that is applicable in S, and $S' = Apply(P_R, S)$ be the state resulting from applying P_R to S. Note that P_R is valid only if S' contains the "hard" goal set G_H. Like $P_P(S)$, the cost of P_R is the sum of the costs of all actions in P_R. The utility of the plan P_R according to state S is defined as follows: $U(Apply(P_R, S)) = U(G(S')) - U(G(S))$. For a given state S, the *best beneficial remaining plan* P_S^B is a valid plan applicable in S such that there is no other valid plan P applicable in S for which $U(Apply(P, S)) - C(P) > U(Apply(P_S^B, S)) - C(P_S^B)$. This value can then be used to indicate how promising it is to extend the state S If we have P_S^B, then we can use it to define the $h^*(S)$ value as follows:

$$h^*(S) = U(Apply(P_S^B, S)) - C(P_S^B) \tag{7.2}$$

In our ongoing example, from state S_1, the most beneficial plan turns out to be $P_{S_1}^B = \{travel(DL, SJ), travel(SJ, SF)\}$, and $U(Apply(P_{S_1}^B, S_1)) = U_{\{g_1,g_2,g_3\}} - U_{\{g_2\}} = 300 + 100 + 100 - 100 = 400$, $C(P_{S_1}^B) = 200 + 20 = 220$, and thus $h^*(S_1) = 400 - 220 = 180$.

Computing $h^*(S)$ value directly is impractical as searching for P_S^B is as hard as solving the PSP problem optimally. In the following section, we will discuss a heuristic approach to approximate the h^* value of a given search node S by essentially approximating P_S^B using a relaxed plan from S.

The complete search algorithm used by *Sapa*^{ps} is described in Figure 35. In this algorithm, search nodes are categorized as follows:

Goal Node: *S_G is a goal node if $G_H \subset S_G$*

Thus, a goal node S_G represents a valid plan leading from S_{init} to S_G.

State Queue: *SQ*={S_{init}}
Best beneficial node: $N_B = \emptyset$
Best benefit: $B_B = -\infty$
while *SQ*$\neq\{\}$
    S:= *Dequeue*(*SQ*)
    if S is a termination node **then**
        Terminate Search;
    Nondeterministically select *a* applicable in *S*
        S' := *Apply*(*a*,*S*)
        if S' is a goal node and $g(S') > B_B$ **then**
            $Print\ BestBeneficialNode(S')$
            $N_B \leftarrow S'$;
            $B_B \leftarrow g(S')$
        end if;
        if $f(S') \leq B_B$ **then**
            $Discard(S')$
        else *Enqueue*(*S'*,*SQ*)
end while;

Figure 35. Anytime A* search algorithm for PSP problems.

Best beneficial node: *S_B is a best beneficial node if: (i) S_B is a goal node; and (ii) there is no visited goal node S such that $g(S) > g(S_B)$*

Note that if all the goals are hard, then all goal nodes satisfy the same set of goals and thus the comparison to decide the best beneficial node is purely based on the total cost of actions leading to the state represented by that goal node. On the other hand, if all the goals are soft, then any search node (including S_{init}) is a goal node. Because $g(S_{init}) = 0$, any subsequent visited best beneficial node S_B should have value $g(S_B) > 0$.

Termination Node: *S_T is a termination node if: (i) S_T is a goal node, (ii) $h(S_T) = 0$, and (iii) $\forall S : g(S_T) > f(S)$.*

Termination node S_T is the *best* beneficial node in the queue. Moreover, because $h(S_T) = 0$, there is no benefit of extending S_T and therefore we can terminate the search at S_T. Notice that if the heuristic is *admissible*,[2] then the set of actions leading to S_T represents an optimal solution

[2]In this case, a heuristic is admissible if $h(S)$ over-estimates (higher than or equal to) the $U(Apply(P_S^B, S)) - C(P_S^B)$

for the PSP problem.

Unpromising Node: *S is a unpromising node if $f(S) \leq g(S_B)$ with S_B is a best beneficial node visited so far.*

The net benefit value of the best beneficial node (B_B) found during search can be used to set up the *lower-bound* value and thus nodes that have f values smaller than that lower-bound can be discarded. Thus, if the heuristic is "perfect", then unpromising nodes can never be extended to reach state which is more beneficial than the best plan found so far during search.

As described in Figure 35, the search algorithm starts with the initial state S_{init} and keeps dequeuing the best promising node S (i.e. highest f value). If S is a termination node, then we stop the search. If not, then we extend S by applying applicable actions a to S. If the newly generated node $S' = Apply(a, S)$ is a goal node and has a better $g(S')$ value than the best beneficial node visited so far, then we print the plan leading from S_{init} to S'. Finally, if S' is not a unpromising node, then we will put it in the search queue SQ sorted in the decreasing order of f values. Notice that because we keep outputting the best beneficial nodes while conducting search (until a terminal node is found), this is an *anytime algorithm*. The benefit of this approach is that the planner can return some plan with a positive net-benefit fast and keep on returning plans with better net benefit, if given more time to do more search. Thus, we can impose the time or search node limit on the algorithm and try to find the best plan within those limits. To demonstrate the anytime search framework, let's assume that the nodes S_1, S_2, S_3, S_4 are generated in that order when we extend S_{init}. Starting with the best benefit value of $B_B = -\infty$, the planner will first generate the plan $P_1 = P_P(S_1) = A_1$ leading to S_1, even though $g(S_1) = 100 - 90 = 10 > B_B = -\infty$, S_1 is not a goal node and thus P_1 is not a valid plan. Then, when S_2 is generated, because $g(S_2) = 70 > B_B = -\infty$ and S_2 satisfies the only hard goal g_1, the planner outputs $P_2 = P_P(S_2) = A_2$ as the first best plan. Nodes

value.

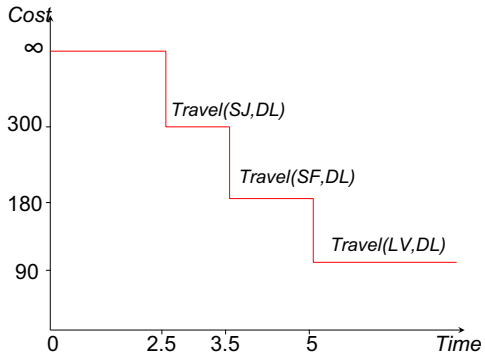


Figure 36. Cost function of goal $At(DL)$

S_3 and S_4 are less beneficial and are just put back in SQ. Assuming perfect heuristic,[3] the planner will pick S_1 to extend. By applying action $A_7 = travel(DL, SJ)$ to S_1, we get to state S_7 that is more beneficial than the best state visited ($g(S_7) = 400 - 290 = 110 > B_B = 70$) and is also a goal node. Therefore, we will output $P_3 = P_P(S_7) = \{travel(LV, DL), travel(DL, SJ)\}$. The algorithm continues until we reach the termination node $S_8 = Apply(travel(SJ, SF), S_7)$.

Notice that while the categorization of nodes was based on "perfect" heuristic, the current heuristic used in *Sapa*^{ps} is not admissible. Therefore: (i) a pruned unpromising nodes may actually be promising (i.e. extendible to reach node S with $g(S) > B_B$); and (ii) a termination node may not be the best beneficial node. In our implementation, even though weight $w = 1$ is used in equation $f = g + w * h$ to sort nodes in the queue, another value $w = 2$ is used for pruning (unpromising) nodes with $f = g + w * h \leq B_B$. Thus, only nodes S with estimated heuristic value $h(S) \leq 1/w * h^*(S)$ are pruned. For the second issue, we can continue the search for a better beneficial nodes after a termination node is found until some criteria are met (e.g. reached certain number of search node limit).

7.2. Heuristic for *Sapa*^{ps}

For a given state S, while calculating the $g(S)$ value is trivial, estimating the $h^*(S)$ value is not an easy task as we have to first guess the plan P_S^B. If all the goals are reachable, actions have uniform cost and goals have substantial higher utilities than action cost then finding the least cost solution for a traditional planning problem is a special case of finding $P_{S_{init}}^B$ for the PSP problem. Hoffman ([41]) showed that solving this problem for even the *relaxed* problems (ignoring the delete list) is NP-hard.

Sapa^{ps} also uses relaxed-plan heuristic extracted from the cost-sensitive planning graph discussed in Section 4. In recall, we first build the relaxed plan supporting *all* the goals until the cost to achieve all the goals are stabilized. Assume that the student can only go to SJ and SF from LV by airplane, which take respectively 1.0 and 1.5 hour. He can also travel by car from LV, SJ, and SF to DL in 5.0, 1.5 and 2.0 hours, respectively. Figure 36 shows the cost function for goal $g_2 = At(DL)$, which indicates that the earliest time to achieve g_2 is at 2.5 (hour) with the lowest cost of 300 (route: $LV \rightarrow SJ \rightarrow DL$). The lowest cost to achieve g_2 reduces to 180 at $t = 3.5$ (route: $LV \rightarrow SF \rightarrow DL$) and again at $t = 5.0$ to 90 (direct path: $LV \rightarrow DL$). Using the cost-function based relaxed plan extraction technique discussed in Section 4, we can heuristically extract the least cost plan that achieves the remaining goals. For example, if we need to find a supporting action to support goal g_2 at time $t = 4$, then the least cost action is $A = travel(SF, DL)$ (Figure 36). Starting with the top level goals, if we choose an action A to satisfy goal g, then we add the preconditions of A to the set of goals to be achieved. In our ongoing example, if we select $A = travel(DL, SF)$ to satisfy $g_3 = HaveFun(SF)$, then the goal $g = at(DL)$ is added to the current set of subgoals.

One of the pitfalls of the algorithm discussed above is that the actions selected to support

[3]The optimal plan for this example is given in the first section.

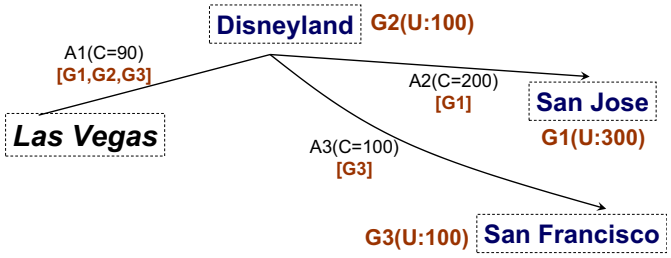


Figure 37. A relaxed plan and goals supported by each action.

a given goal may out-cost the utility of that goal. Therefore, after the cost functions are built, we then use the second scan through the extracted relaxed plan to remove goals that are not beneficial, along with the actions that contribute solely to the achievement of those goals. For this purpose, we build the *supported-goals* list GS for each action a and fluent f starting from the top level goals as follows:

- $GS(a) = \bigcup GS(f) : f \in Eff(a)$
- $GS(f) = \bigcup GS(a) : f \in Prec(a)$

Assume that our algorithm extracts the relaxed plan $f = R_P(S_{init}) = \{a_1 : travel(LV, DL), a_2 : travel(DL, SJ), a_3 : travel(DL, SF)\}$ (shown in Figure 37 along with goals each action supports). For this relaxed plan, action a_2 and a_3 support only g_1 and g_3 so $GS(a_2) = \{g_1\}$ and $GS(a_3) = \{g_3\}$. The precondition of those two actions, $At(DL)$, would in turn contribute to both these goals $GS(At(DL)) = \{g_1, g_3\}$. Finally, because a_1 supports both g_2 and $At(DL)$, $GS(a_1) = GS(g_2) \cup GS(At(DL)) = \{g_1, g_2, g_3\}$.

Using the supported-goals sets, for each subset S_G of soft goals, we can identify the subset $SA(S_G)$ of actions that contribute only to the goals in S_G. If the cost of those actions exceeds the sum of utilities of goals in S_G, then we can remove S_G and $SA(S_G)$ from the relaxed plan. In our example, action a_3 is the only one that solely contributes to the achievement of g_3. Since $C_{a_3} \geq U_{g_3}$, we can remove a_3 and g_3 from consideration. The other two actions a_1, a_2 and goals g_1, g_2 all

```
Domain: Satellite
(:durative-action TURN-TO
    :parameters (?s - satellite ?d_new - direction ?d_prev - direction)
    :cost (* (slew_time ?d_prev ?d_new) (slew_energy_rate ?s))
.............
(:durative-action TAKE-IMAGE
    :parameters (?s - satellite ?d - direction ?i - instrument ?m - mode)
    :cost (* (data ?d ?m) (data_process_energy_rate ?s ?i))

Domain: ZenoTravel
(:durative-action BOARD
    :parameters (?p - person ?a - aircraft ?c - city)
    :cost (+ (* (boarding-time ?c) (labor-cost ?c)) (airport-fee ?c))
.............
(:durative-action FLY
    :parameters (?a - aircraft ?c1 ?c2 - city)
    :cost (+ (airport-aircraft-fee ?a ?c1) (+ (airport-aircraft-fee ?a ?c2)
            (* (distance ?c1 ?c2) (slowburn-maintainance-cost ?a))))
.............
(:durative-action REFUEL
    :parameters (?a - aircraft ?c - city)
    :cost (* (fuel-cost ?c) (- (capacity ?a) (fuel ?a)))
```

Figure 38. Action costs in the extended PDDL2.1 Level 3 with *cost field.*

appear beneficial. In our current implementation, we consider all subsets of goals of size 1 or 2 for possible removal. After removing non beneficial goals and actions (solely) supporting them, the cost of the remaining relaxed plan and the utility of the goals that it achieves will be used to compute the h value. Thus, in our ongoing example, $h(S) = (U(g_1) + U(g_2)) - (C(A_1) + C(A_2)) = (100 + 300) - (90 + 200) = 110$. Notice that while this approach derives a quite effective heuristic (as shown in the next section), it does not guarantee the admissibility of the final $h(S)$ value and thus the solution is not guaranteed to be optimal. Deriving an effective admissible heuristic for PSP Net Benefit problem is still remaining as a big challenge and we will pursue it in the future.

7.3. *Sapa*^{ps} : Implementation

We have implemented *Sapa*^{ps} search algorithm and heuristic estimate mechanic discussed in the previous sections. Unfortunately, no benchmarks are available for the type of problems discussed in this chapter. Given that in general, a given action cost is decided by the amount of metric resources consumed and/or the time spent by that action, we decided to generate the PSP Net Benefit problems from the set of metric temporal planning problems used in the last IPC 3. In particular, we generated the PSP versions of the problems in the ZenoTravel and Satellite domains. In this section, we will first discuss how we generate the problems and conduct the experiments.

Domain File: We modify the domain files by adding the cost field to each action description. Each action cost is represented as a mathematical formula involving metric functions that exist in the original problem descriptions and also new functions that we add to the domain description file. Figure 38 shows the cost field of several actions in the *ZenoTravel* and *Satellite* domains. The cost field utilizes the functions representing metric quantity in the original problem descriptions such as: $(slew - time\ ?d\_prev\ ?d\_new)$, $(data\ ?d\ ?m)$, $(boarding - time\ ?c)$, $(distance\ ?c1\ ?c2)$, $(capacity\ ?a)$, $(fuel\ ?a)$ and introduce new cost-related functions like: $(slew\_energy\_rate\ ?s)$, $(data\_process\_energy\_rate\ ?s\ ?i)$, $(labor - cost\ ?c)$, $(slowburn - maintainance - cost\ ?a)$, and $(fuel - cost\ ?c)$. The newly introduced functions are used to convert the temporal and resource consumption aspects of each action into a uniform plan benefit represented by the amount of money spent (e.g. ZenoTravel domain) or energy consumption (e.g. Satellite domain). In the Appendix A.3, we include the full new domain and problem files for the PSP variations of these two domains.

Problem File: For each domain, we write a Java program that parses the problem file used in the IPC2002 in each domain and generates the PSP version of that problem with cost-related function

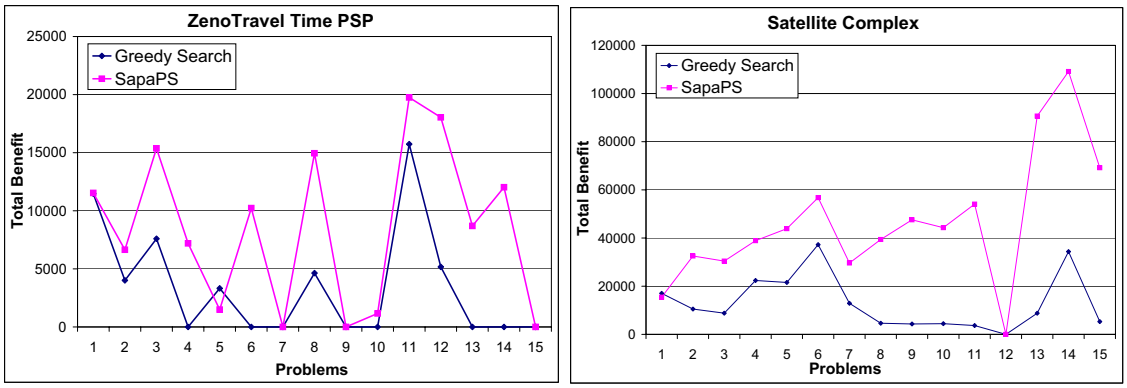


Figure 39. Comparing *Sapa*^{ps} against greedy search in the ZenoTravel

values randomly generated within appropriate upper and lower bounds. The goal utilities are also randomly generated within different upper/lower bounds. The goals of different types are either all "soft" or being designated as "hard" with a certain probability. For example, in the ZenoTravel domain, the goals related to the final location of airplanes are all "soft" while the final locations of people are assigned "hard" with the probability of 0.20 (20%). Similarly, for the Satellite domain, having images of directions are assigned "hard goal" with probability of 20% and the final pointing directions of different satellites are all assigned "soft". In addition to the goal predicates in the original problem, we also populate the goal set with additional goals. For example, if there is a person that is declared in the ZenoTravel problem but his location is not specified as one of the goals, then we will add a "soft" goal with its final location randomly chosen. Similarly, in the Satellite domain, if there is a declared direction but having its image is not one of the goals, then we also add a "soft" goal of requiring that image of that given direction is taken with one of the available mode (randomly selected). All additional goals are soft and the utilities are also randomly generated, but with lower upper/lower bounds on the utility values than the goals of the same type but declared in the original problem. Moreover, for the same type of goal (e.g. $have - image(location, mode)$) then the goal classified as "hard" has higher (doubled) upper and lower bounds, compared to the

"soft" goal of the same type. For example, if the lower and upper bounds of the soft goal of type g is $[1000 - 3000]$ then the bounds for hard goals of the same type is $[2000 - 6000]$.

Examples of the full domain and problem files for the two domains are presented in the Appendix A.3. Eventually, we want to use this approach to generate PSP versions of domains/problems used in the previous International Planning Competitions to create many more benchmarks for testing *Sapa*^{ps} and other PSP solving algorithms.

Greedy Search: To evaluate the *Sapa*^{ps} algorithm, we compare it with a greedy search strategy on the two domains discussed above. The greedy search algorithm that we implemented is called "static greedy" because it decides a static order of goals to achieve according to the decreasing order of goal utilities. Starting from the initial state, we try to first find a lowest cost plan that satisfies all hard goals. Then, we continuously pick one soft goal at a time and try to find lowest cost plan that satisfies that single goal *and* does not delete any of the achieved goals. If there is no plan found that has less cost than the utility of the goal that it achieves, then we will skip that goal and move on to the next highest utility goal. This process continues until there is no goal left.

Figure 39 shows the comparisons between the *Sapa*^{ps} 's algorithm discussed in this chapter and the greedy search algorithm discussed above for the first 15 problems of the two *ZenoTravel* (*Time* setting) and *Satellite* (*Complex* setting) domains. All results were collected using a Pentium IV 1.4GHz machine with running time limit of 1200 seconds. Both domains and problem sets are original from the third IPC, and the procedure to make the PSP variations out of them was described above. The results show that except for one problem in each domain, the anytime A* search in *Sapa*^{ps} produces plans which have higher total benefit values than the greedy search. In the ZenoTravel domain, the average improvement over problems that both approaches can find beneficial solutions is 1.8 times. Moreover, there are 5 instances for which *Sapa*^{ps} can find beneficial solutions while the greedy approach can not find any. Thus, in those problems, there seem to be

no beneficial plan that achieves a single goal but only plans that sharing actions to achieve multiple goals can be beneficial. For the *Satellite* domain, the average improvement is 6.1 times. The size of the plans in the two domains are quite big, with the largest plans found in the *Satellite* domain contain around 300 actions.

7.4. Summary and Discussion

In this chapter, we discuss *Sapa*^{ps} , a variation of the *Sapa* planner, that can handle Partial-Satisfaction Planning Net Benefit problem. In this type of problem, goals, which can be either "hard" or "soft", have different utilities and the plan quality is decided by the tradeoff between the total achieved goal utility and the total cost of actions in that plan. *Sapa*^{ps} adapts *Sapa*'s best-first search and heuristic framework and return "beneficial" solutions in an anytime fashion.

Given that partial satisfaction planning is an area where not much research have been done, our work discussed in this chapter only scratched the surface and there is a whole range of exciting problems to tackle. First, there is a variation of the PSP problem involving time-dependent goal utility for goals with deadline that was discussed by Haddawy & Hanks [38]. The other is the over-subscription planning problem where there are constraints on the amount of resource, or money available. This is a variation of PSP Net Benefit that exists in many domains (because it is unrealistic to assume that the available amount of money or resource is infinite). Even though the *Satellite* problems that we tested in Section 7.3 already have this type of constraint, we have not investigated techniques that specifically deal with them.

Effective heuristic and good state management strategies are important issues in the anytime best-first search framework of *Sapa*^{ps} (e.g. which explored states to keep and which to discard in the anytime search framework). For the heuristic part, we want to test the other effective heuristics such as the one introduced by Smith in the orienting planner [85] or the heuristics using residual

cost in *AltAlt*^{ps} [88]. The first heuristic seems to be particularly effective for *transportation*-style planning domains. To be able to use this type of heuristic in a general domain-independent planner like *Sapa*^{ps} , besides extending the heuristic, the other possible option is using automatic domain analysis tool such as TIM [31] to automatically identify problems involving transportation generic type. Upon discovery, heuristics specialized in this type of problem such as solving the orienting problem can be used. This approach has shown to be successful in domain-independent planner such as Hybrid-STAN [30].

The current-heuristic framework in *Sapa*^{ps} for solving PSP problem is also over-dependent on the cost aspect, even though the goal utility is as important as the action cost in deciding the overall benefit value of the final plan (and the relaxed plan when evaluating heuristic values). We plan on investigating backward utility propagation similar to the approach of building the *utility table* discussed in [17]. Specifically, we are investigating two approaches of utility propagation either: (i) *offline*: one-time as a pre-processing phase; or (ii) *oneline*: when extracting the relaxed plan for each state and using only actions and goals involved in the relaxed plan. The backward propagated utility information can then be combined with the forward-propagated cost functions to give better overall benefit estimation.

The other interesting problem that we want to tackle is the scenario where there exist dependencies between different action cost or goal utilities. For example, the cost to buy two (left and right) shoes at a given store may be much smaller than the cost to buy each of them separately. Moreover, the utility of having a pair of shoes is much higher than having each of them separately. The current framework of removing “unbeneficial” goals and associated actions in *Sapa*^{ps} can handle the scenarios where goal utilities are pair-wise dependent. However, of bigger subsets of goals, then other techniques need to be investigated. Besides the inter-dependency relations between different goals, there are other types of goals that may allow partial satisfaction for each individual of

them. This is mostly only relevant to metric goals where satisfying a portion of them gives partial utility value. For example, getting half of the shipment still give some utility more than not getting anything (but may not be half the utility value of getting the whole shipment). To this end, we are implementing the “possible metric value” propagation framework over the planning graph building process and hope that it would give better estimation on what are the estimated incurring cost to achieve each level of some (goal-related) metric quantity.

CHAPTER 8

Related Work and Discussion

There are various works in planning directly related to the main contributions of this dissertation. These include techniques to handle metric temporal constraints, planning graph based heuristics, forward state space search management, position-constrained and order-constrained plan conversion, and partial-satisfaction planning. Even though we have cited many of them in previous parts of the dissertation, in this chapter we will give a more thorough discussion on their relations with *Sapa* and its components.

8.1. Metric Temporal Planning

Although there have been several recent domain-independent heuristic planners for temporal domains, most of them have been aimed at makespan optimization, ignoring the cost aspects. For example, both TGP [81] as well as TP4 [39] focus on makespan optimization and ignore the cost aspects of the plan. As we have argued in this paper, ultimately, metric temporal planners need to deal with objective functions that are based on both makespan and cost. Nevertheless, the makespan estimates in both of these planners are better than *Sapa* because they both reason about mutex relations between actions and facts. *Sapa* employs the forward search algorithm and there is no good way of avoiding the planning graph rebuild procedure for each generated search state. Until

now, keeping the cost of building the planning graph minimal by removing the mutex propagation process seems to be a good strategy (with the price of sacrifycing the makespan-related heuristic quality). Currently, we have an option in *Sapa* to use the mutex relations to order the actions in the extracted relaxed plan and thus improve the heuristic quality. However, the extracted relaxed-plan in itself may not contains actions that collectively make a good makespan estimation of the real plan. To improve the makespan estimation, we are currently looking at using only the static mutex in the graphplan building process and skip the dynamic mutex propagation. However, this approach still requires reasoning about mutexes explicitly; therefore, we believe that a better approach may be to first pre-process the binary representation in PDDL and convert it into k-ary representation (SAS+) using the tool provided by Helmert [40]. This would allow implicit reasoning about mutexes when building the graph and can give better heuristics without necessarily increasing the planning graph building cost.

One recent research effort that recognizes the multi-objective nature of planning is the MO-GRT system [80]. On one hand, the MO-GRT approach is more general than ours in the sense that it deals with a set of non-combinable quality metrics. The MO-GRT approach however treats time similar to other consumable resources (with infinite capacity). Temporal constraints on the planning problems (such as when an effect should occur during the course of action), goal deadlines, or concurrency are *ignored* in order to scale down the problem to the classical planning assumptions. Metric-FF [43] and MIPS [24] are two other forward state space planners that can handle resource constraints (both of them generate sequential plans). MIPS handles durative actions by putting in the action durations and post-processing the sequential p.c plans. Our state-space search for temporal planning algorithm is inspired by the TLPlan [1] in which concurrent durative actions are allowed in the state representation. Unlike *Sapa*, TLPlan relies on domain-control knowledge written in temporal logic to guide its searches. While the approach of simplifying or ignoring

some of the temporal constraints while conducting search in MIPS and MO-GRT has advantage of managing simpler search states and the heuristic estimation routine (and thus can speed up the planner and reduce memory consumption), the ignorance of temporal aspects of actions can lead to: (i) lower heuristic quality for objective functions related to time; and (ii) the inability to handle some types of temporal constraints. For example, it is not clear how the classical-like graphplan can help derive time-related heuristic estimate. Moreover, it's not clear how an approach of building a sequential plan and then post-process to produce concurrent plan later can handle domains such as the *Burn-Match* example in the PDDL2.1 manual [28] where actions are forced to execute in parallel to achieve the goals. This later problem did not show up in the domains used in the IPC-2002. However, we believe that for a more complicated temporal problems that require those type of concurrency-forcing constraints and beyond, it is necessary to employ the state representation similar to TLPlan and *Sapa.*

Multi-Pegg [101] is another recent planner that considers cost-time tradeoffs in plan generation. Multi-Pegg is based on the Graphplan approach, and focuses on classical planning problems with non-uniform cost actions. Multi-Pegg has a unique ability of searching for all possible plans within a given level limit. This approach is particular useful for the multi-objective problems where there are multiple non-combinable dimensions in plan quality metrics and thus a pareto set of solution is needed[1]. *Sapa* currently uses a single combined objective function and is not efficiently engineered for this multi-dimension optimization problem. However, $Sapa^{ps}$ is able to find better quality plans in an anytime fashion and we think that extending this algorithm with some modification in node judgment (e.g. beneficial node, termination node) is a good direction to extend *Sapa* to handle the pareto-set optimization.

Utilizing the local search framework, ASPEN [14] is another planner that recognizes the

[1]Nevertheless, like all Graphplan-based planners, the overall plan quality is limited by the number of "levels" in the planning graph and thus the global best solution is not guaranteed.

multi-attribute nature of plan quality. ASPEN advocates an iterative repair approach for planning, that assumes the availability of a variety of hand-coded plan repair strategies and their characterization in terms of their effects on the various dimensions of plan quality. Like ASPEN, LPG [33] is another planner that employs local search techniques over the action-graph. Unlike ASPEN, LPG considers domain independent repair strategies that involve planning graph-based modifications. While the local search strategy seems to be very flexible in dealing with different objective functions and is a good strategy for multi-objective search, some of its drawbacks are the difficulties in finding global optimum and discovering the insolvability of the problem.

Although we evaluated our cost-sensitive heuristics in the context of *Sapa*, a forward chaining planner, the heuristics themselves can also be used in other types of planning algorithms. It is possible due to the fact that directional searches (forward/backward) all need to evaluate the distances between an initial state and a set of temporal goals. In classical planning, works in [70, 71] and [98] have shown that heuristics derived from the classical planning graph can help guide backward state space and partial order classical planners effectively. Besides backward search planners, graphplan-based planners such as TGP can also be made cost-sensitive by propagating the cost functions as part of planning graph expansion phase. These cost functions can then be used as a basis for variable and value ordering heuristics to guide its backward branch-and-bound search. Given that a similar approach in graphplan-based search for classical planning has been shown to be successful in [51], similar approach in metric temporal planning can be promising. Different from the current strategy in *Sapa*, for backward search and graphplan-based planners, because we only need to build the planning graph once, employing additional (most time-consuming) techniques to help improving the information encoded in the planning graph may be more beneficial. Examples are the more aggressive use of the mutex information and better cost-propagation techniques (compared to the simple assumption in the *max* or *sum* rules).

In the context of other approaches that use planning graphs as the basis for deriving heuristic estimates such as Graphplan-HSP [51], AltAlt [70], RePOP [71], and FF [41] [2], our contribution can be seen as providing a way to track cost as a function of time on planning graphs. An interesting observation is that cost propagation is in some ways inherently more complex than makespan propagation. For example, once a set of literals enter the planning graph (and are not mutually exclusive), the estimate of the makespan of the shortest plan for achieving them does not change as we continue to expand the planning graph. In contrast, the estimate of the cost of the cheapest plan for achieving them can change until the planning graph levels off. This is why we needed to carefully consider the effect of different criteria for stopping the expansion of the planning graph on the accuracy of the cost estimates (Section 4.3). Another interesting point is that within classical planning, there was often a confusion between the notions of cost and makespan. For example, the "length of a plan in terms of number of actions" can either be seen as a cost measure (if we assume that actions have unit costs), or a makespan measure (if we assume that the actions have unit durations). These notions get teased apart naturally in metric temporal domains.

In this dissertation, we concentrated on developing heuristics that can be sensitive to multiple dimensions of plan quality (specifically, makespan and cost). An orthogonal issue in planning with multiple criteria is how the various dimensions of plan quality should be combined during optimization. The particular approach we adopted in our empirical evaluation–namely, considering a linear combination of cost and time–is by no means the only reasonable way. Other approaches involve non-linear combinations of the quality criteria, as well as "tiered" objective functions (e.g. rank plans in terms of makespan, breaking ties using cost). A related issue is how to help the user

[2] Note that there are two different ways of extracting the heuristic values from the planning graph. The first approach used in [70] and [71] estimate heuristic using the "level" information at which goals are achievable and an approach in FF that extract the relaxed plan. The heuristics based on the *level* information in [70, 71] can not directly be extended to use in temporal planning due to the fact that they assume all goals appear at the same time/level. The second approach of extracting the relaxed plan is more flexible and does not make such an assumption. Moreover, the relaxed-plan based heuristics work with an actual set of actions and thus is open for various techniques of adjustment for heuristic improvement (e.g. mutex, add/remove actions).

decide the "weights" or "tiers" of the different criteria. Often the users may not be able to articulate their preferences between the various quality dimensions in terms of precise weights. A more standard way out of this dilemma involves generating all non-dominated or Pareto-optimal plans[3], and presenting them to the user. Unfortunately, often the set of non-dominated plans can be exponential [73]. The users are then expected to pick the plan that is most palatable to them. Unfortunately, the users may not actually be able to judge the relative desirability of plans when the problems are complex and the plans are long. Thus, a more practical approach may involve resorting to other indirect methods such as preference elicitation techniques [13, 92].

8.2. Partialization

The complementary tradeoffs provided by the p.c. and o.c. plans have been recognized in classical planning. One of the earliest efforts in attempt to improve the temporal flexibility of plans was the work by Fade and Regnier [26] who discussed an approach for removing redundant orderings from the plans generated by STRIPS system. Later work by Mooney [66] and Kambhampati & Kedar [49]characterized this partialization process as one of explanation-based order generalization. These works assume STRIPS representation with-non durative action, our approach works for metric temporal plans where there are substantially more complicated set of constraints and a large set of useful objective functions for the partialization process. Moreover, the work in [90] and [49] can be seen as providing a greedy value ordering strategy over the partialization encoding for classical plans. In [90], the value ordering for each S_A^p is set to the *latest* action A' that gives p and is positioned before A in the original t.o plan. In [49], the value ordering is improved by choosing the *earliest* consistent supporter ordered according to the original t.o plan instead of the *latest* one. Compare with the previous approach, the new ordering can lead to equal or better

[3] A plan P is said to be dominated by P' if the quality of P' is strictly superior to that of P in at least one dimension, and is better or equal in all other dimensions [16, 73].

quality plan in terms of makespan if applied to the same sequential plan. Regardless of the variable ordering, the greedy value ordering in the two approaches discussed above will lead to linear-time backtrack-free algorithms to find a consistent o.c. plan. The orderings are based on the total ordering between actions in the original p.c. plan and is insensitive to any objective function and thus do not guarantee the solution is optimal in term of any objective function discussed in the literature. Nevertheless, while the greedy strategy in [49] is geared toward the optimization criterion of minimizing the parallel *level* of the final o.c plan, our greedy technique is aimed toward minimizing plan with smaller *makespan*. Unlike the strategies we presented in Sections 6.3, all previous value ordering strategies in greedy searches assume the starting p.c plan is sequential and actions are instantaneous. Therefore, there is only one ordering between a given pair of action while there can be multiple orderings representing different temporal relations between a given pair of actions in our approaches. The recent work by Winner & Veloso [96] extended the de-ordering techniques in [90] to planning problems with conditional effects. This is done by building the *need tree* to capture the possible supporting list. The final plan is built greedily using the need tree and also does not guarantee any optimality. More recent de-ordering techniques are the post-processing routine used in the MIPS planner [25] and the "push-up" techniques used in the AltAltP planner [72] to produce parallel plans. There is not much difference between the post-processing approach in MIPS and the greedy partialization routine in *Sapa* except that MIPS assumes a sequential plan while *Sapa* produces parallel plans. In AltAltP, the "push-up" technique is used "online" instead of "off-line" and is invoked whenever a new action is added to the partial plan. Because it's done online, this can help improve the heuristic estimation regarding the makespan value and thus improve the parallelism of the final plan. In *Sapa,* even though the partial plan is parallel and thus gives an adequate g value, the experimental results in Section 6.5 show that the starting time of those parallel actions can be pushed earlier to give a better indication of the makespan of the partial plan (g value). Therefore,

variation of the "push-up" technique in AltAltP can potentially used in *Sapa* to improve this part of the heuristic estimate.

Backstrom [2] categorized approaches for partialization into "de-ordering" approaches and "re-ordering" approaches. Both of them assume the seed plan to be sequential. The order generalization algorithms discussed above fall under the de-ordering category. He was also the first to point out the NP-hardness of maximal partialization with the objective function of minimizing the number of orderings and to characterize the previous algorithms as greedy approaches. The greedy algorithm discussed in Section 6.3, while working for both sequential and parallel plans, can be categorized as "de-ordering" according to Backstrom's [2] criteria because it makes use of the temporal orderings between actions in the seed p.c plan. Setting up the CSOP encoding (Section 6.2) and solving it to optimality (Section 6.4) encompasses both de-ordering and re-ordering partialization– based on whether or not we include the optional constraints to make the orderings on P_{oc} consistent with P_{pc}. However, while the "de-ordering" and "re-ordering" algorithms are only discussed for classical planning problems, both greedy and optimal techniques discussed in this thesis work for both the sequential and parallel plans and for a more complex problems involving both temporal and metric resource constraints. Moreover, while only one polynomial algorithm for the easiest class of *minimal de-ordering* is presented in [2], we provide several algorithms to build the o.c. plans with different criteria. It's also interesting to note that while there are several implemented variations of the greedy de-ordering technique, there was no implementation of the re-ordering problem. To our knowledge, we are the first to have actually implemented an optimal partialization technique that encompasses the re-ordering scenario.

It is interesting to note that our encoding for partialization is closely related to the so-called "causal encodings" [52]. Unlike causal encodings, which need to consider supporting a precondition or goal with every possible action in the action library, the partialization encodings only need

to consider the actions that are present in P_{pc}. In this sense, they are similar to the encodings for replanning and plan reuse described in [65]. Also, unlike causal encodings, the encodings for partialization demand optimizing rather than satisficing solutions. Finally, in contrast to our encodings for partialization which specifically handle metric temporal plans, causal encodings in [52] are limited to classical domains. In the same line of work, the recent work by Vidal & Geffner [91] captures the causal relationship of actions in temporal planning. This CSP encoding when solved will return an optimal makespan *canonical plan* where each ground action instance can appear at most once. This encoding shows a lot of similarity with our CSOP encoding discussed in Section 6.2. They are mostly different in the set of actions involved in the encoding and the way the CSOP encoding is solved. While we convert it into the MILP encoding and solve it to optimality using an off-the-shelf solver, Vidal & Geffer [91] use an CSOP branch and bound solver with fine-tuned variable and value orderings for this particular type of encoding. Moreover, they only capture temporal constraints and cannot handle metric constraints.

In scheduling, building the CSP encoding to capture the orderings between tasks is a common approach [11, 12]. However, unlike planning where the causal relations between actions are the most critical, most of the constraints in scheduling capture only the resource contention ordering relations. Those constraints are in some sense similar to the resource mutex constraints discussed in Section 6.2. Nevertheless, this problem has been more thoroughly investigated in scheduling so it would be interesting to see how they can be used in the partialization problem in planning to help give better encoding for resource-related constraints.

8.3. Partial Satisfaction (Over-Subscription) Problem

As we mentioned earlier, there has been very little work on PSP in planning. One possible exception is the PYRRHUS planning system [95] which considers an interesting variant of the

partial satisfaction planning problem. In PYRRHUS, the quality of the plans is measured by the utilities of the goals and the amount of resources consumed. Utilities of goals decrease if they are achieved later than the goals' deadlines. Unlike the PSP problem discussed in this dissertation, all the logical goals still need to be achieved by PYRRHUS for the plan to be valid. Haddawy & Hanks [38] extended the work in [95] to a more expressive goal utility model where partial satisfaction of individual goals is discussed. Moreover, besides achievable goals with deadlines, handling of goals of maintainance is also discussed. While independence is assumed for different goals' utilities and also the attributes in each goal's utility model, it would be interesting to extend the PSP model to consider utility dependency between the set of individual goals (e.g. utility of the left and right shoes). While the theoretical discussions in PYRRHUS concern many important issues in partial satisfaction planning problems, the implementation is domain dependent and do not seem to be able to scale up well. We are extending the domain independent technique in *Sapa*^{ps} to handle several issues discussed in PYRRHUS, especially the time-dependent goal utility issue.

The first domain-independent heuristic planner that solves a partial satisfaction planning problem is the Maxp planner, which is a variation of TP4 [39]. Given a time limit, Maxp finds the maximal (biggest size) subset of goals that can be achieved. This is a (stripped down) variation of the PSP Net Benefit where goal utilities are much higher than action costs and there exist a planner's running time limit. More recently, Smith [84] motivated the over-subscription problems in terms of their applicability to the NASA planning problems. On one hand, it is different from the PSP Net Benefit problem described in Chapter 7, the motivated problems belong to a variation where not all the goals can be achieved due to the limitation on resources. On the other hand, the randomly generated *Satellite* problems discussed in *Sapa*^{ps} 's empirical result section (Section 7.3) also have resource limitation constraints (each satellite has limited data-storage) and thus in some sense encompass the resource-limited PSP variation. Smith ([85]) also proposed a planner for over-

subscription planning problems of this type in which the solution of the abstracted planning problem is used heuristically to select the subset of goals and the orders to achieve them. The abstract planning problem is built by propagating the cost on the planning graph and constructing the *orienteering* (a variation of prize-collecting traveling salesman) problem. The subset of goals and their orderings are then found from solving this orienting problem and are used to guide a POCL planner. By heuristically selecting a subset of goals up front and commit to satisfy all goals in this set while neglecting the other, this approach is similar to the $AltAlt^{ps}$ planner discussed in [89]. The main difference between them is that the orienteering problem needs to be constructed using domain-knowledge for different planning domains while $AltAlt^{ps}$ relies on the domain-independent heuristic based on cost propagation on the planning graph. The other difference is that solving the orienteering problems also provides a partial order between goals. This set of orderings can help significantly simplify the planning task given to the base POCL planner. While both orienteering planner [85] and $AltAlt^{ps}$ [89] heuristically select the subset of goals up-front, $Sapa^{ps}$ does not make such commitment and thus it can potentially correct the set of beneficial goals as it searches deeper and goes closer to the goals. Nevertheless, the sophisticated heuristic estimation approach used in those two planners can be used in *Sapa* to evaluate and rank each search node in the queue. In particular, the orienting solution can be a very good heuristic estimate in "transportation" problems, which is the most common type among planning benchmarks. In [85], Smith discussed the problem where solution for the orienting problem in itself does not give a good heuristic estimate and thus it is necessary to solve it repeatedly. It would be better then to employ the solving of the orienting problem as a heuristic routine in $Sapa^{ps}$'s current anytime A* search to avoid being over-dependent on the quality of a single solution to the orienting problem.

Besides the heuristic search, there are several other approaches that can solve the PSP Net Benefit problems to optimal. In [89], van den Briel et. al. introduced *OptiPlan* planner, which

encodes the k-level planning graph using Mixed Integer Linear Programming (MILP) encoding. The PSP Net Benefit specifications (action cost and goal utility) are represented by suitable objective function. While this approach can find optimal solution with upper-bound constraint on the total parallel length of the final plan, there is no easy way to extend it to find the global optimal solution for the PSP Net Benefit problem. Regarding this issue, it seems that encoding the PSP problem as deterministic Markov Decision Process (MDP) [8] can help finding optimal solutions for PSP Net Benefit problems. Nevertheless, given the scaling up problem of MDP representation (compared to heuristic search), it is not clear how this approach compares to the performance of *Sapa*^{ps} using admissible heuristics.

Over-subscription issues have received relatively more attention in the scheduling community. Earlier work in scheduling over-subscription used greedy approaches, in which tasks of higher priorities are scheduled first [56, 78]. More recent efforts have used stochastic greedy search algorithms on constraint-based intervals [32], genetic algorithms [34], and iterative repairing technique [58] to solve this problem more effectively. Specifically, the last two approaches try to find better quality schedules after the first consistent schedule is found. Again, stochastic approach has advantage of easier adaptation to a new objective function, but also has a drawback of not guaranteeing the global optimality.

CHAPTER 9

Conclusion and Future Work

9.1. Summary

The work presented in this dissertation seeks the development of a scalable domain-independent planner that can handle a variety of metric and temporal constraints. This quest for an effective metric temporal planner is motivated from the practical necessity: while many real-world applications involve various temporal constraints and require the handling of continuous variables, previous metric temporal planners mostly relied on domain-control knowledge to scale up.

Sapa, which is the centerpiece of this dissertation, is a domain-independent heuristic forward chaining planner that can handle durative actions, metric resource constraints, and deadline goals. It extends many recent advances in classical planning such as reachability analysis and heuristic estimates based on relaxed planning assumption, and it is also designed to be capable of handling the multi-objective nature of the metric temporal planning. The three main interrelated contributions to metric temporal planning of this dissertation are:

- A temporal planning-graph based method for deriving multi-objective heuristics that are sensitive to both cost and makespan and an easy way of adjusting the heuristic estimates to take the metric resource limitations into account. The heuristics then can be used to effectively guide the forward state-space temporal planner.

- Greedy/optimal partialization routines that can be used to post-process the position-constrained plans to improve their execution flexibility.

- The adaptation of the search algorithm and heuristic in *Sapa* to solve Partial Satisfaction Planning problems where, goals, either "hard" or "soft", have different utilities and the plan quality is measured by the tradeoff between the total achieved goal utility and total cost of actions in the plan.

We described the technical details of the search algorithm and the three main contributions listed above. We also presented the empirical evaluations of the current implementation of *Sapa*, the partialization software, and the *Sapa*^{ps} planner.

9.2. Future Work

While the current implementations of *Sapa* and *Sapa*^{ps} planners perform well on the highest expressive level for metric temporal planning in the IPC3, there are still many places where improvements can be made. In Section 3.3, 4.6, 6.6, and 7.4, we have discussed the potential extensions to different aspects of the planners such as expressiveness or heuristic quality. The most important topics are: (i) supporting more expressive metric temporal constraints such as continuous change and exogenous event; (ii) supporting more complicated formulas for action cost and goal utility (e.g. action costs and goal utilities that change according to action-execution and goal-achievement time); (iii) improving heuristic estimate for multi-objective search.

Nonetheless, metric temporal constraints, while important, are not always the only constraints involved in the real-world applications for planning. There are other important issues such as probability, contingency, and sensing. Even though there have been a lot of work in planning to deal with them, most of them concern the scenarios where no metric or temporal constraints

are involved. Thus, in the future, we plan to investigate effective ways to search for high quality plan in the presence of both uncertainty and metric temporal constraints. Given that forward state space search has shown to be a good option for conformant and contingent planning, combining the techniques in forward state-space metric temporal planning and contingent planning is a promising direction. For probabilistic setting, recent work by Younes & Simmons [100] provides a framework for generating probabilistic concurrent plan (policy) with continous time by simplifying each step to a normal PDDL2.1 durative actions. It would be interesting to see how we can adapt the current forward search algorithm into this scenario where concurrent temporal plan is required, but the final plan should still have a high probability of success.

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APPENDIX A

Planning Domain and Problem Representation

Following are some examples in the PDDL planning language, the files are taken from the IPC3's repository. The input of planners consists of two files: (i) the domain file contains object type declaration and action schema; and (ii) the problem instance file contains actual object declarations. We present the sample domain and problem files in the PDDL1.0 format for classical planning, PDDL2.1 Level 3 format for representing durative actions and metric resources, and the extended format for representing action cost and goal utility in the PSP Net Benefit problems.

We choose two domains: *ZenoTravel* that represents the simple travelling domain that is close to the representative example used through out this dissertation and the *Satellite* domain that is inspired by a NASA application. For the PDDL1.0 and PDDL2.1 representations, we only present the domain and problem files for the *Satellite* domain. For the extended format of PDDL2.1 Level 3 for partial satisfaction planning problems, we present the domain and problem files for both domains (this representation subsumes the PDDL2.1 Level 3). The repository for domain and problem files of these two domains and other benchmarks in all three levels of PDDL2.1 description language can be found at the IPC3's website (http://planning.cis.strath.ac.uk/competition/).

A.1. STRIPS Representation in PDDL1.0 Planning Language

A.1.1. Domain Specification: *Satellite*.

```
(define (domain satellite)
  (:requirements :strips :equality :typing)
  (:types satellite direction instrument mode)
  (:predicates
       (on_board ?i - instrument ?s - satellite)
       (supports ?i - instrument ?m - mode)
       (pointing ?s - satellite ?d - direction)
```

```
     (power_avail ?s - satellite)
     (power_on ?i - instrument)
     (calibrated ?i - instrument)
     (have_image ?d - direction ?m - mode)
     (calibration_target ?i - instrument ?d - direction))

(:action turn_to
 :parameters (?s - satellite ?d_new - direction
              ?d_prev - direction)
 :precondition (and (pointing ?s ?d_prev)
                 (not (= ?d_new ?d_prev)))
 :effect (and  (pointing ?s ?d_new)
               (not (pointing ?s ?d_prev)))
)

(:action switch_on
 :parameters (?i - instrument ?s - satellite)
 :precondition (and (on_board ?i ?s) (power_avail ?s))
 :effect (and (power_on ?i) (not (calibrated ?i))
              (not (power_avail ?s))
)

(:action switch_off
 :parameters (?i - instrument ?s - satellite)
```

```
   :precondition (and (on_board ?i ?s) (power_on ?i))
   :effect (and (not (power_on ?i)) (power_avail ?s))
  )

  (:action calibrate
   :parameters (?s - satellite ?i - instrument ?d - direction)
   :precondition (and (on_board ?i ?s) (pointing ?s ?d)
      (calibration_target ?i ?d) (power_on ?i))
   :effect (calibrated ?i)
  )

  (:action take_image
   :parameters (?s - satellite ?d - direction
                ?i - instrument ?m - mode)
   :precondition (and (calibrated ?i) (on_board ?i ?s)
                      (supports ?i ?m) (power_on ?i)
                      (pointing ?s ?d) (power_on ?i))
   :effect (have_image ?d ?m)
  )
)
```

A.1.2. Problem Specification: *Satellite*.

```
(define (problem strips-sat-x-1)
(:domain satellite)
```

```
(:objects
satellite0 satellite1 - satellite
instrument0 instrument1 instrument2 - instrument
infrared0 infrared1 thermograph2 - mode
GroundStation1 Star0 Star2 Planet3 Star4
Planet5 Star6 Star7 Phenomenon8 Phenomenon9 - direction
)
(:init
(supports instrument0 thermograph2)
(supports instrument0 infrared0)
(calibration_target instrument0 Star0)
(on_board instrument0 satellite0)
(power_avail satellite0)
(pointing satellite0 Star6)
(supports instrument1 infrared0)
(supports instrument1 thermograph2)
(supports instrument1 infrared1)
(calibration_target instrument1 Star2)
(supports instrument2 thermograph2)
(supports instrument2 infrared1)
(calibration_target instrument2 Star2)
(on_board instrument1 satellite1)
(on_board instrument2 satellite1)
(power_avail satellite1)
```

```
(pointing satellite1 Star0)
)
(:goal (and
(pointing satellite1 Planet5)
(have_image Planet3 infrared1)
(have_image Star4 infrared1)
(have_image Planet5 thermograph2)
(have_image Star6 infrared1)
(have_image Star7 infrared0)
(have_image Phenomenon8 thermograph2)
(have_image Phenomenon9 infrared0))
)
)
```

A.2. Metric Temporal Planning with PDDL2.1 Planning Language

A.2.1. Domain Specification: *Satellite*.

```
(define (domain satellite)
 (:requirements :strips :typing :fluents :durative-actions)
 (:types satellite direction instrument mode)
 (:predicates
       (on_board ?i - instrument ?s - satellite)
       (supports ?i - instrument ?m - mode)
       (pointing ?s - satellite ?d - direction)
       (power_avail ?s - satellite)
```

```
     (power_on ?i - instrument)
     (calibrated ?i - instrument)
     (have_image ?d - direction ?m - mode)
     (calibration_target ?i - instrument ?d - direction))

(:functions (slew_time ?a ?b - direction)
     (calibration_time ?a - instrument ?d - direction)
     (data_capacity ?s - satellite)
     (data ?d - direction ?m - mode)
     (data-stored)
)

(:durative-action turn_to
 :parameters (?s - satellite ?d_new - direction
              ?d_prev - direction)
 :duration (= ?duration (slew_time ?d_prev ?d_new))
 :condition (and (at start (pointing ?s ?d_prev))
                 (over all (not (= ?d_new ?d_prev))))
 :effect (and  (at end (pointing ?s ?d_new))
               (at start (not (pointing ?s ?d_prev))))
)

(:durative-action switch_on
 :parameters (?i - instrument ?s - satellite)
```

```
 :duration (= ?duration 2)
 :condition (and (over all (on_board ?i ?s))
                 (at start (power_avail ?s)))
 :effect (and (at end (power_on ?i))
              (at start (not (calibrated ?i)))
              (at start (not (power_avail ?s))))
)

(:durative-action switch_off
 :parameters (?i - instrument ?s - satellite)
 :duration (= ?duration 1)
 :condition (and (over all (on_board ?i ?s))
                 (at start (power_on ?i)))
 :effect (and (at start (not (power_on ?i)))
              (at end (power_avail ?s)))
)

(:durative-action calibrate
 :parameters (?s - satellite ?i - instrument ?d - direction)
 :duration (= ?duration (calibration_time ?i ?d))
 :condition (and (over all (on_board ?i ?s))
 (over all (calibration_target ?i ?d))
                 (at start (pointing ?s ?d))
                 (over all (power_on ?i))
```

```
                    (at end (power_on ?i)))
    :effect (at end (calibrated ?i))
  )

  (:durative-action take_image
   :parameters (?s - satellite ?d - direction
                ?i - instrument ?m - mode)
   :duration (= ?duration 7)
   :condition (and (over all (calibrated ?i))
                   (over all (on_board ?i ?s))
                   (over all (supports ?i ?m) )
                   (over all (power_on ?i))
                   (over all (pointing ?s ?d))
                   (at end (power_on ?i))
                   (at start (>= (data_capacity ?s) (data ?d ?m))))
   :effect (and (at start (decrease (data_capacity ?s)
                                    (data ?d ?m)))
                (at end (have_image ?d ?m))
                (at end (increase (data-stored) (data ?d ?m))))
  )
)
```

A.2.2. Problem Specification: *Satellite*.

```
(define (problem strips-sat-x-1)
```

```
(:domain satellite)
(:objects
satellite0 satellite1 - satellite
instrument0 instrument1 instrument2 instrument3 - instrument
image1 infrared0 spectrograph2 - mode
Star1 Star2 Star0 Star3 Star4
Phenomenon5 Phenomenon6 Phenomenon7 - direction
)

(:init
(supports instrument0 spectrograph2)
(supports instrument0 infrared0)
(calibration_target instrument0 Star1)
(= (calibration_time instrument0 Star1) 37.3)
(supports instrument1 image1)
(calibration_target instrument1 Star2)
(= (calibration_time instrument1 Star2) 15.9)
(supports instrument2 infrared0)
(supports instrument2 image1)
(calibration_target instrument2 Star0)
(= (calibration_time instrument2 Star0) 38.1)
(on_board instrument0 satellite0)
(on_board instrument1 satellite0)
(on_board instrument2 satellite0)
```

```
(power_avail satellite0)
(pointing satellite0 Star4)
(= (data_capacity satellite0) 1000)
(supports instrument3 spectrograph2)
(supports instrument3 infrared0)
(supports instrument3 image1)
(calibration_target instrument3 Star0)
(= (calibration_time instrument3 Star0) 16.9)
(on_board instrument3 satellite1)
(power_avail satellite1)
(pointing satellite1 Star0)
(= (data_capacity satellite1) 1000)
(= (data Star3 image1) 208)
(= (data Star4 image1) 156)
(= (data Phenomenon5 image1) 205)
(= (data Phenomenon6 image1) 247)
(= (data Phenomenon7 image1) 122)
(= (data Star3 infrared0) 164)
(= (data Star4 infrared0) 196)
(= (data Phenomenon5 infrared0) 95)
(= (data Phenomenon6 infrared0) 67)
(= (data Phenomenon7 infrared0) 248)
(= (data Star3 spectrograph2) 125)
(= (data Star4 spectrograph2) 6)
```

```
(= (data Phenomenon5 spectrograph2) 44)
(= (data Phenomenon6 spectrograph2) 222)
(= (data Phenomenon7 spectrograph2) 78)
(= (slew_time Star1 Star0) 34.35)
(= (slew_time Star0 Star1) 34.35)
(= (slew_time Star2 Star0) 8.768)
(= (slew_time Star0 Star2) 8.768)
(= (slew_time Star2 Star1) 18.57)
(= (slew_time Star1 Star2) 18.57)
(= (slew_time Star3 Star0) 25.66)
(= (slew_time Star0 Star3) 25.66)
(= (slew_time Star3 Star1) 25.96)
(= (slew_time Star1 Star3) 25.96)
(= (slew_time Star3 Star2) 17.99)
(= (slew_time Star2 Star3) 17.99)
(= (slew_time Star4 Star0) 71.99)
(= (slew_time Star0 Star4) 71.99)
(= (slew_time Star4 Star1) 1.526)
(= (slew_time Star1 Star4) 1.526)
(= (slew_time Star4 Star2) 35.34)
(= (slew_time Star2 Star4) 35.34)
(= (slew_time Star4 Star3) 49.61)
(= (slew_time Star3 Star4) 49.61)
(= (slew_time Phenomenon5 Star0) 67.92)
```

```
(= (slew_time Star0 Phenomenon5) 67.92)
(= (slew_time Phenomenon5 Star1) 4.095)
(= (slew_time Star1 Phenomenon5) 4.095)
(= (slew_time Phenomenon5 Star2) 30.24)
(= (slew_time Star2 Phenomenon5) 30.24)
(= (slew_time Phenomenon5 Star3) 7.589)
(= (slew_time Star3 Phenomenon5) 7.589)
(= (slew_time Phenomenon5 Star4) 0.5297)
(= (slew_time Star4 Phenomenon5) 0.5297)
(= (slew_time Phenomenon6 Star0) 77.1)
(= (slew_time Star0 Phenomenon6) 77.1)
(= (slew_time Phenomenon6 Star1) 47.3)
(= (slew_time Star1 Phenomenon6) 47.3)
(= (slew_time Phenomenon6 Star2) 64.11)
(= (slew_time Star2 Phenomenon6) 64.11)
(= (slew_time Phenomenon6 Star3) 51.56)
(= (slew_time Star3 Phenomenon6) 51.56)
(= (slew_time Phenomenon6 Star4) 56.36)
(= (slew_time Star4 Phenomenon6) 56.36)
(= (slew_time Phenomenon6 Phenomenon5) 67.57)
(= (slew_time Phenomenon5 Phenomenon6) 67.57)
(= (slew_time Phenomenon7 Star0) 9.943)
(= (slew_time Star0 Phenomenon7) 9.943)
(= (slew_time Phenomenon7 Star1) 13.3)
```

```
(= (slew_time Star1 Phenomenon7) 13.3)
(= (slew_time Phenomenon7 Star2) 60.53)
(= (slew_time Star2 Phenomenon7) 60.53)
(= (slew_time Phenomenon7 Star3) 53.93)
(= (slew_time Star3 Phenomenon7) 53.93)
(= (slew_time Phenomenon7 Star4) 67.87)
(= (slew_time Star4 Phenomenon7) 67.87)
(= (slew_time Phenomenon7 Phenomenon5) 43.97)
(= (slew_time Phenomenon5 Phenomenon7) 43.97)
(= (slew_time Phenomenon7 Phenomenon6) 32.34)
(= (slew_time Phenomenon6 Phenomenon7) 32.34)
(= (data-stored) 0)
)

(:goal (and
(pointing satellite0 Phenomenon5)
(have_image Star3 infrared0)
(have_image Star4 spectrograph2)
(have_image Phenomenon5 spectrograph2)
(have_image Phenomenon7 spectrograph2)
))

(:metric minimize (total-time)))
```

A.3. Extending PDDL2.1 for PSP Net Benefit

A.3.1. Domain Specification: *ZenoTravel*.

```
(define (domain zeno-travel)
(:requirements :durative-actions :typing :fluents)
(:types aircraft person city - object)
(:predicates (at ?x - (either person aircraft) ?c - city)
             (in ?p - person ?a - aircraft))
(:functions (fuel ?a - aircraft)
            (distance ?c1 - city ?c2 - city)
            (slow-speed ?a - aircraft)
            (fast-speed ?a - aircraft)
            (slow-burn ?a - aircraft)
            (fast-burn ?a - aircraft)
            (capacity ?a - aircraft)
            (refuel-rate ?a - aircraft)
            (total-fuel-used)
            (boarding-time ?c - city)
            (debarking-time ?c - city)

            (labor-cost ?c - city)
            (fuel-cost ?c - city)
            (maintainance-cost ?a - aircraft)
            (airport-aircraft-fee ?a - aircraft ?c - city)
```

```
            (airport-fee ?c - city)
            )


(:durative-action board
 :parameters (?p - person ?a - aircraft ?c - city)
 :duration (= ?duration (boarding-time ?c))
 :cost (+ (* (boarding-time ?c) (labor-cost ?c)) (airport-fee ?c))
 :condition (and (at start (at ?p ?c))
                 (over all (at ?a ?c)))
 :effect (and (at start (not (at ?p ?c)))
              (at end (in ?p ?a))))


(:durative-action debark
 :parameters (?p - person ?a - aircraft ?c - city)
 :duration (= ?duration (debarking-time ?c))
 :cost (+ (* (debarking-time ?c) (labor-cost ?c)) (airport-fee ?c))
 :condition (and (at start (in ?p ?a))
                 (over all (at ?a ?c)))
 :effect (and (at start (not (in ?p ?a)))
              (at end (at ?p ?c))))
```

```
(:durative-action fly
 :parameters (?a - aircraft ?c1 ?c2 - city)
 :duration (= ?duration (/ (distance ?c1 ?c2) (slow-speed ?a)))
 :cost (+ (airport-aircraft-fee ?a ?c1)
          (+ (airport-aircraft-fee ?a ?c2)
             (* (distance ?c1 ?c2) (maintainance-cost ?a))))
 :condition (and (at start (at ?a ?c1))
                 (at start (>= (fuel ?a)
                               (* (distance ?c1 ?c2) (slow-burn ?a)))))
 :effect (and (at start (not (at ?a ?c1)))
              (at end (at ?a ?c2))
              (at end (increase total-fuel-used
                                (* (distance ?c1 ?c2) (slow-burn ?a))))
              (at end (decrease (fuel ?a)
                                (* (distance ?c1 ?c2) (slow-burn ?a))))))


(:durative-action zoom
 :parameters (?a - aircraft ?c1 ?c2 - city)
 :duration (= ?duration (/ (distance ?c1 ?c2) (fast-speed ?a)))
 :cost (+ (airport-aircraft-fee ?a ?c1)
          (+ (airport-aircraft-fee ?a ?c2)
        (* (distance ?c1 ?c2) (maintainance-cost ?a))))
 :condition (and (at start (at ?a ?c1))
```

```
                (at start (>= (fuel ?a)
                              (* (distance ?c1 ?c2) (fast-burn ?a)))))
 :effect (and (at start (not (at ?a ?c1)))
              (at end (at ?a ?c2))
              (at end (increase total-fuel-used
                                (* (distance ?c1 ?c2) (fast-burn ?a))))
              (at end (decrease (fuel ?a)
                                (* (distance ?c1 ?c2) (fast-burn ?a))))))


(:durative-action refuel
 :parameters (?a - aircraft ?c - city)
 :duration (= ?duration (/ (- (capacity ?a) (fuel ?a))
                           (refuel-rate ?a)))
 :cost (* (fuel-cost ?c) (/ (- (capacity ?a) (fuel ?a))
                            (refuel-rate ?a)))
 :condition (and (at start (> (capacity ?a) (fuel ?a)))
                 (over all (at ?a ?c)))
 :effect (at end (assign (fuel ?a) (capacity ?a))))
)
```

A.3.2. Problem Specification: *ZenoTravel*.

```
(define (problem ZTRAVEL-1-2)
(:domain zeno-travel)
```

```
(:objects
plane1 - aircraft
person1 person2 - person
city0 city1 city2 - city
)
(:init
(at plane1 city0)
(at person1 city0)
(at person2 city2)

(= (slow-speed plane1) 198)
(= (fast-speed plane1) 449)
(= (capacity plane1) 10232)
(= (fuel plane1) 3956)
(= (slow-burn plane1) 4)
(= (fast-burn plane1) 15)
(= (refuel-rate plane1) 2904)

(= (distance city0 city0) 0)
(= (distance city0 city1) 678)
(= (distance city0 city2) 775)
(= (distance city1 city0) 678)
(= (distance city1 city1) 0)
(= (distance city1 city2) 810)
```

```
(= (distance city2 city0) 775)
(= (distance city2 city1) 810)
(= (distance city2 city2) 0)
(= (total-fuel-used) 0)

(= (boarding-time city0) 0.3)
(= (boarding-time city1) 0.6)
(= (boarding-time city2) 0.45)
(= (debarking-time city0) 0.6)
(= (debarking-time city1) 0.5)
(= (debarking-time city2) 0.9)

(= (labor-cost city0) 15)
(= (labor-cost city1) 16)
(= (labor-cost city2) 12)

(= (fuel-cost city0) 0.5)
(= (fuel-cost city1) 0.65)
(= (fuel-cost city2) 0.45)

(= (maintainance-cost plane1) 0.1)

(= (airport-aircraft-fee plane1 city0) 100)
(= (airport-aircraft-fee plane1 city1) 80)
```

```
(= (airport-aircraft-fee plane1 city2) 140)


(= (airport-fee city0) 10)
(= (airport-fee city1) 7.5)
(= (airport-fee city2) 14)
)
(:goal (and
((at plane1 city1),soft,6000)
((at person1 city0),hard,15000)
((at person2 city2),soft,8000)
))

(:metric minimize (+ (* 4 (total-time))
                     (* 0.005 (total-fuel-used))))
)
```

A.3.3. Domain Specification: *Satellite*.

```
(define (domain satellite)
 (:requirements :strips :typing :fluents :durative-actions)
 (:types satellite direction instrument mode)
 (:predicates
       (on_board ?i - instrument ?s - satellite)
       (supports ?i - instrument ?m - mode)
```

```
        (pointing ?s - satellite ?d - direction)
        (power_avail ?s - satellite)
        (power_on ?i - instrument)
        (calibrated ?i - instrument)
        (have_image ?d - direction ?m - mode)
        (calibration_target ?i - instrument ?d - direction))

  (:functions
   (slew_time ?a ?b - direction)
(calibration_time ?a - instrument ?d - direction)
(data_capacity ?s - satellite)
(data ?d - direction ?m - mode)
(data-stored)

;; Additional functions for cost (PSP) purpose
(slew_energy_rate ?s - satellite)
(switch_on_energy ?s - satellite ?i - instrument)
(switch_off_energy ?s - satellite ?i - instrument)
(calibration_energy_rate ?s - satellite ?i - instrument)
(data_process_energy_rate ?s - satellite ?i - instrument)
   )

  (:durative-action turn_to
   :parameters (?s - satellite ?d_new - direction
```

```
              ?d_prev - direction)
 :duration (= ?duration (slew_time ?d_prev ?d_new))
 :cost (* (slew_time ?d_prev ?d_new) (slew_energy_rate ?s))
 :condition (and (at start (pointing ?s ?d_prev))
                 (over all (not (= ?d_new ?d_prev)))
            )
 :effect (and  (at end (pointing ?s ?d_new))
               (at start (not (pointing ?s ?d_prev)))
         )
)

(:durative-action switch_on
 :parameters (?i - instrument ?s - satellite)
 :duration (= ?duration 2)
 :cost (switch_on_energy ?s ?i)
 :condition (and (over all (on_board ?i ?s))
                   (at start (power_avail ?s)))
 :effect (and (at end (power_on ?i))
              (at start (not (calibrated ?i)))
              (at start (not (power_avail ?s)))
         )

)
```

```
(:durative-action switch_off
 :parameters (?i - instrument ?s - satellite)
 :duration (= ?duration 1)
 :cost (switch_off_energy ?s ?i)
 :condition (and (over all (on_board ?i ?s))
                  (at start (power_on ?i))
               )
 :effect (and (at start (not (power_on ?i)))
              (at end (power_avail ?s))
         )
)

(:durative-action calibrate
 :parameters (?s - satellite ?i - instrument ?d - direction)
 :duration (= ?duration (calibration_time ?i ?d))
 :cost (* (calibration_time ?i ?d)
          (calibration_energy_rate ?s ?i))
 :condition (and (over all (on_board ?i ?s))
    (over all (calibration_target ?i ?d))
                  (at start (pointing ?s ?d))
                  (over all (power_on ?i))
                  (at end (power_on ?i))
               )
 :effect (at end (calibrated ?i))
```

```
  )

  (:durative-action take_image
   :parameters (?s - satellite ?d - direction
                ?i - instrument ?m - mode)
   :duration (= ?duration 7)
   :cost (* (data ?d ?m) (data_process_energy_rate ?s ?i))
   :condition (and (over all (calibrated ?i))
                   (over all (on_board ?i ?s))
                   (over all (supports ?i ?m))
                   (over all (power_on ?i))
                   (over all (pointing ?s ?d))
                   (at end (power_on ?i))
                   (at start (>= (data_capacity ?s) (data ?d ?m))))
   :effect (and (at start (decrease (data_capacity ?s) (data ?d ?m)))
                (at end (have_image ?d ?m))
                (at end (increase (data-stored) (data ?d ?m))))
  )
)
```

A.3.4. Problem Specification: *Satellite*.

```
;; Automatically generated by Satellite_Gen
;; Original problem file: pfile1 | Random Seed:1000
(define (problem strips-sat-x-1)
```

```
(:domain satellite)
(:objects
satellite0 - satellite
instrument0 - instrument
image1 spectrograph2 thermograph0 - mode
star0 groundstation1 groundstation2 phenomenon3
        phenomenon4 star5 phenomenon6 - direction
)
(:init
(supports instrument0 thermograph0)
(calibration_target instrument0 groundstation2)
(on_board instrument0 satellite0)
(power_avail satellite0)
(pointing satellite0 phenomenon6)

(= (calibration_time instrument0 groundstation2) 5.9)
(= (data_capacity satellite0) 1000.0)
(= (data phenomenon3 image1) 22.0)
(= (data phenomenon4 image1) 120.0)
(= (data star5 image1) 203.0)
(= (data phenomenon6 image1) 144.0)
(= (data phenomenon3 spectrograph2) 125.0)
(= (data phenomenon4 spectrograph2) 196.0)
(= (data star5 spectrograph2) 68.0)
```

```
(= (data phenomenon6 spectrograph2) 174.0)
(= (data phenomenon3 thermograph0) 136.0)
(= (data phenomenon4 thermograph0) 134.0)
(= (data star5 thermograph0) 273.0)
(= (data phenomenon6 thermograph0) 219.0)
(= (slew_time groundstation1 star0) 18.17)
(= (slew_time star0 groundstation1) 18.17)
(= (slew_time groundstation2 star0) 38.61)
(= (slew_time star0 groundstation2) 38.61)
(= (slew_time groundstation2 groundstation1) 68.04)
(= (slew_time groundstation1 groundstation2) 68.04)
(= (slew_time phenomenon3 star0) 14.29)
(= (slew_time star0 phenomenon3) 14.29)
(= (slew_time phenomenon3 groundstation1) 89.48)
(= (slew_time groundstation1 phenomenon3) 89.48)
(= (slew_time phenomenon3 groundstation2) 33.94)
(= (slew_time groundstation2 phenomenon3) 33.94)
(= (slew_time phenomenon4 star0) 35.01)
(= (slew_time star0 phenomenon4) 35.01)
(= (slew_time phenomenon4 groundstation1) 31.79)
(= (slew_time groundstation1 phenomenon4) 31.79)
(= (slew_time phenomenon4 groundstation2) 39.73)
(= (slew_time groundstation2 phenomenon4) 39.73)
(= (slew_time phenomenon4 phenomenon3) 25.72)
```

```
(= (slew_time phenomenon3 phenomenon4) 25.72)
(= (slew_time star5 star0) 36.56)
(= (slew_time star0 star5) 36.56)
(= (slew_time star5 groundstation1) 8.59)
(= (slew_time groundstation1 star5) 8.59)
(= (slew_time star5 groundstation2) 62.86)
(= (slew_time groundstation2 star5) 62.86)
(= (slew_time star5 phenomenon3) 10.18)
(= (slew_time phenomenon3 star5) 10.18)
(= (slew_time star5 phenomenon4) 64.5)
(= (slew_time phenomenon4 star5) 64.5)
(= (slew_time phenomenon6 star0) 77.07)
(= (slew_time star0 phenomenon6) 77.07)
(= (slew_time phenomenon6 groundstation1) 17.63)
(= (slew_time groundstation1 phenomenon6) 17.63)
(= (slew_time phenomenon6 groundstation2) 50.73)
(= (slew_time groundstation2 phenomenon6) 50.73)
(= (slew_time phenomenon6 phenomenon3) 14.75)
(= (slew_time phenomenon3 phenomenon6) 14.75)
(= (slew_time phenomenon6 phenomenon4) 2.098)
(= (slew_time phenomenon4 phenomenon6) 2.098)
(= (slew_time phenomenon6 star5) 29.32)
(= (slew_time star5 phenomenon6) 29.32)
(= (data-stored) 0.0)
```

```
;; (slew_energy_rate ?satellite) : 0.5 - 2 (random)
(= (slew_energy_rate satellite0) 1.57)

;; (switch_on_energy ?satellite ?instrument) : 10 - 20
(= (switch_on_energy satellite0 instrument0) 12.47)

;; (switch_off_energy ?satellite ?instrument) : 5 - 15
(= (switch_off_energy satellite0 instrument0) 10.75)

;; (calibration_energy_rate ?satellite ?instrument) : 20 - 40
(= (calibration_energy_rate satellite0 instrument0) 29.21)

;; (data_process_energy_rate ?satellite ?instrument) : 1 - 10
(= (data_process_energy_rate satellite0 instrument0) 9.52)
)
(:goal (and
;; Goals: (pointing ?sat ?dir) - soft
;;        (have_image ?dir ?mode) 80% soft
;; Goal utility: random with bounds [2000 - 6000]
((have_image phenomenon4 thermograph0) hard 2157.62)
((have_image star5 thermograph0) soft 3945.64)
((have_image phenomenon6 thermograph0) soft 3782.95)
```

```
;; Additional goals. Utility: 1000-5000 (random)
((have_image star0 spectrograph2) soft 3403.26)
((have_image groundstation1 thermograph0) soft 3201.50)
((have_image groundstation2 image1) soft 3632.23)
((have_image phenomenon3 spectrograph2) soft 4897.99)
((pointing satellite0 star5) soft 3520.31)
)
```

APPENDIX B

CSOP and MILP Encoding

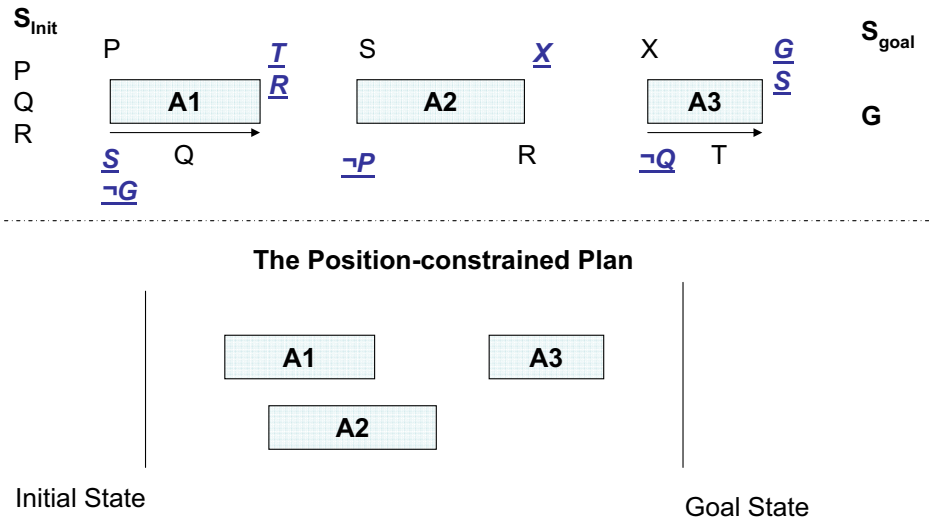

Figure 40.

In this Appendix, we present a simple position-constrained plan and the CSOP and MILP encoding for this problem to produce the optimal order-constrained plans. We assume the PDDL2.1 representation for actions in the plan.

The initial state, goal state, and action descriptions (three) are provided in Figure 40. For each action description, the propositions in italic and underline are action's effect, the other are action's precondition. For example: $Precond(A_1) = \{p, q\}$ where q must hold true through out A_1's duration and p only needs to be true at A_1's start time. Action A_1 has four effects: $s, \neg g$ at A_1's start time and t, r at A_1's end time. This example will be used as a basis for all the encodings discussed in this appendix.

B.1. CSOP Encoding for Partialization

Variables:

- Action starting time: $ST_{A_1}, ST_{A_2}, ST_{A_3}$.

- Causal effect for action's conditions: $S^p_{A_1}, S^q_{A_1}$, $S^s_{A_2}, S^r_{A_2}$, $S^x_{A_3}, S^t_{A_3}$. Variable domains: $Dom(S^p_{A_1}) = \{A_{init}\}$, $Dom(S^q_{A_1}) = \{A_{init}\}$, $Dom(S^s_{A_2}) = \{A_1, A_3\}$, $Dom(S^r_{A_2}) = \{A_{init}, A_1\}$, $Dom(S^x_{A_3}) = \{A_2\}$, $Dom(S^t_{A_3}) = \{A_1\}$, $Dom(S^g_{A_{goal}}) = \{A_3\}$.

- Interference: $I^p_{A_1A_2}, I^q_{A_1A_3}, I^g_{A_1A_3}$; interference variables are binary variables.

Constraints:

- Causal-link protection:

  $S^p_{A_1} = A_{init} \Rightarrow I^p_{A_1A_2} = \prec$

  $S^q_{A_1} = A_{init} \Rightarrow I^q_{A_1A_3} = \prec$

  $S^g_{A_{goal}} = A_3 \Rightarrow I^g_{A_1A_3} = \prec$.

- Constraints between ordering variables and action starting times:

  $S^s_{A_2} = A_1 \Rightarrow ST_{A_1} < ST_{A_2}$

  $S^r_{A_2} = A_1 \Rightarrow ST_{A_1} + D_{A_1} < ST_{A_2} + D_{A_1}$

  $S^x_{A_3} = A_2 \Rightarrow ST_{A_2} + D_{A_2} < ST_{A_3}$

  $S^g_{A_{goal}} = A_3 \Rightarrow ST_{A_3} + D_{A_3} < ST_{A_{goal}}$

  $I^p_{A_1A_2} = \prec \Leftrightarrow ST_{A_1} < ST_{A_2}$

  $I^p_{A_1A_2} = \succ \Leftrightarrow ST_{A_2} < ST_{A_1}$

  $I^q_{A_1A_3} = \prec \Leftrightarrow ST_{A_1} + D_{A_1} < ST_{A_3}$

  $I^q_{A_1A_3} = \succ \Leftrightarrow ST_{A_1} > ST_{A_3}$

  .....

Objective functions: Minimal makespan: *minimize* $ST_{A_{goal}}$

B.2. MILP Encoding

Variables:

- Continous variables: $ST_{A_1}, ST_{A_2}, ST_{A_3}, ST_{A_{goal}}$.
- Causal effects (binary) variables: $X^p_{A_{init}A_1}$, $X^p_{A_{init}A_1}$, $X^q_{A_{init}A_1}$, $X^s_{A_1A_2}, X^s_{A_3A_2}$, $X^r_{A_{init}A_2}, X^r_{A_1A_2}, X^x_{A_2A_3}, X^t_{A_1A_3}, X^g_{A_3A_{goal}}$.
- Interference variables: $Y^p_{A_1A_2}, Y^p_{A_2A_1}, Y^q_{A_1A_3}, Y^q_{A_3A_1}, Y^g_{A_1A_3}, Y^g_{A_3A_1}$

Constraints:

- Mutual Exclusion:

  $Y^p_{A_1A_2} + Y^p_{A_2A_1} = 1$

  $Y^q_{A_1A_3} + Y^q_{A_3A_1} = 1$

  $Y^g_{A_1A_3} + Y^g_{A_3A_1} = 1$

- Only one supporter:

  $X^s_{A_1A_2} + X^s_{A_3A_2} = 1$

  $X^r_{A_{init}A_2} + X^r_{A_1A_2} = 1$

- Causal-link Protection:

  $(1 - X^p_{A_{init}A_1} + Y^p_{A_1A_2} \geq 1$

  $(1 - X^q_{A_{init}A_1} + Y^q_{A_1A_3} \geq 1$

  $(1 - X^g_{A_3A_{goal}} + Y^g_{A_1A_3} \geq 1.$

- Ordering and temporal variables relation:

  $M.(1 - X^s_{A_1A_2}) + (ST_{A_2} - ST_{A_1}) > 0$

  $M.(1 - X^s_{A_3A_2}) + ((ST_{A_2} + D_{A_2}) - ST_{A_3}) > 0$

  $M.(1 - X^r_{A_1A_2}) + ((ST_{A_2} + D_{A_2}) - (ST_{A_1} + D_{A_1})) > 0$

  .....

- Mutex and temporal variables relation:

  $M.(1 - Y^{p}_{A_1A_2}) + (ST_{A_2} - ST_{A_1}) > 0$

  $M.(1 - Y^{q}_{A_1A_3}) + (ST_{A_3} - (ST_{A_1} + D_{A_1})) > 0$

  $M.(1 - Y^{q}_{A_3A_1}) + (ST_{A_1} - ST_{A_3}) > 0$

  .....

Objective function:

Minimizing Makespan: *Minimize* $ST_{A_{goal}}$