



## BACKGROUND — PROBABILISTIC PLANNING

A probabilistic transition system  $\langle S, L, C, T, G \rangle$  consists of *states*  $S$ , *labels*  $L$ , a *cost function*  $C : L \rightarrow \mathbb{R}_0^+$ , *stochastic transitions*,  $T \subseteq S \times L \times \text{Dist}(S)$  and goal states  $G \subseteq S$ , where every set is finite and non-empty.

*Policies* are partial functions  $\pi : S \rightarrow T$  with  $\pi(s) = \langle s, \ell, \delta \rangle$ , if  $s \in \pi$ . If  $s \notin \pi$ ,  $\pi$  terminates in  $s$ . The expected cost of  $\pi$  from state  $s$  is defined as

$$J^\pi(s) := \mathbb{E} \left[ \sum_{i=0}^{T-1} C(\pi(S_i)) \mid S_0 = s \right] \quad \text{where} \quad \begin{array}{l} T := \inf \{i \mid S_i \notin \pi\} \\ S_{i+1} \sim \pi(S_i), \text{ for } i < T. \end{array}$$

A solution for  $s \in \text{Sols}(s)$  terminates in a goal state with certainty. A solution  $\pi \in \text{Sols}(s)$  is *optimal* for  $s$  iff  $J^\pi(s) = J^*(s) := \inf_{\pi \in \text{Sols}(s)} J^\pi(s)$ .

A *probabilistic planning task*  $\langle \mathcal{V}, \mathcal{O}, I, G \rangle$  consists of variables  $\mathcal{V}$  with domains  $\mathcal{D}(v)$ , *operators*  $\mathcal{O}$  with *preconditions*  $pre(o)$ , cost  $cost(o) \in \mathbb{R}_0^+$  and stochastic *effects*  $eff_1(o), \dots, eff_{aty(o)}(o)$  with probabilities  $Pr_1(o), \dots, Pr_{aty(o)}(o)$ , initial variable assignment  $I$  and partial goal assignment  $G$ . Every task naturally induces a corresponding PTS.

## CONSTRUCTION OF CARTESIAN ABSTRACTIONS

To construct Cartesian abstractions, we employ counter-example guided abstraction refinement (CEGAR), with policies instead of plans.

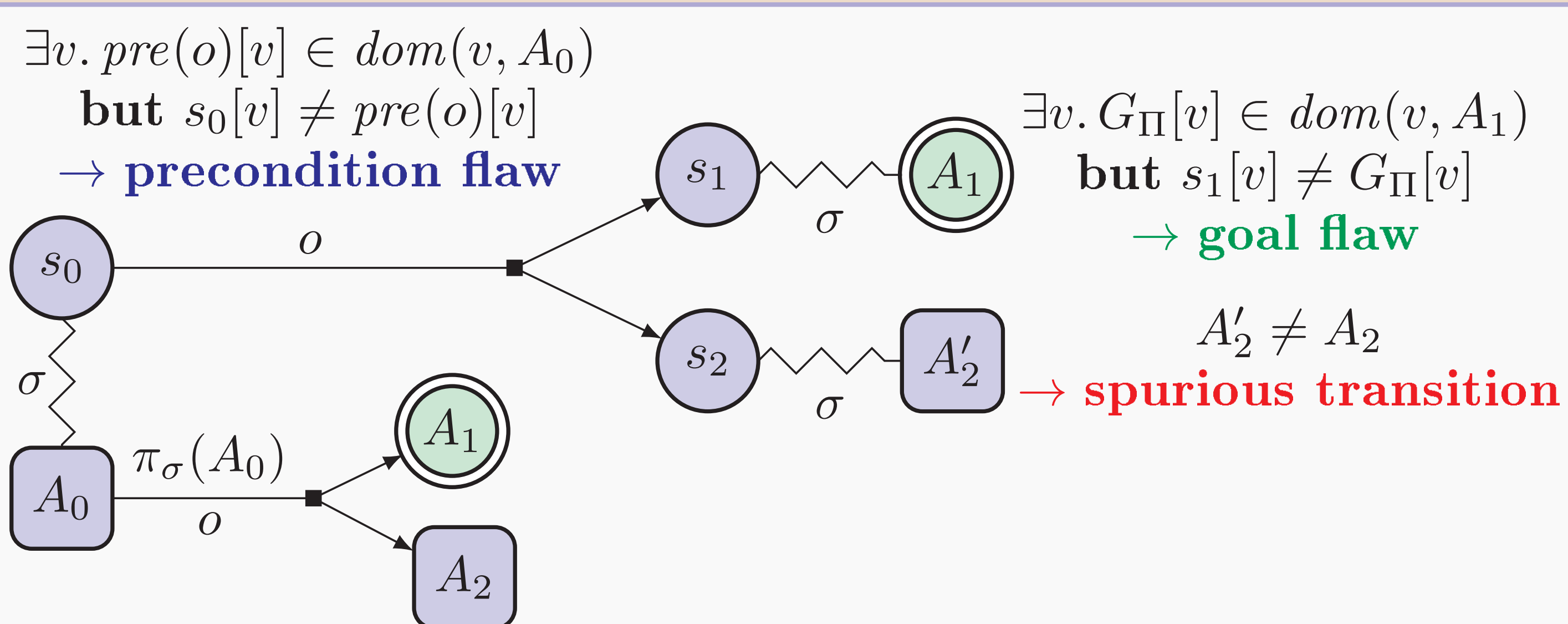
**Algorithm 1:** CEGAR refinement loop (policy-based).

**Input:** Probabilistic Planning Task  $\Pi$

- 1  $\langle \Theta_\sigma, \sigma \rangle \leftarrow \text{TRIVIALABSTRACTION}(\Pi)$
- 2 **while not**  $\text{TERMINATIONCONDITION}()$  **do**
- 3      $\pi_\sigma \leftarrow \text{FINDOPTIMALSOLUTION}(\Theta_\sigma, \sigma(I_\Pi))$
- 4     **if not**  $\pi_\sigma$  exists: **return** “Task unsolvable”
- 5      $\phi \leftarrow \text{FINDFLAW}(\Pi, \Theta_\sigma, \pi_\sigma)$
- 6     **if not**  $\phi$  exists: **return** “Optimal solution found”
- 7      $\langle \Theta_\sigma, \sigma \rangle \leftarrow \text{REFINE}(\Theta_\sigma, \sigma, \phi)$
- 8 **return**  $\Theta_\sigma$

## FINDING FLAWS IN THE ABSTRACTION

Execute abstract policy  $\pi_\sigma$  as a concrete policy in the concrete state space, by choosing for  $s$  the operator of the corresponding abstract transition  $\pi_\sigma(\sigma(s))$ . Can fail or be suboptimal for three reasons:



Expand the policy graph of this policy from the initial state, checking for flaws on-the-fly. If no flaw is found, the policy is optimal. Otherwise, return a pair  $\langle s, c \rangle$  of state  $s$  and cartesian set  $c$  such that  $s \notin c \subsetneq \sigma(s)$ .  $c$  represents the property  $s$  was expected to satisfy, but violated instead.

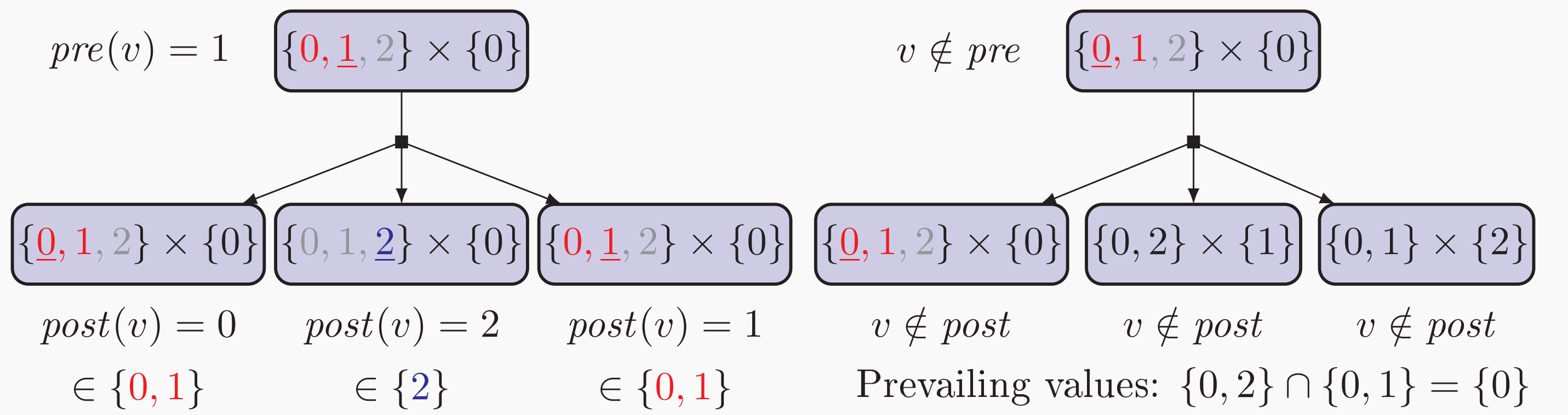
## REFINING THE ABSTRACT PTS

Given flaw  $\langle s, c \rangle$ , pick a split variable  $v$  with  $s[v] \notin \text{dom}(v, c) \subsetneq \text{dom}(v, \sigma(s))$ . Split  $\sigma(s)$  along  $v$  into two split states  $A_1$  and  $A_2$  by defining  $\text{dom}(v, A_1) := \text{dom}(v, c)$ ,  $\text{dom}(v, A_2) = \text{dom}(v, \sigma(s)) \setminus \text{dom}(v, c)$ .

Next, rewire abstract transitions involving  $\sigma(s)$  to the split states. Which of  $A_1, A_2$  depends on which values for  $v$  can occur for the outcome:

**Case 1: Non-Prevail Effects** ( $v \in \text{post}$ )

**Case 2: Prevail Effects** ( $v \notin \text{post}$ )



**Algorithm 2:** Rewire an abstract transition.

**Input:** Split  $\langle \sigma(s), A_1, A_2, v \rangle$

Abstract Transition  $\langle B_0, o, \langle B_1, \dots, B_{aty(o)} \rangle \rangle$

- 1  $B'_0, \dots, B'_{aty(o)} \leftarrow B_0, \dots, B_{aty(o)}$  // Rewired targets
- 2 **for**  $i = 0$  **to**  $aty(o)$  **do** // Rewire non-prevail effects
- 3     **if**  $B_i = \sigma(s)$  **and**  $v \in \text{post}_i(o)$ :
- 4          $B'_i \leftarrow \begin{cases} A_1 & \text{post}_i(o)[v] \in \text{dom}(v, A_1) \\ A_2 & \text{else, i.e., post}_i(o)[v] \in \text{dom}(v, A_2) \end{cases}$
- 5  $\text{PrevailingEffectTargets} \leftarrow \{i \mid B_i = \sigma(s) \wedge v \notin \text{post}_i(o)\}$
- 6 **if**  $\text{PrevailingEffectTargets} = \emptyset$ :
- 7     **return**  $\langle B'_0, o, \langle B'_1, \dots, B'_{aty(o)} \rangle \rangle$
- 8  $\text{PrevailingValues} \leftarrow \bigcap_{i: B_i \neq \sigma(s) \wedge v \notin \text{post}_i(o)} \text{dom}(v, B_i)$
- 9 **for**  $A \in \{A_1, A_2\}$  **do** // Uniformly rewire prevail effects
- 10     **if**  $\text{PrevailingValues} \cap \text{dom}(v, A) \neq \emptyset$ :
- 11         **for**  $i \in \text{PrevailingEffectTargets}$  **do**  $B'_i \leftarrow A$
- 12     **output**  $\langle B'_0, o, \langle B'_1, \dots, B'_{aty(o)} \rangle \rangle$

## SATURATED COST PARTITIONING

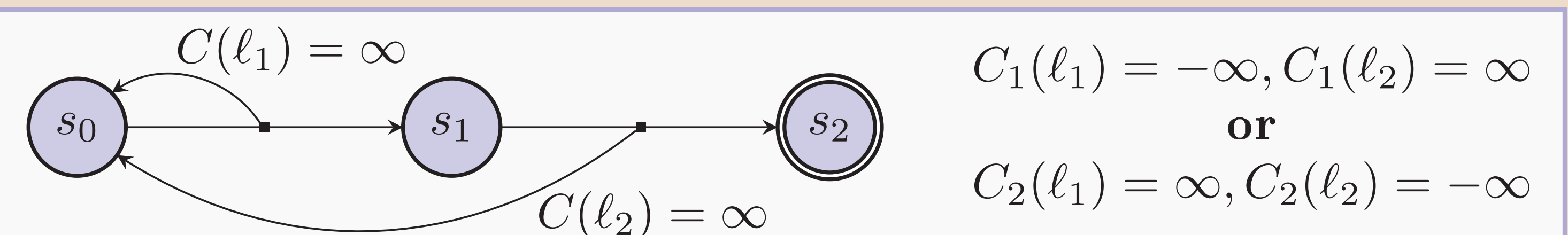
We use *saturated cost partitioning* to combine multiple cartesian abstractions, constructed in succession. To compute the saturated and remaining costs during the procedure, we use the following saturated cost function.

**Theorem.** Let  $\Theta$  be a PTS and  $T^{\text{fin}} := \{\langle s, \ell, \delta \rangle \in T \mid \forall t \in \text{supp}(\delta). J_\Theta^*(t) \neq \infty\}$ . The cost function  $scf(\ell) := \infty$  if  $C(\ell) = \infty$  and otherwise

$$scf(\ell) := \sup_{\langle s, \ell, \delta \rangle \in T^{\text{fin}}} J_\Theta^*(s) - \sum_{t \in S} \delta(t) \cdot J_\Theta^*(t)$$

preserves the optimal state costs of  $\Theta$ .

**Observation:** The minimal saturated cost function is **not unique!**



## EXPERIMENTS

Domains	$h^{\text{blind}}$ and single abstraction					multiple abstractions													
	$h^{\text{blind}}$	$h^{\text{PDB}}_{\text{CEGAR}}$	$h^{\text{Cart}_1}_{\text{det}}$	$h^{\text{Cart}_1}_{\text{iLAO}^*}$	$h^{\text{Cart}_1}_{A^*}$	$h^{\text{roc}}$	$h^{\text{SYS-1}}_{\text{Can}}$	$h^{\text{SYS-2}}_{\text{Can}}$	$h^{\text{SYS-3}}_{\text{Can}}$	$h^{\text{HC}}_{\text{Can}}$	$h^{\text{DC}}_{\text{Max}}$	$h^{\text{SYS-1}}_{\text{SCP}}$	$h^{\text{SYS-2}}_{\text{SCP}}$	$h^{\text{SYS-3}}_{\text{SCP}}$	$h^{\text{HC}}_{\text{SCP}}$	$h^{\text{DC}}_{\text{SCP}}$	$h^{\text{Cart}_k}_{\text{det}}$	$h^{\text{Cart}_k}_{\text{iLAO}^*}$	$h^{\text{Cart}_k}_{A^*}$
BLOCKSW	7	8	7	7	7	7	9	9	8	9	8	9	9	9	9	9	7	7	7
BOXWORLD	4	5	7	5	7	4	5	5	4	6	4	5	7	7	6	6	6	7	6
ELEVATORS	10	11	10	11	10	10	13	12	8	17	15	13	15	17	17	17	15	14	16
PARCPR	8	8	8	8	8	20	13	8	8	19	11	14	20	6	20	18	12	14	12
RANDOM	14	17	18	17	18	14	16	17	13	18	17	18	18	13	18	16	18	16	18
SCHEDULE	12	15	13	13	12	11	12	13	12	14	13	14	12	12	13	13	13	12	12
SYSADMIN	12	12	12	11	11	12	12	12	8	12	12	12	12	12	12	12	12	12	12
TTIREWORLD	5	9	7	9	7	7	7	7	8	9	9	7	7	8	9	9	7	9	7
ZENOTRAVEL	5	10	8	11	10	7	9	10	9	10	9	9	9	9	10	10	8	10	10
Sum (of 180)	77	95	90	92	90	92	96	93	78	114	98	101	109	93	114	110	98	100	101

