

# Integrating Planning and Scheduling: Status and Prospects

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## Planning vs. Scheduling

← A Continuum →

### Scheduling

- Set of jobs (may have of tasks in some (partial) order)
- Temporal constraints on jobs
  - » EST, LFT, Duration
- Contention constraints
  - » Each task can be done on a subset of machines

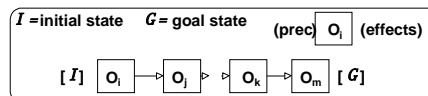
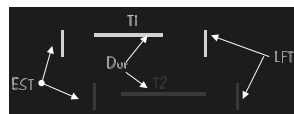
Find start times for jobs that are optimal (wrt make-spans, resource consumption etc)

Resource Reasoning

### Planning

- Initial state & a set of Goals,
  - A library of actions
    - » Preconditions/effects
      - Discrete/Continuous
    - » Resource requirements
- Synthesize a sequence of actions capable of satisfying goals

Causal Reasoning



--Research into planning and scheduling methods  
has largely been de-coupled

## Need for Integration

- ◇ **Most existing schedulers concentrate only on resource allocation, ignoring action selection**
  - E.g. HSTS operation scheduling
- ◇ **Most existing planners concentrate on action selection, ignoring resource allocation**
  - Plan-based interfaces
  - Interactive decision support

- ◇ **Many real-world problems require *both* capabilities**
  - Supply Chain Management problems
    - » *I2, ILOG, Manugistics*
  - Planning in domains with durative actions, continuous change
    - » NASA RAX experiment

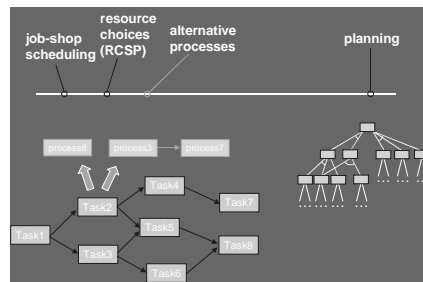
## Why now?

- ◇ **Significant scale-up in plan synthesis in last 4-5 years**
  - 5/6 action plans in minutes to 100 action plans in minutes
  - Breakthroughs in search space representation, heuristic and domain-specific
- ◇ **Significant strides in our understanding of connections between planning and scheduling**
  - Rich connections between planning and CSP/SAT/ILP
    - » Vanishing separation between planning techniques and scheduling techniques

## Approaches for Integration

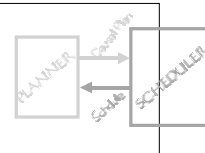
◇ Extend schedulers to handle action and resource choices

◇ Extend planners to deal with resources, durative actions and continuous quantities



### ◇ Coupled Architectures

- De-coupled
- Loosely Coupled (RealPlan System)



## Overview

- ✓ Why integrate planning and scheduling?
- ➔ Planning: The state of the art
- ◇ Scheduling: The state of the art
- ◇ Integrating Planning and Scheduling

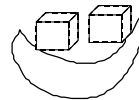
# Planning: The State of the Art

**Overview**

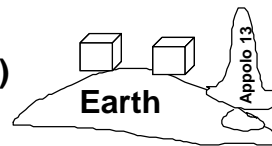
- ◇ Why integrate planning and scheduling?
- ◇ Planning: The state of the art
- ◇ Scheduling: The state of the art
- ◇ Integrating Planning and Scheduling

## (Deterministic) Planning: The problem

- ◇ States are modeled in terms of (binary) state-variables (factored rep.)
  - Complete initial state, partial goal state
- ◇ Actions are modeled as state transformation functions
  - Syntax: ADL language (Pednault)
- ◇ Plans are sequences of actions



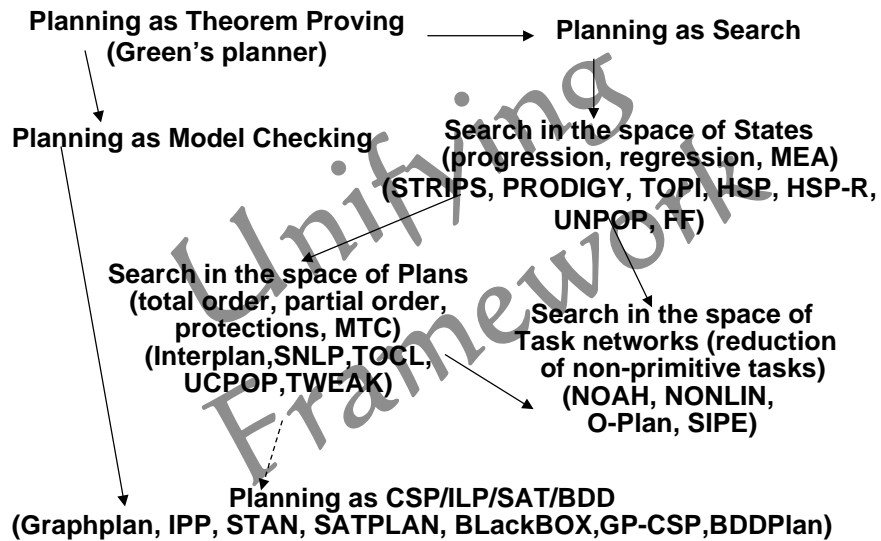
$At(A,M), At(B,M)$   
 $\neg In(A), \neg In(B)$



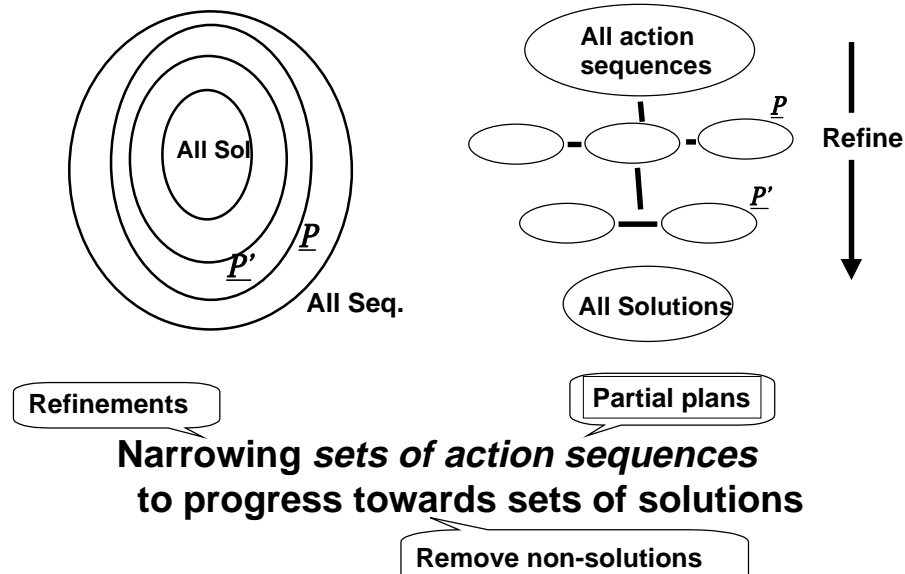
$At(A,E), At(B,E), At(R,E)$

	<div style="border: 1px solid black; padding: 2px; display: inline-block;">Effects</div> $In(o_1)$	
	<div style="border: 1px solid black; padding: 2px; display: inline-block;">Load(<math>o_1</math>)</div>	
<div style="border: 1px solid black; padding: 2px; display: inline-block;">Preconditions</div>	$At(o_1, l_1), At(R, l_1)$	
	$\neg In(o_1)$ <div style="border: 1px solid black; padding: 2px; display: inline-block;">Unload(<math>o_1</math>)</div>	
	$In(o_1)$	
		$At(R,M), \neg At(R,E)$ $\forall x In(x) \Rightarrow At(x,M)$ & $\neg At(x,E)$ <div style="border: 1px solid black; padding: 2px; display: inline-block;">Fly()</div>
		$At(R,E)$

## The (too) many brands of classical planners

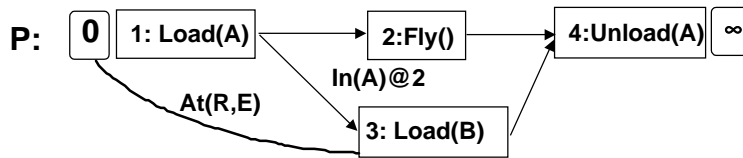


## Refinement Planning: The idea



# Plan Representation

Partial plan =  $\langle \text{Steps, Orderings, Aux. Constraints} \rangle$

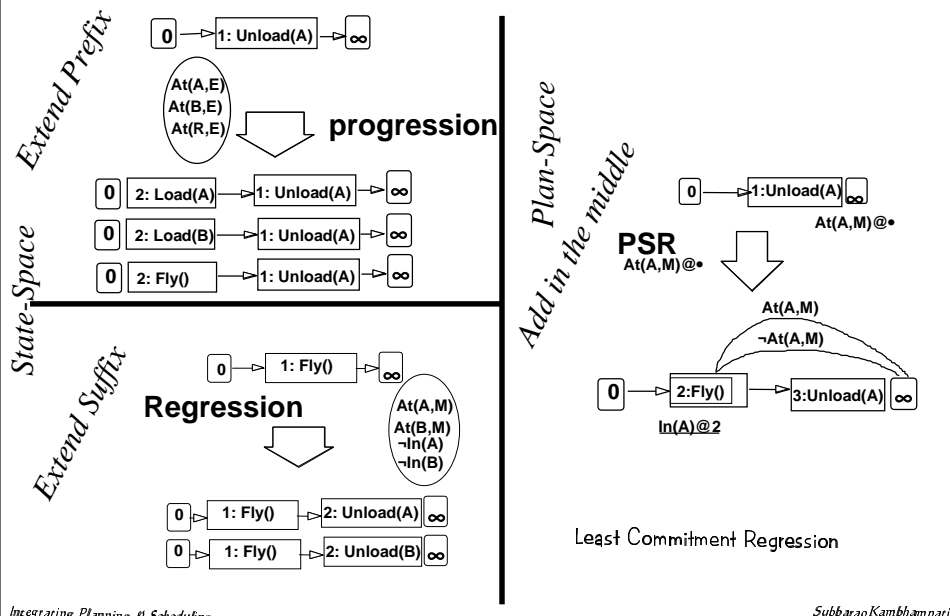


Semantics in terms of Candidate sets

--Candidate is an action sequence that satisfies all the plan constraints (but can have additional actions)

Refinements split and prune candidate sets

# (The) Three Refinement Strategies

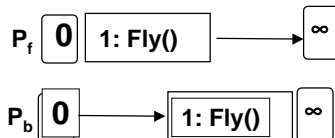


# Tradeoffs among Refinements

*The Tastes great/  
Less Filling holy wars*

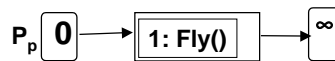
**FSR and BSR must commit to both position and relevance of actions**

- + Give state information (Easier plan validation)
- Leads to premature commitment
- Too many states when actions have durations

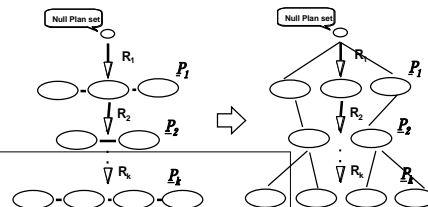


**Plan-space refinement (PSR) avoids constraining position**

- + Reduces commitment (large candidate set /branch)
- Increases plan-validation costs
- + Easily extendible to actions with duration



# A flexible Split & Prune search for Refinement Planning

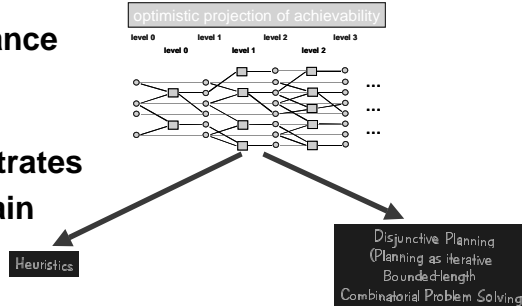


**Refineplan( $\underline{P}$ : Plan)**

- 0\*. If « $\underline{P}$ » is empty, Fail.
1. If a minimal candidate of  $\underline{P}$  is a solution, terminate.
2. Select a refinement strategy  $\underline{R}$ .  
Apply  $\underline{R}$  to  $\underline{P}$  to get a new plan set  $\underline{P}'$
3. Split  $\underline{P}'$  into  $k$  plansets
4. Non-deterministically select one of the plansets  $\underline{P}'_i$   
Call Refine( $\underline{P}'_i$ )

# Broad Themes in the Planning Renaissance

- ◇ Disjunctive Representations
- ◇ Reachability/Relevance Analysis
- ◇ Connections to combinatorial substrates
- ◇ Sophisticated domain pre-processing Techniques

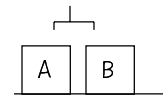


Tutorial on Recent Advances in AI Planning (UCAI-99,AAAI-00)  
<http://rakaposhi.eas.asu.edu/planning-tutorial>

Pickup(A)

Init:  
 Ontable(A), Ontable(B),  
 Clear(A), Clear(B), hand-empty  
 Goal:  
 ~clear(B), hand-empty

Pickup(B)



Progression Search

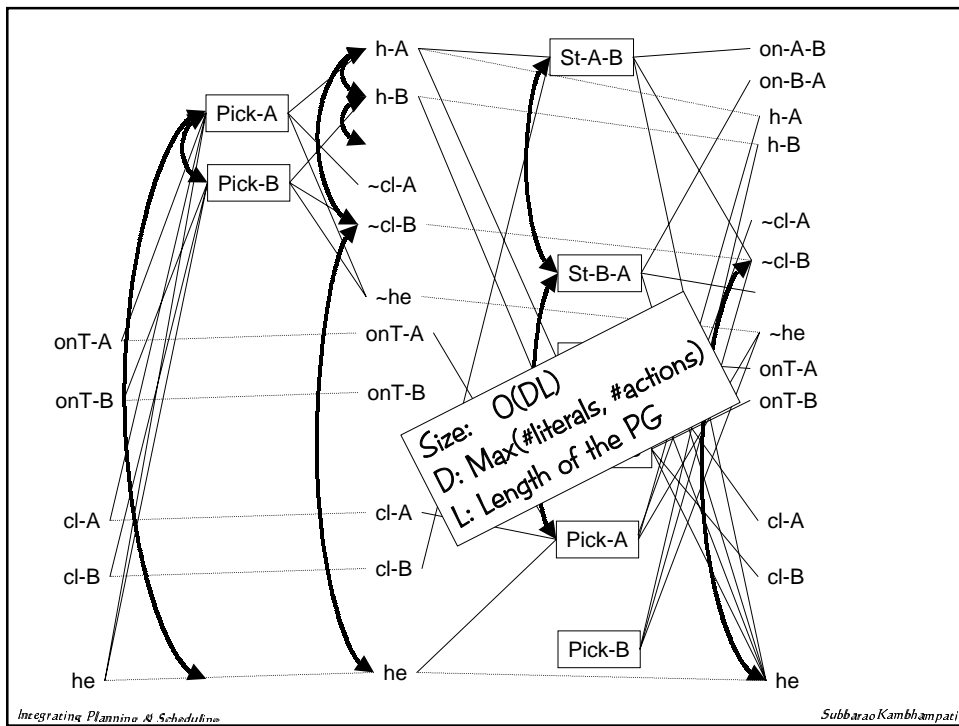
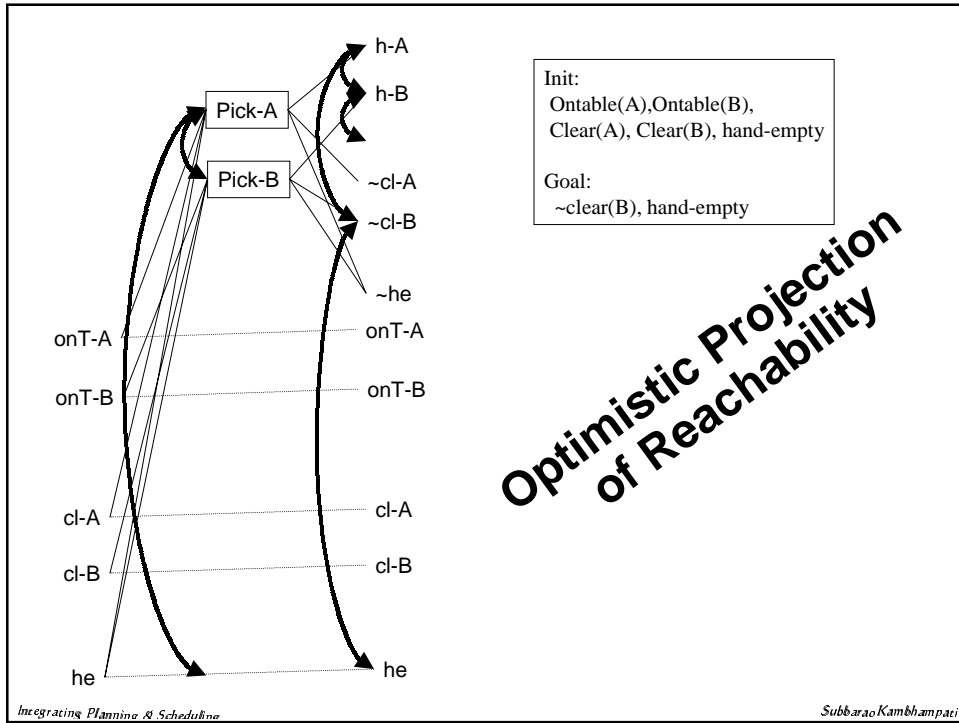
Regression Search  
 Putdown(A)

??How promising are  
 the intermediate  
 States/Plans?

Stack(A,B)

Putdown(B)??





## Heuristics based on the Planning Graph

- ◇  $lev(S)$ : index of the first level where all props in  $S$  appear nonmutexed.
  - If there is no such level, then
    - If the graph is grown to level off, then  $\infty$
    - Else  $k+1$  ( $k$  is the current length of the graph)

**Set-Level heuristic:  $h(S) = lev(S)$**   
 Admissible but not very informed

**Sum heuristic:  $h(S) = \sum_{p \in S} lev(\{p\})$**  Inadmissible  
 Assumes that sub-goals are independent

Yesterday's Talk  
(AIMA System)

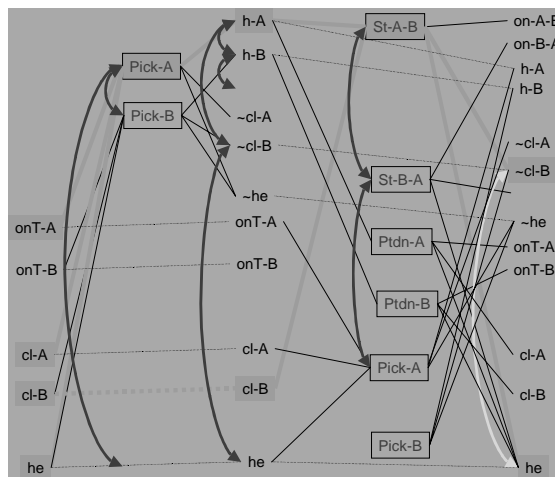
**Adjusted Sum heuristic: [Sanchez et. al., 2000]**  
 $H_{AdjSum2M}(S) = length(RelaxedPlan(S)) + \max_{p,q \in S} \delta(p,q)$  Inadmissible  
 where  $\delta(p,q) = lev(\{p,q\}) - \max\{lev(p), lev(q)\}$

## Planning as Plangraph Solution Extraction

If there exists a  $k$ -length plan,  
 it will be a subgraph of the  
 $k$ -length planning graph.

Planning is thus searching for  
 a "valid" subgraph of the  
 planning graph.

**Combinatorial search.**  
 Can be cast into any  
 combinatorial substrate  
 (e.g. CSP, SAT, ILP...)



## (very) Quick overview of CSP/SAT concepts

### Constraint Satisfaction Problem (CSP)

#### - Given

- » A set of discrete variables
- » Legal domains for each of the variables
- » A set of constraints on values groups of variables can take

- Find an assignment of values to all the variables so that none of the constraints are violated

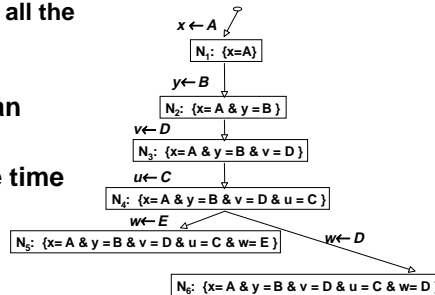
### SAT Problem = CSP with boolean variables

- » TCSP = CSP where variables are time points and constraints describe allowed distances

$x, y, u, v: \{A, B, C, D, E\}$   
 $w: \{D, E\} \mid \{A, B\}$   
 $x=A \Rightarrow w \neq E$   
 $y=B \Rightarrow u \neq D$   
 $u=C \Rightarrow l \neq A$   
 $v=D \Rightarrow l \neq B$

#### A solution:

$x=B, y=C, u=D, v=E, w=D, l=B$



## Important ideas in solving CSPs

### Variable order heuristics:

Pick the most constrained variable

- Smallest domain, connected to most other variables,
- causes most unit propagation,
- causes most resource contention,
- has the most distance etc...

### Value ordering heuristics

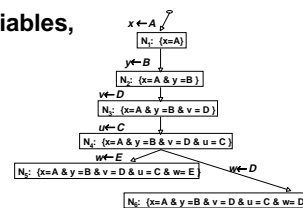
Pick the least constraining value

### Consistency enforcement

- k-consistency; adaptive consistency. (pre-processing)
- Forward Checking, unit propagation during search (dynamic)

### Search/Backtracking

- DDB/EBL: Remember and use interior node failure explanations
- Randomized search



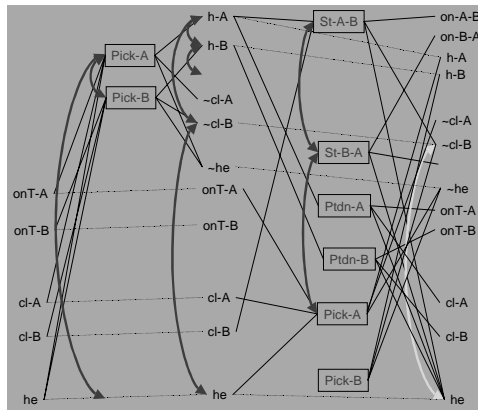
$x, y, u, v: \{A, B, C, D, E\}$   
 $w: \{D, E\} \mid \{A, B\}$   
 $x=A \Rightarrow w \neq E$   
 $y=B \Rightarrow u \neq D$   
 $u=C \Rightarrow l \neq A$   
 $v=D \Rightarrow l \neq B$

## Posing Plangraph Solution Extraction as a CSP/SAT

Variables: literals in proposition lists

Values: actions supporting them

Constraints: Mutex and Activation constraints



Variables: Domains

$\sim$ cl-B-2: { #, St-A-B-2, Pick-B-2}

he-2: { #, St-A-B-2, St-B-A-2, Ptdn-A-2, Ptdn-B-2}

h-A-1: { #, Pick-A-1}

h-B-1: { #, Pick-B-1}

....

Constraints:

he-2 = St-A-B-2  $\Rightarrow$  h-A-1  $\neq$  #  
{activation}

On-A-B-2 = St-A-B-2  
 $\Rightarrow$  On-B-A-2  $\neq$  St-B-A-2  
{mutex constraints}

Goals:

$\sim$ cl-B-2  $\neq$  #    he-2  $\neq$  #

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## Compilation to Integer Linear Programming

ILP: Given a set of real valued variables, a linear objective function on the variables, a set of linear inequalities on the variables, and a set of integrality restrictions on the variables, Find the values of the feasible variables for which the objective function attains the maximum value

-- o/I integer programming corresponds closely to SAT problem

### ◇ Motivations

- Ability to handle numeric quantities, and do optimization
- Heuristic value of the LP relaxation of ILP problems

### ◇ Conversion

- Convert a SAT/CSP encoding to ILP inequalities
  - » E.g.  $X \vee \sim Y \vee Z \Rightarrow x + (1 - y) + z \geq 1$
- Explicitly set up tighter ILP inequalities
  - » If X,Y,Z are pairwise mutex, we can write  $x+y+z \leq 1$   
(instead of  $x+y \leq 1$  ;  $y+z \leq 1$  ;  $z+x \leq 1$ )

*[Waker & Kautz,  
Vossen et. al.  
Bockmayr & Dimopoulos]*

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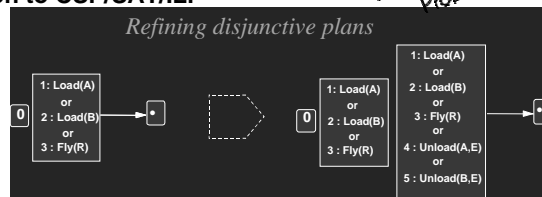
## Relative Tradeoffs Offered by the various compilation substrates

- ◇ CSP encodings support implicit representations
  - More compact encodings [Do & Kambhampati, 2000]
  - Easier integration with Scheduling techniques
- ◇ ILP encodings support numeric quantities
  - Seamless integration of numeric resource constraints [Walser & Kautz, 1999]
  - Not competitive with CSP/SAT for problems without numeric constraints
- ◇ SAT encodings support axioms in propositional logic form
  - May be more natural to add (for whom ;-)
- ◇ BDDs are very popular in CAD community
  - Commercial interest may spur effective algorithms (which we can use)

## Disjunctive Planning

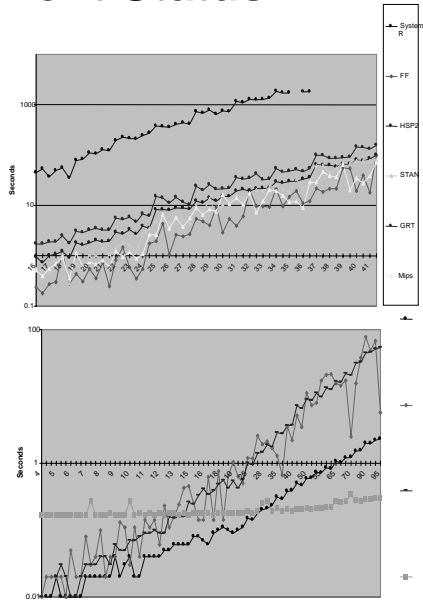
- ◇ Idea: Consider Partial plans with disjunctive step, ordering, and auxiliary constraints
- ◇ Motivation: Provides a lifted search space, avoids re-generating the same failures multiple times (also, rich connections to combinatorial problems)
- ◇ Issues:
  - Refining disjunctive plans
    - » Graphplan (Blum & Furst, 95)
  - Solution extraction in disjunctive plans
    - » Direct combinatorial search
    - » Compilation to CSP/SAT/ILP

*Solution Extraction is a combinatorial Problem*



## Planning: Current Status

- ◇ Disjunctive planners as well as heuristic state-search planners scale well
  - Plans with upto 100 actions synthesized in minutes
  - Impressive performances in AIPS-1998 and AIPS-2000 Competitions
- ◇ Plan-space planners with comparable performance are still to be developed [Long & Kambhampati, IJCAI-2001 (may be)]



## Scheduling: The State of the Art

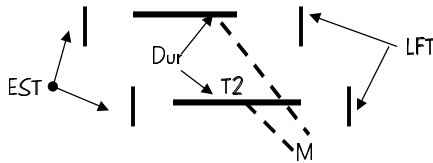
### Overview

- ◇ Why integrate planning and scheduling?
- ◇ Planning: The state of the art
- ◇ Scheduling: The state of the art
- ◇ Integrating Planning and Scheduling

# Scheduling: Brief Overview

## Jobshop scheduling

- Set of jobs
  - » Each job consists of tasks in some (partial) order
- Temporal constraints on jobs
  - » EST, LFT, Duration
- Contention constraints
  - » Each task can be done on a subset of machines



## CSP Models

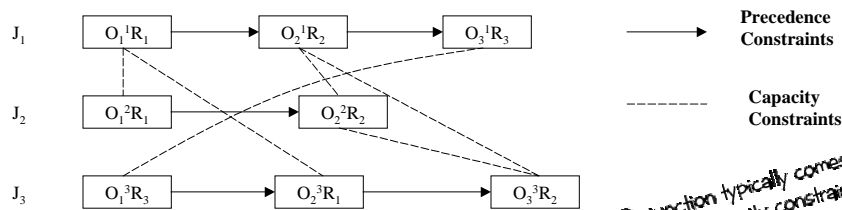
- Time point model
  - » Tasks as variables, Time points as values
  - » EST, LFT, Machine contention as constraints
- Inter-task precedences as variables (PCP model)

## CSP Techniques

- Customized consistency enforcement techniques
  - » ARC-B consistency
  - » Edge-finding
- Customized variable/value ordering heuristics
  - » Contention-based
  - » Slack-based
- MaxCSP; B&B searches

# Job Shop Scheduling as a CSP

## Jobs



## Start Point Representation

Variables: Start time  $st_i^1$   
Domain:  $[est_i^1 \dots lst_i^1]$   
Precedence constraints:  
 $st_i^1 + du_i^1 \leq st_j^1$   
Capacity Constraints:  
 $st_i^1 + du_i^1 \leq st_j^1 \vee st_j^1 + du_j^1 \leq st_i^1$

Simple Search

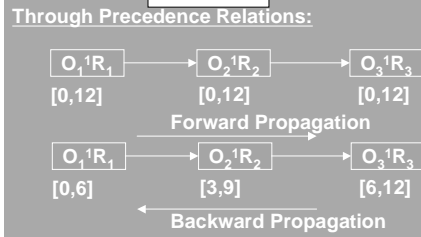
## PCP Representation

Variables: Ordering(i,j,R) for task i and j contending for resource R.  
Domain: {i-before-j, j-before-i}  
Constraints: Posting and propagation in the underlying temporal constraint network (time points and intervals)

More Flexible

# Constraint Propagation

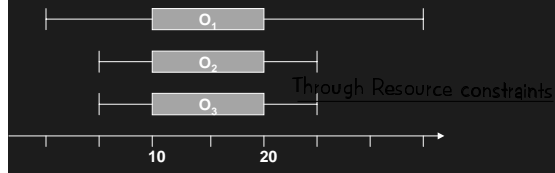
## Arc-Bounds



## Edge-Finding

- S is a set of operations competing for resource R.
- O is an operation not in S also requiring R.

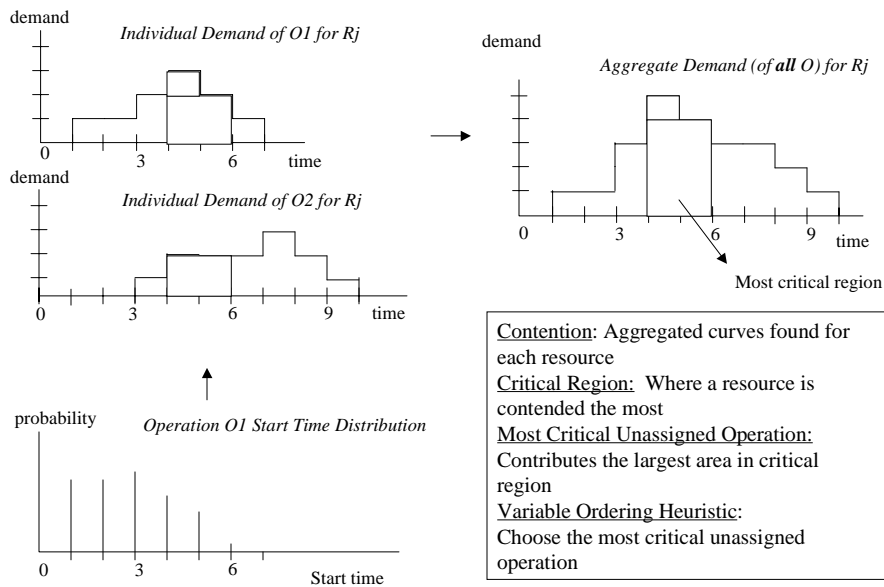
$$((LFT(S) - EST(S) < Dur(O) + Dur(S)) \rightarrow EST(O) \geq EST(S) + Dur(S) \wedge (LFT(S) - EST(O) < Dur(O) + EST(O))$$



S = {O2,O3}; O = O1 → Start Time O1 = 25

# Contention-based Ordering Heuristic

[Sadeh, 1991]

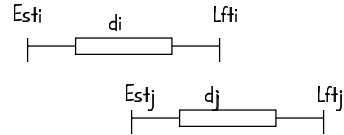




[Cheng & Smith, 1996]

## Slack-based Ordering Heuristic

(Precedence constraint-posting slack)

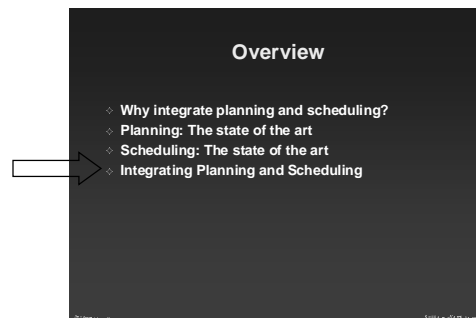


- ◇ For two unordered operations I and J
  - $\text{Slack}(I \rightarrow J) = \text{Lft}_j - \text{Est}_i - (\text{Dur}_i + \text{Dur}_j)$
  - $\text{Bslack}(I \rightarrow J) = \text{Slack}(I \rightarrow J) / f(S)$ , ( $f(S)$  is similarity measure)
- ◇ **Min-Slack Selection (Variable Ordering)**
  - Choose operations pairs with minimum value of  $\text{Min}(\text{Bslack}(I \rightarrow J), \text{Bslack}(J \rightarrow I))$
- ◇ **Max-Slack Posting (Value Ordering)**
  - Select the precedent constraint that leaves maximum remaining slack  $\text{Max}(\text{Bslack}(I \rightarrow J), \text{Bslack}(J \rightarrow I))$
- ◇ This slack-based heuristic performs competitively with contention-based heuristic
- ◇ Significantly improved by combining with consistency enforcement methods (Baptiste, Le Pape, Nuijten, 1995)

## Current State of Scheduling as CSP

- ◇ **Constraint-based scheduling techniques are an integral part of the scheduling suites by ILOG/I2**
  - Optimization results comparable to best approximation algorithms currently known on standard benchmark problems.
  - Best known solutions to more idiosyncratic, “multi-product hoist scheduling” application (PCB electroplating).
- ◇ **Better in most large-scale problems than IP formulations**

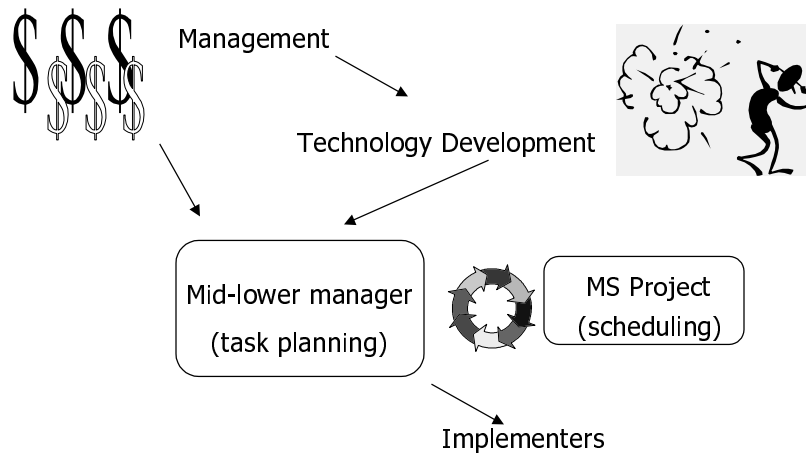
# Integrating Planning & Scheduling



## Approaches

- ◇ **Decoupled**
  - Existing approaches
- ◇ **Monolithic**
  - Extend Planners to handle time and resources
  - Extend Schedulers to handle choice
- ◇ **Loosely Coupled**
  - Making planners and schedulers interact

## Decoupled approaches (which is how Project Mgmt Done now)

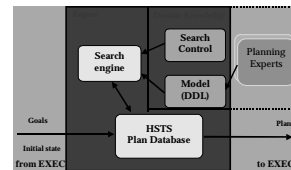


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## Extending Planners

- ◇ ZENO [Penberthy & Weld], IxTET [Ghallab & Laborie], HSTS/RAX [Muscettola] extend a conjunctive plan-space planner with temporal and numeric constraint reasoners
- ◇ LPSAT [Wolfman & Weld] integrates a disjunctive state-space planner with an LP solver to support numeric quantities
- ◇ IPPlan [Kautz & Walser; 99] constructs ILP encodings with numeric constraints
- ◇ TGP [Smith & Weld; 99] supports actions with durations in Graphplan



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## Actions with Resources and Duration

Load(P:package, R:rocket, L:location)

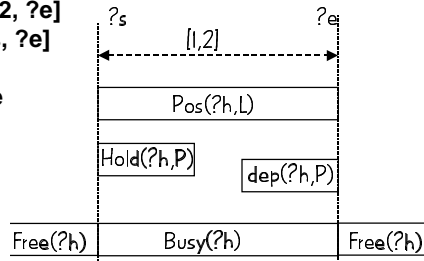
**Resources:** ?h : robot hand

**Preconditions:** Position(?h,L)      [?s, ?e]  
 Free(?h)                                      ?s  
 Charge(?h) > 5                              ?s

**Effects:** holding(?h, P)                      [?s, ?t1]  
 depositing(?h,P,R)                      [?t2, ?e]  
 Busy(?h)                                      [?s, ?e]  
 Free(?h)                                      ?e  
 Charge - = .03\*(?e - ?s)                      ?e

**Constraints:** ?t1 < ?t2  
 ?e - ?s in [1.0, 2.0]

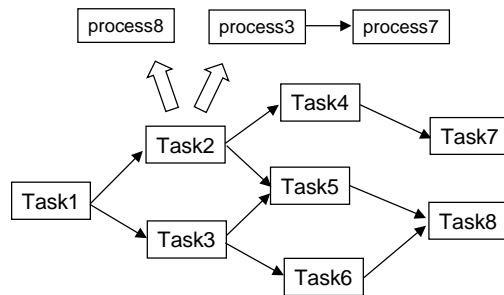
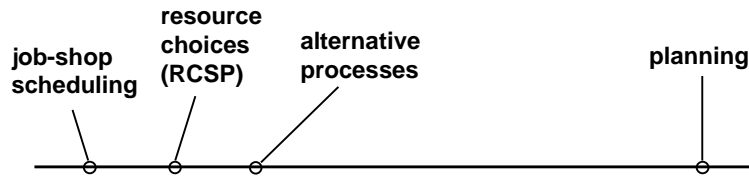
Capacity(robot) = 3



## What planners are good for handling resources and time?

- ◇ State-space approaches have an edge in terms of ease of monitoring resource usage
  - *Time-point based representations are known to be better for multi-capacity resource constraints in scheduling*
- ◇ Plan-space approaches have an edge in terms of durative actions and continuous change
  - Notion of state not well defined in such cases (Too many states)
  - *PCP representations are known to be better for scheduling with single-capacity resources*

# Extending Scheduling



Ordering choices  
Resource choices  
Process choices

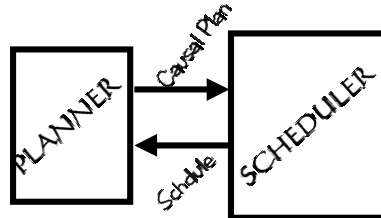
# Monolithic Architectures Scale Poorly

- ◇ **Extended planning systems are hard to control**
  - RAX uses a very error-prone hand-coded search control strategy
- ◇ **Extended scheduling systems tend to lose effectiveness due to increased disjunction**
- ◇ **Monolithic systems can sometimes show counter-intuitive behavior (by multiplying search failures)**

Performance worsens with increased resources!



## Loosely Coupled Architectures



Schedulers already routinely handle resources and metric/temporal constraints.

- Let the “planner” concentrate on causal reasoning
- Let the “scheduler” concentrate on resource allocation, sequencing and numeric constraints for the generated causal plan

Need better coupling to avoid inter-module thrashing....

## Making Loose Coupling Work

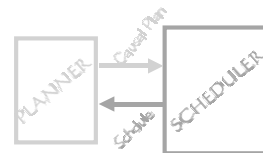
◇ How can the Planner keep track of consistency?

- Low level constraint propagation
  - » Loose path consistency on TCSPs
  - » Bounds on resource consumption,
  - » LP relaxations of metric constraints
- Pre-emptive conflict resolution

The more aggressive you do this, the less need for a scheduler..

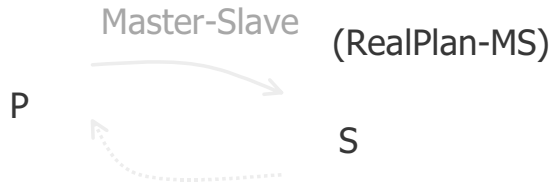
◇ How do the modules interact?

- Failure explanations; Partial results



# RealPlan--Master/Slave

(Srivastava & Kambarampati  
ECP-99:  
AAAI, 2000)

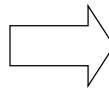


Planner does causal reasoning.

Scheduler attempts resource allocation

If scheduler fails, planner has to restart

Level	Actions by level	# Robots
1	Unstack_R_bkf_bkE	1
2	Unstack_R_bkE_bkD	2
3	Unstack_R_bkD_bkC	3
4	Unstack_R_bkC_bkB	4
5	Putdown_R_bkC	5
6	Unstack_R_bkB_bkA	5
7	Stack_R_bkf_bkC	5
8	Pickup_R_bkA	4
9	Stack_R_bkB_bkE	3
10	Stack_R_bkA_bkE	2
	Stack_R_bkD_bkA	1



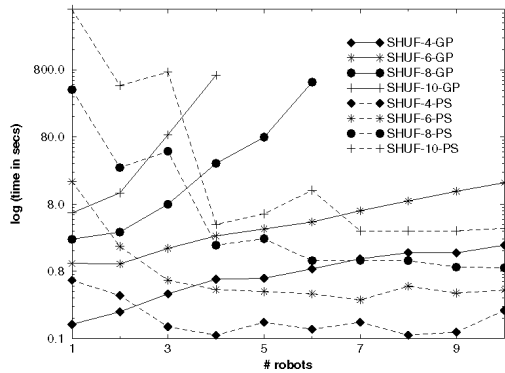
Allocation Policy	Constraint on values
Maintain concurrency (Class FINRES)	$PA_i = i, PA_j = j,$ $RA_i = RA_j = \{1, \dots, N\}$ $PF_{ij} = PF_{ji} = \perp$ $HR_{ij} = HR_{ji} = \perp$
Serialize plan	$PA_i = \{i, i^{MAX}\},$ $PA_j = \{j, j^{MAX}\},$ $RA_i = RA_j = \{1, \dots, N\}$ $PF_{ij} = PF_{ji} = \perp$ $HR_{ij} = HR_{ji} = \perp$
Introduce Free/Resillocate action (Class FINRES)	
Class FIX	$PA_i = i, PA_j = j,$ $RA_i = RA_j = \{1, \dots, N\}$ $PF_{ij} = \{i, j\},$ $PF_{ji} = \{j, i\},$ $HR_{ij} = HR_{ji} = \{1, \dots, N\}$
Class SAMELEN	$PA_i = \{i, i-1\},$ $PA_j = \{j, j\},$ $RA_i = RA_j = \{1, \dots, N\}$ $PF_{ij} = \{i, j, i-1, j\},$ $PF_{ji} = \{j, i-1, j, i\},$ $HR_{ij} = HR_{ji} = \{1, \dots, N\}$
Class INCRLEN	$PA_i = \{i, i^{MAX}, i\},$ $PA_j = \{j, j^{MAX}\},$ $RA_i = RA_j = \{1, \dots, N\}$ $PF_{ij} = \{i, j, i-1, j^{MAX}, i-1\},$ $PF_{ji} = \{j, i-1, j^{MAX}, i\},$ $HR_{ij} = HR_{ji} = \{1, \dots, N\}$

Table 1: Allocation policy and restrictions on values of variables.  $i^{MAX}$  is some maximum length ( $i^{MAX} > i$ ) upto which the steps of the plan can be increased.

# Performance of Master-Slave Coupling

When scheduler fails, no specific guidance is given to the planner

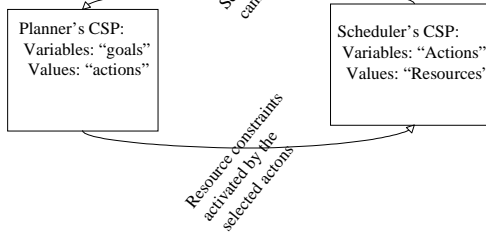
Performance of Graphplan v/s Planning+Scheduling  
in the Shuffle Problems in Blocks World



# RealPlan: Peer-to-Peer

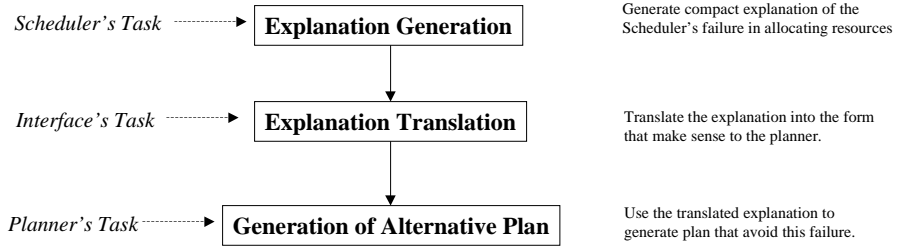
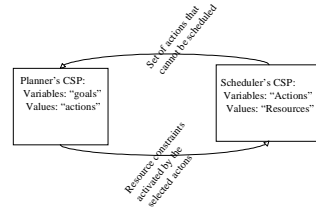
Explanation-directed backtracking between Planner and Scheduler

Peer-Peer (RealPlan-PP)





# Inter-module Dependency Directed Backtracking

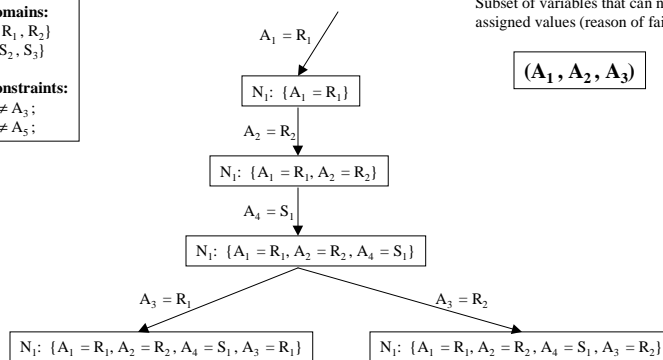


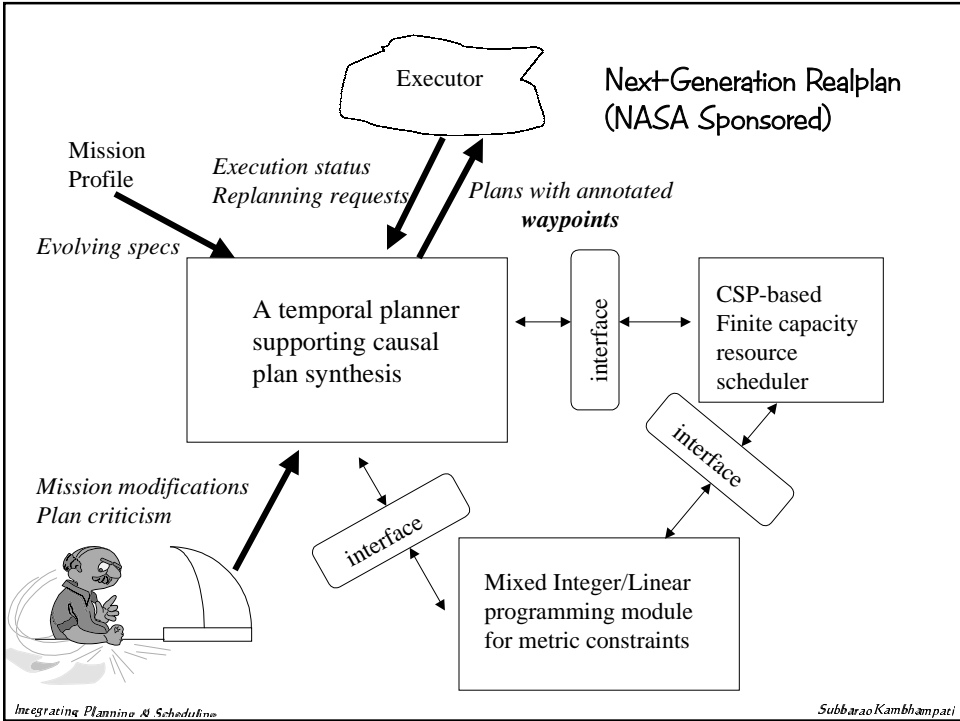
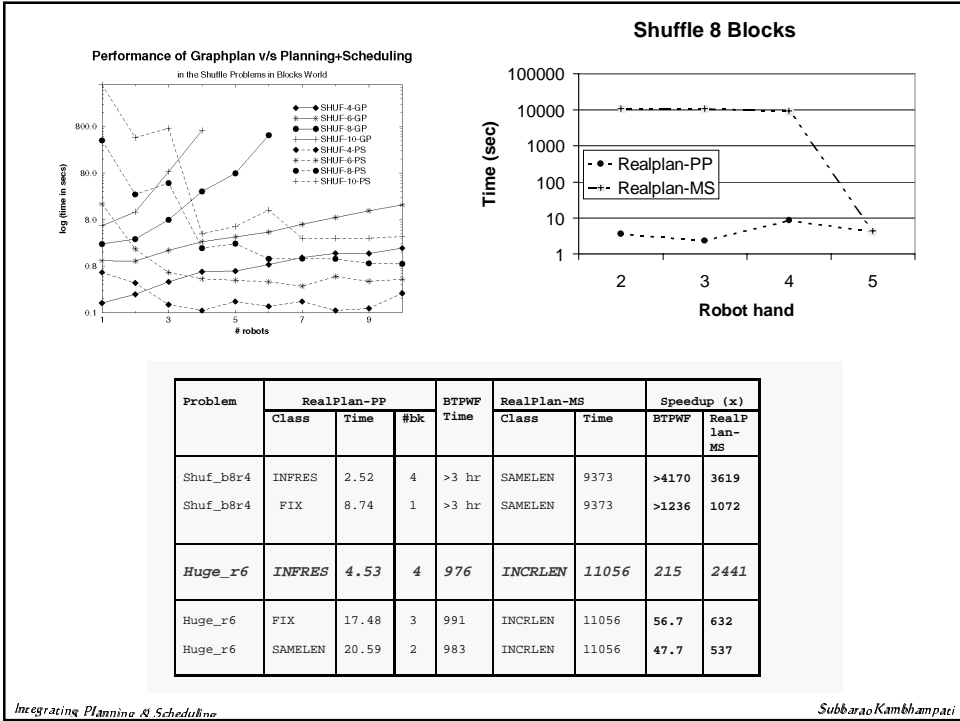
**Resource Domains:**  
 $A_1, A_2, A_3: \{R_1, R_2\}$   
 $A_4, A_5: \{S_1, S_2, S_3\}$

**Resource Constraints:**  
 $A_1 \neq A_2; A_2 \neq A_3;$   
 $A_1 \neq A_3; A_4 \neq A_5;$

Subset of variables that can not be assigned values (reason of failure):

$(A_1, A_2, A_3)$





## Summary & Conclusion

- ◇ **Motivated the need for integrating Planning and Scheduling**
- ◇ **Discussed the state of the art in Planning and Scheduling**
- ◇ **Discussed approaches for Integrating them**
  - **Loosely coupled architectures are a promising approach**