

**CALCULUS OF VARIATIONS IN DISCRETE SPACE
FOR CONSTRAINED NONLINEAR DYNAMIC
OPTIMIZATION**

Yixin Chen and Benjamin W. Wah

**Department of Electrical and Computer Engineering
and the Coordinated Science Laboratory
University of Illinois at Urbana-Champaign
Urbana, IL 61801, USA**

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Outline

- Introduction
 - Discrete-space dynamic optimization problems
 - Existing approaches
- Calculus of variations in discrete time and discrete state space
 - Necessary and sufficient conditions for constrained local minima
 - Variational search algorithm with node dominance
- Implementations in ASPEN
 - Some sample results
- Conclusions

INTRODUCTION

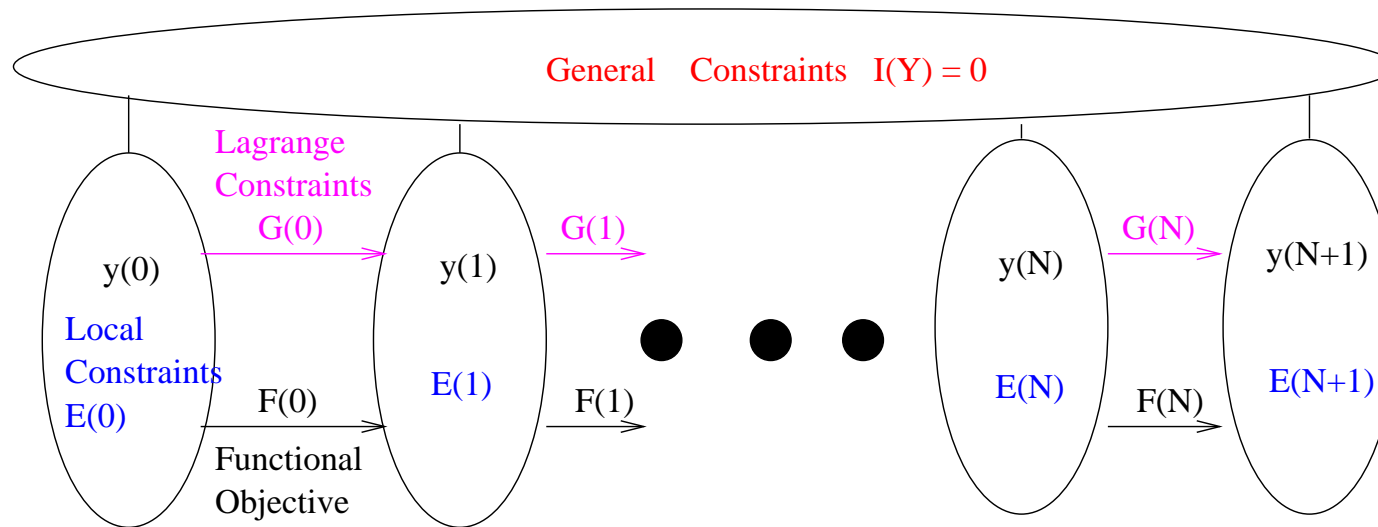
Dynamic Optimization Problems

Optimization problems with **time varying dynamic variables**

| State \ Time | Continuous | Discrete |
|--------------|-------------------------------------|-----------------------------------|
| Continuous | Continuous–time Continuous–state | Discrete–time Continuous–state |
| Discrete | Continuous–time Discrete–state | Discrete–time Discrete–state |

**Control theory and
classical theory of
calculus of variations**

Discrete-Time Discrete-State Constrained Dynamic Problems



$$\text{minimize } J[\{y(j)\}] = \sum_{j=0}^N F(j, y(j+1), y(j)) \quad (1)$$

$$\text{s.t. } G(j, y(j+1), y(j)) = 0, \quad j = 0, 1, \dots, N \quad (2)$$

$$E(j, y(j)) = 0, \quad (3)$$

$$I(Y) = 0 \quad (4)$$

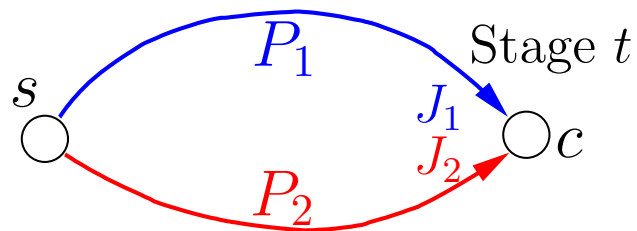
where $y(j)$ is defined in *discrete* space \mathcal{Y} ,

F , G and I are *not* necessarily continuous or differentiable

Unconstrained Problems or Problems with Lagrange Constraints

- Path Dominance: Principle of Optimality

- Principle of Optimality in dynamic programming applied on feasible state c



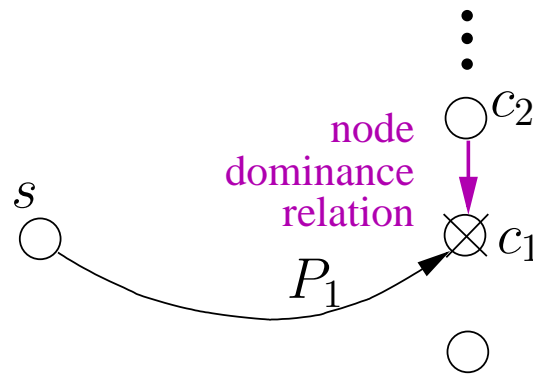
If c lies on the optimal path between s and d and $J_2 \leq J_1 \implies P_2 \rightarrow P_1$

- Polynomial worst-case complexity: $O(N|\mathcal{Y}|^2)$

Problems with General Constraints

- Path dominance not applicable
 - A dominating path may become infeasible due to general constraints
 - **Exponential worst-case complexity: $O(|\mathcal{Y}|^N)$** , assuming NP hard

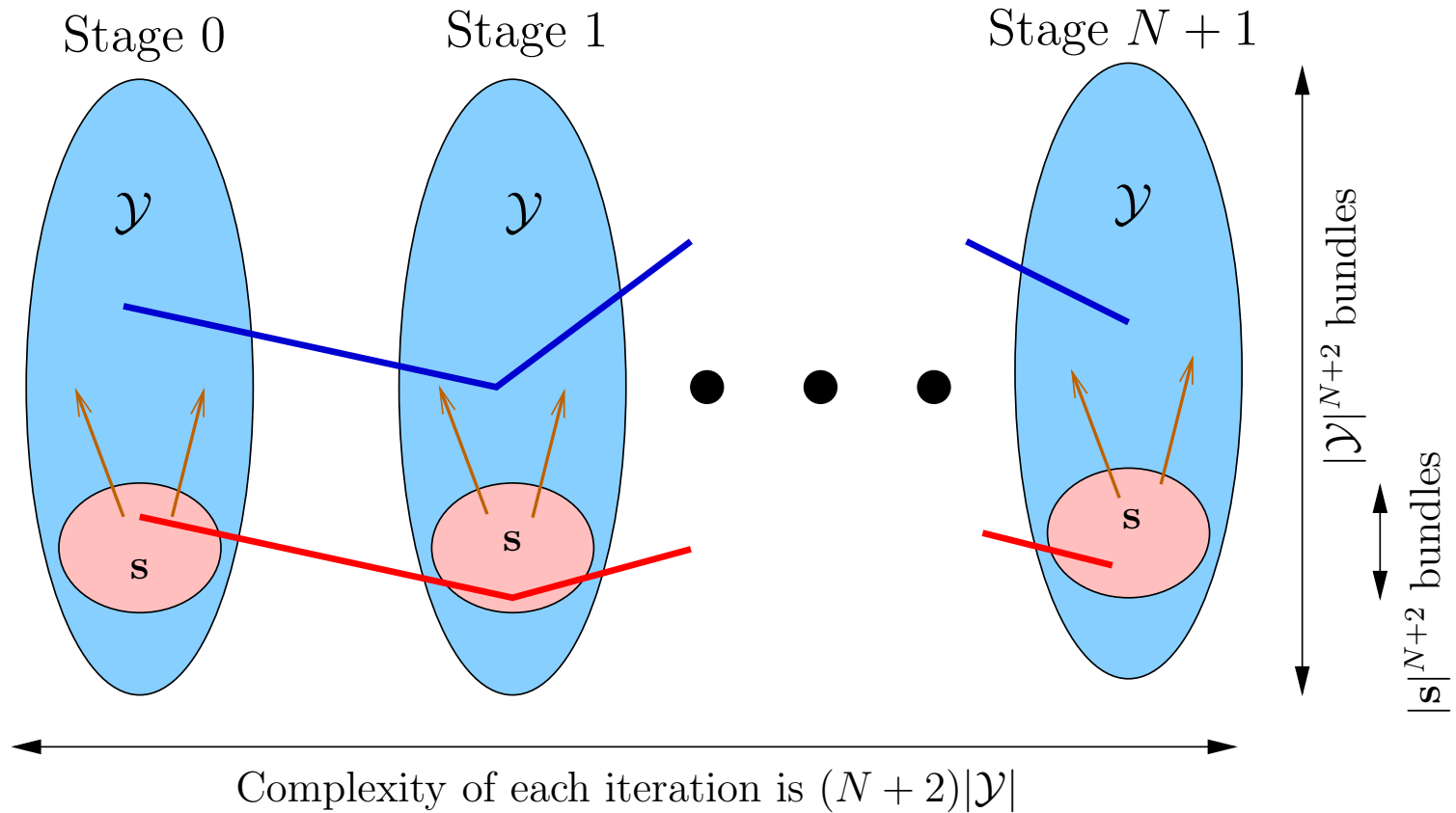
- **Node dominance** applicable



Termination of c_1 by
node dominance relation

- Worst-case complexity without path dominance: $O(N|\mathcal{Y}||s|^N)$
 - * Assuming $|s|$ nodes are not pruned in each stage
 - * Substantially less than $O(|\mathcal{Y}|^N)$ when $|s| \ll |\mathcal{Y}|$

Benefits of Using Node Dominance



- Not utilizing node dominance ● Dominating nodes at each stage
- Utilizing node dominance ● Dominated nodes at each stage

Worst-Case Complexities in Path and Node Dominance

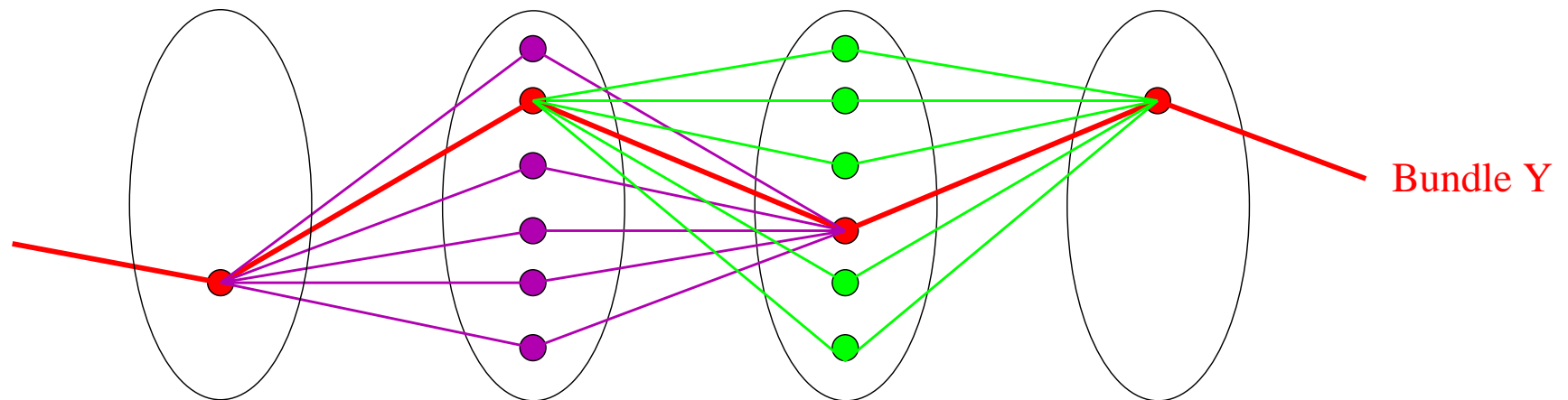
| Constraint Type | Without General Constraints (Conventional DP) | | With General Constraints (Without Path Dominance) | |
|-----------------|---|------------------------------|---|--------------------------|
| | With Path Dominance | With Path and Node Dominance | Without Node Dominance | With Node Dominance |
| Complexity | $O(N \mathcal{Y} ^2)$ | $O(N \mathcal{Y} + N s ^2)$ | $O(\mathcal{Y} ^N)$ | $O(N \mathcal{Y} s ^N)$ |

Node dominance works well when $|s| \ll |\mathcal{Y}|$

CALCULUS OF VARIATIONS IN DISCRETE SPACE

Constrained Local-Minimum Bundle in Discrete Space

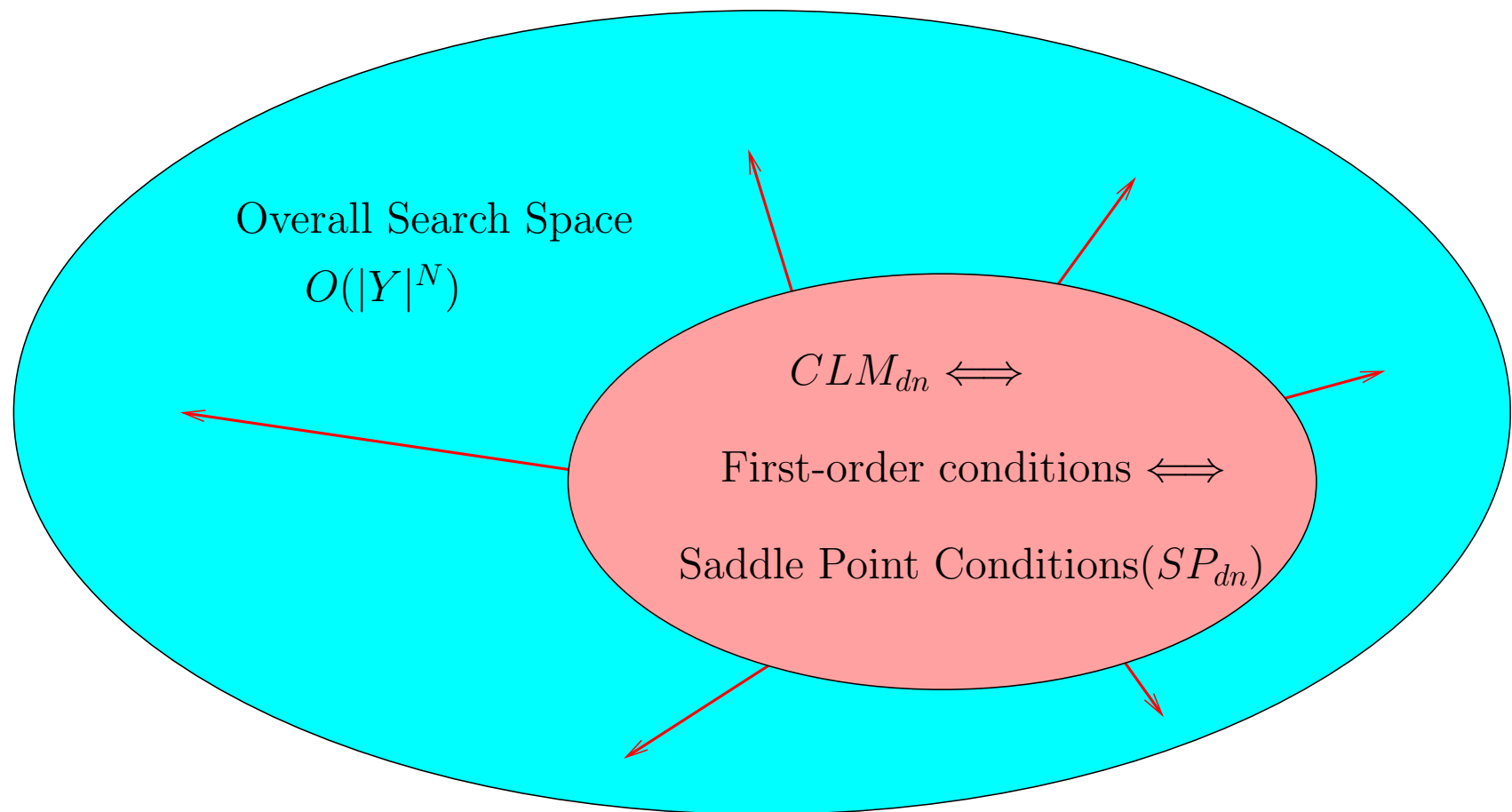
- State vector s in discrete state space \mathcal{Y} has user-defined **discrete neighborhood**
- **Discrete neighborhood of bundle** $Y = \{y(j)\}$ is the union of discrete neighborhoods of all stages, each defined on neighborhoods of states in each stage



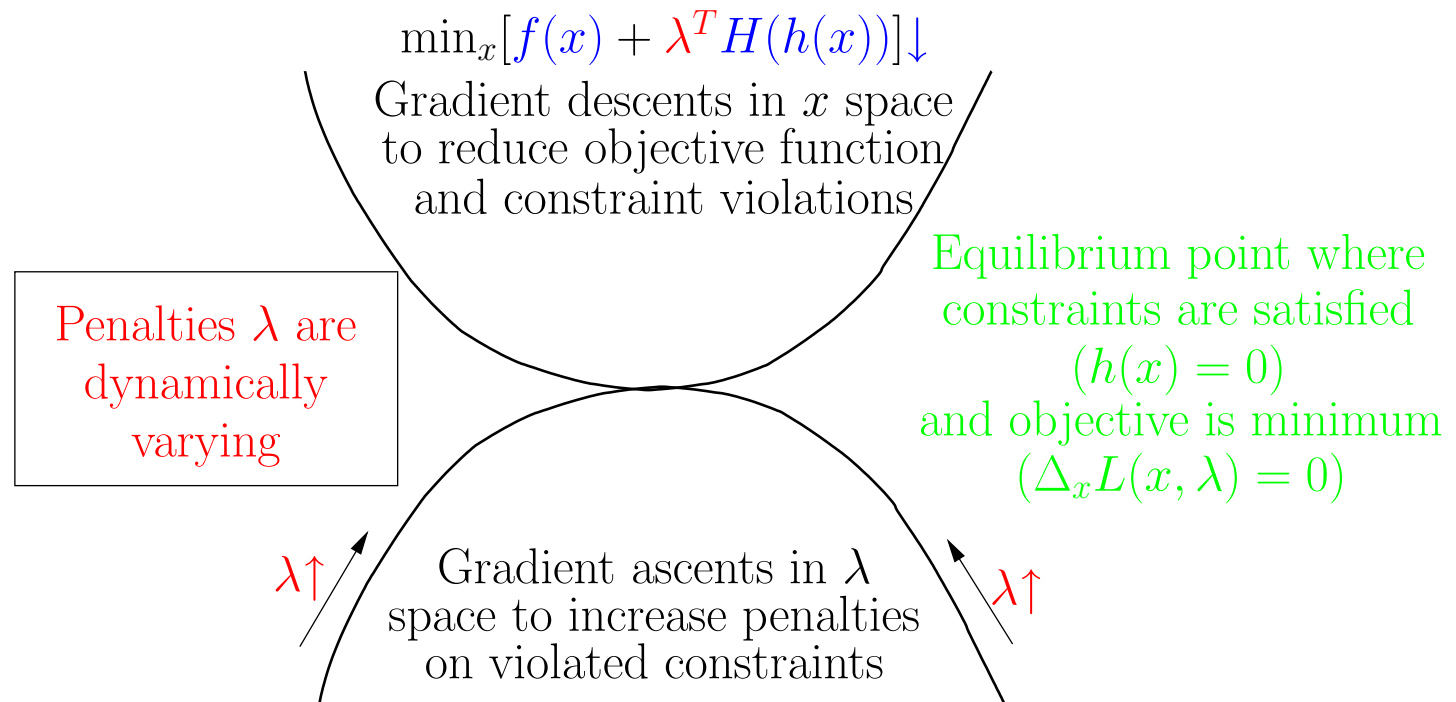
- Bundle Y is a **constrained local minimum in discrete space** (CLM_{dn}) if
 - Y is feasible
 - No feasible bundle in $\mathcal{N}_b(Y)$ has better functional value than $J[Y]$

Solving Overall Problem using Discrete-Space Lagrangian Theory

- **First-order necessary and sufficient conditions** based on the theory of Lagrange multipliers in discrete space



Intuitive Meaning Behind Saddle Points



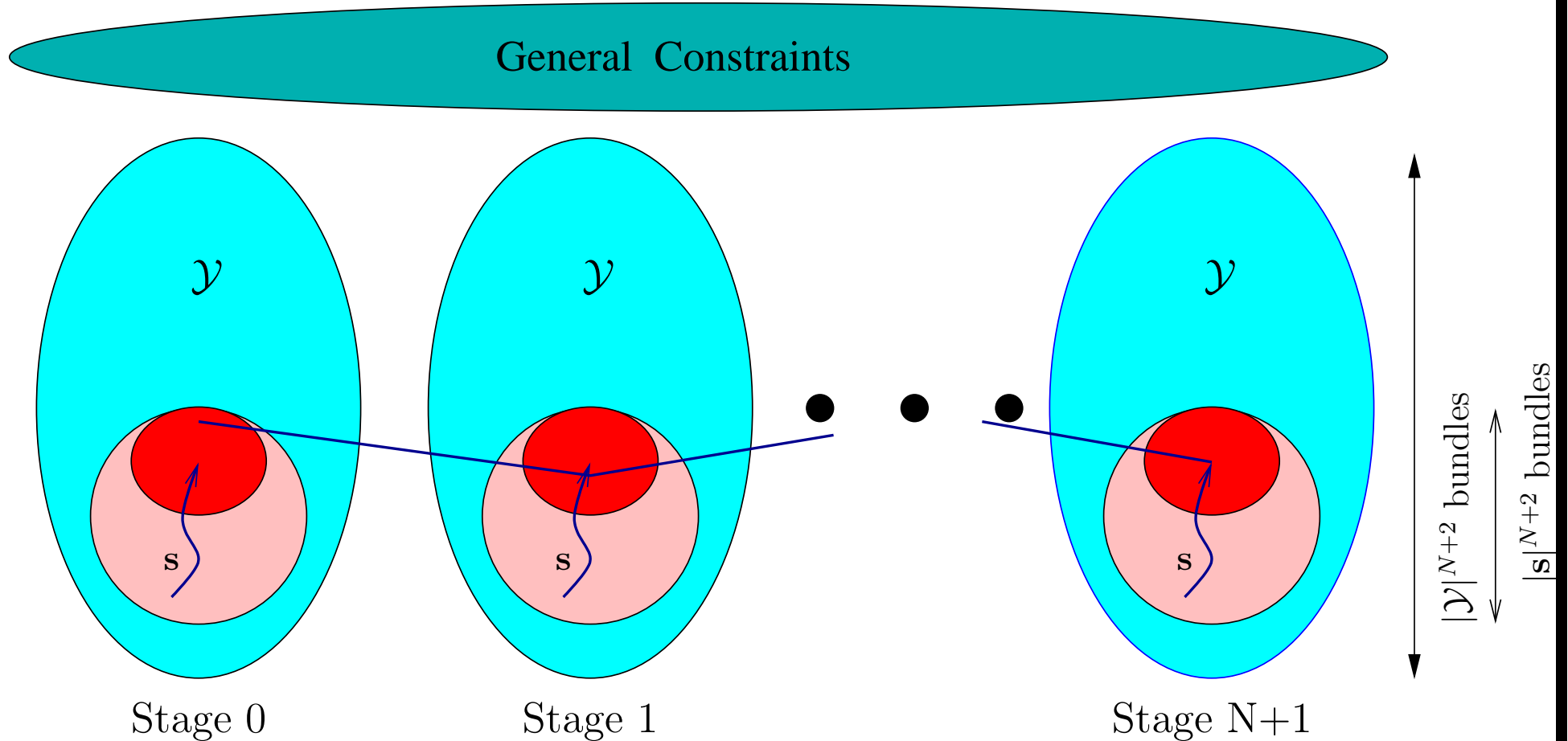
Discrete-Time Discrete-State Euler-Lagrange Equation

- Decompose first-order condition into **Discrete-Space Euler-Lagrange Equations** (ELE_{dn}) for each stage
- Decompose SP_{dn} in into $N + 2$ **distributed saddle-point conditions** DSP_{dn}
- Distributed necessary and sufficient conditions for CLM_{dn}

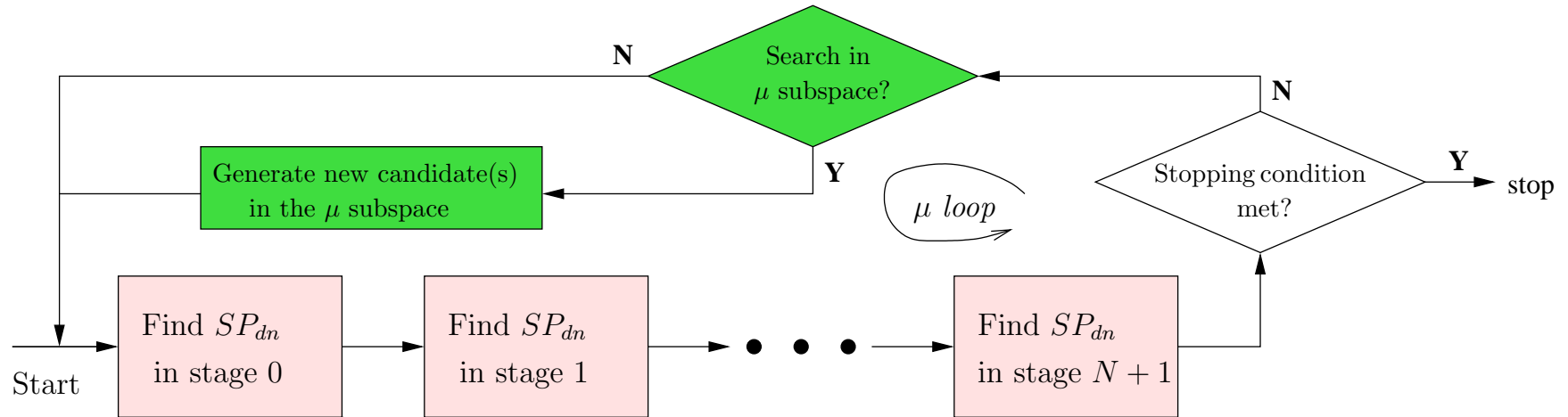
$$CLM_{dn} \equiv ELE_{dn} \equiv DSP_{dn}$$

- Only necessary when there are general constraints
- Differences from continuous variational calculus theory
 - Do not require differentiability or continuity of functions
 - Continuous ELE conditions are only necessary but not sufficient, even in the absence of general constraints

Solving Distributed Subproblems Using Node Dominance



Heuristic Search Procedure For Finding DSP_{dn}



Constrained Simulated Annealing(CSA):

- Local Descent in x subspace
- Local Ascent in λ subspace

DEMONSTRATIONS ON ASPEN

ASPEN Planner

- Automated Scheduling and Planning Environment at Jet Propulsion Laboratory
- ASPEN models have discrete time horizons
 - Each time point is a stage
 - Adjacent time points can be collapsed into a single stage
 - Current implementation: maximum 100 stages
- ASPEN repair/optimization actions provide promising descent directions in state-variable subspace
 - Repair actions: resolve conflicts
 - Optimization actions: optimize preferences
- ASPEN does not have the UNDO mechanism

Distributed Lagrangian Formulation

- Assign each conflict c_i a unique Lagrange Multiplier λ_i
- Augmented distributed Lagrangian function of stage t :

$$\Gamma_{dn}(t) = -w_s \cdot \text{Score} + \sum_{c_i \in C(t)} \lambda_i * H(c_i) + \sum_{c_i \in C(t)} \frac{H(c_i)^2}{2}$$

- w_s : weight of score
- Score: preference score of schedule
- $C(t)$: set of conflicts whose time duration intersects with stage t
- $H(c_i)$: non-negative value assigned to a conflict reflecting its degree of violation
 - * $H(c_i) = 1$ in current implementation

Distributed Heuristic Search for Finding SP_{dn} in Stage t

- Descent of $\Gamma_{dn}(t)$ in state subspace
 - Choose probabilistically from repair actions and optimization actions
 - Select random feasible action at each choice point
 - Apply selected action to current schedule in a child process
 - Evaluate $\Gamma_{dn}(t)$ of the new schedule
 - Accept new schedule according to Metropolis probability controlled by a geometrically decreasing temperature
 - Repeat action in parent process if accepted; otherwise, discard result of child process (overcome lack of UNDO but limited to 3685 forks)
- Ascent of $\Gamma_{dn}(t)$ in Lagrange-multiplier subspace

$$\lambda_i \longleftarrow \lambda_i + \alpha_i H(c_i)$$

SOME SAMPLE RESULTS

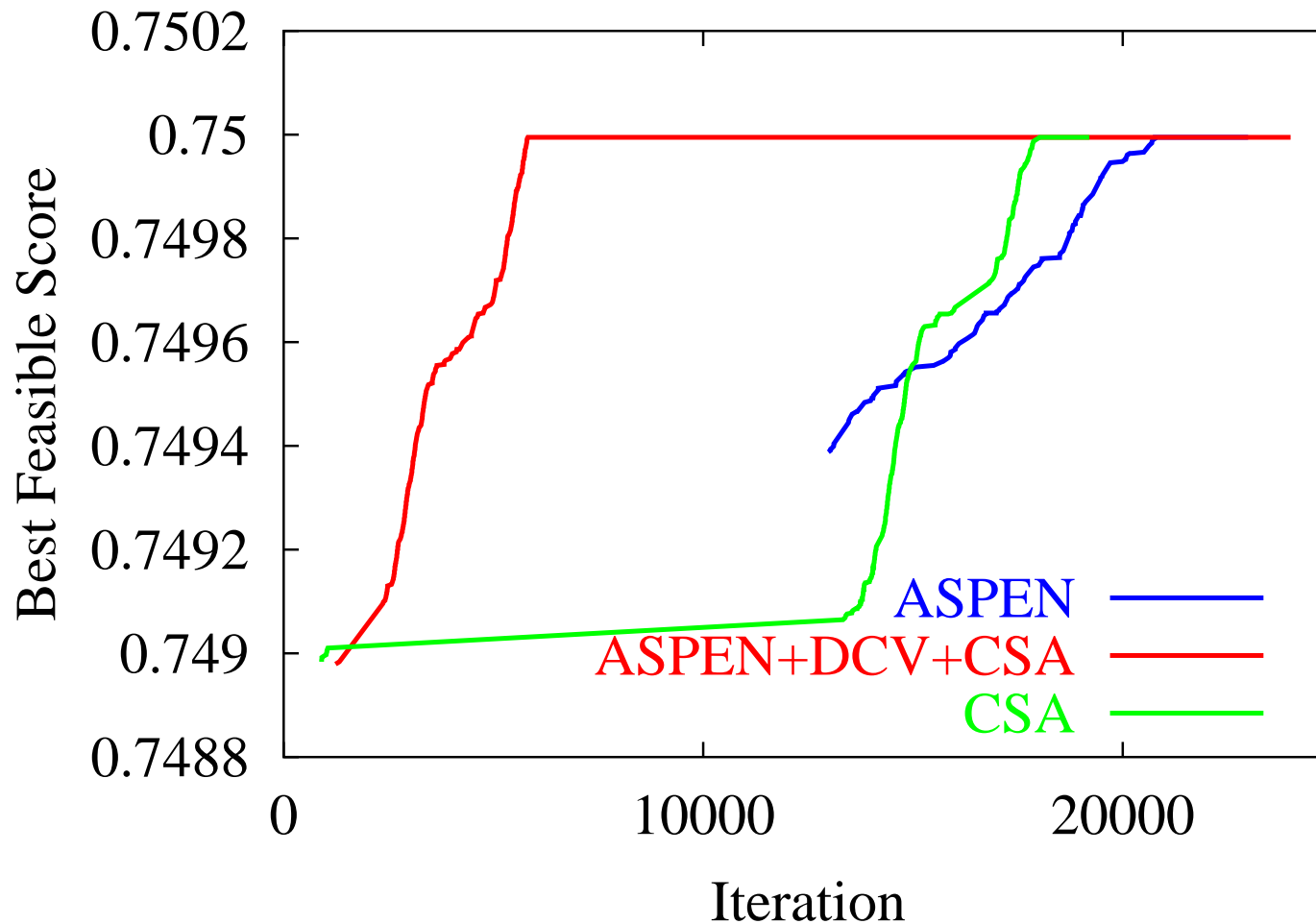
Benchmark CX1-PREF

- Citizen Explorer-I satellite design and operation planning benchmark
 - Multiple competing preferences to be optimized
 - Problem generator to generate different problem instances

perl probgen.pl < random seed > < number of orbits >

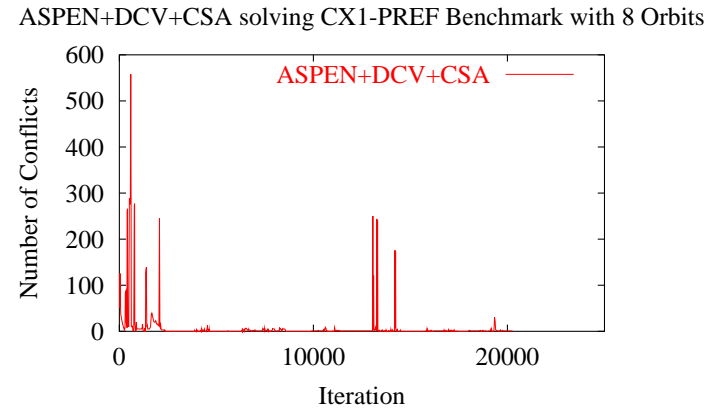
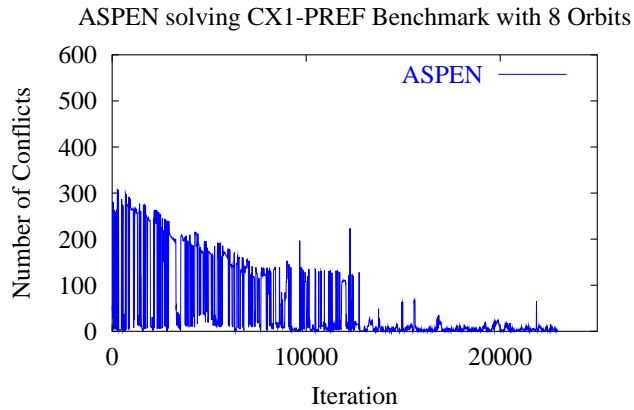
- ASPEN search setting:
 - a) Find feasible schedule using *repair*
 - b) Optimize score using *optimize* (default 200 iterations)
 - c) repeat (a) and (b)

Best Feasible Solution on an 8-Orbit Problem

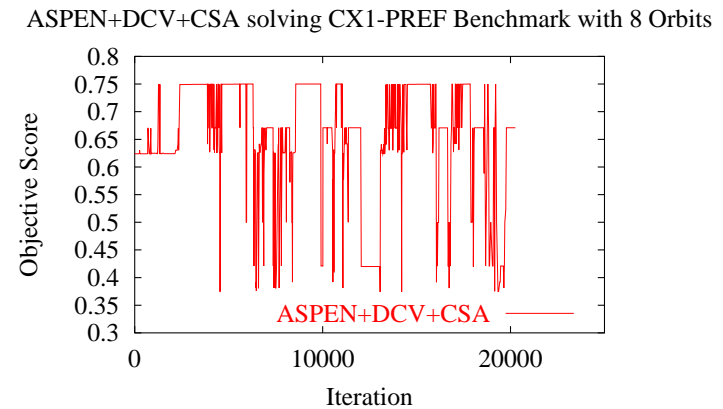
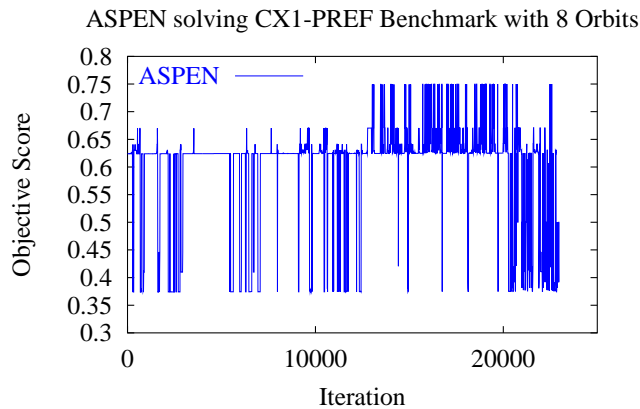


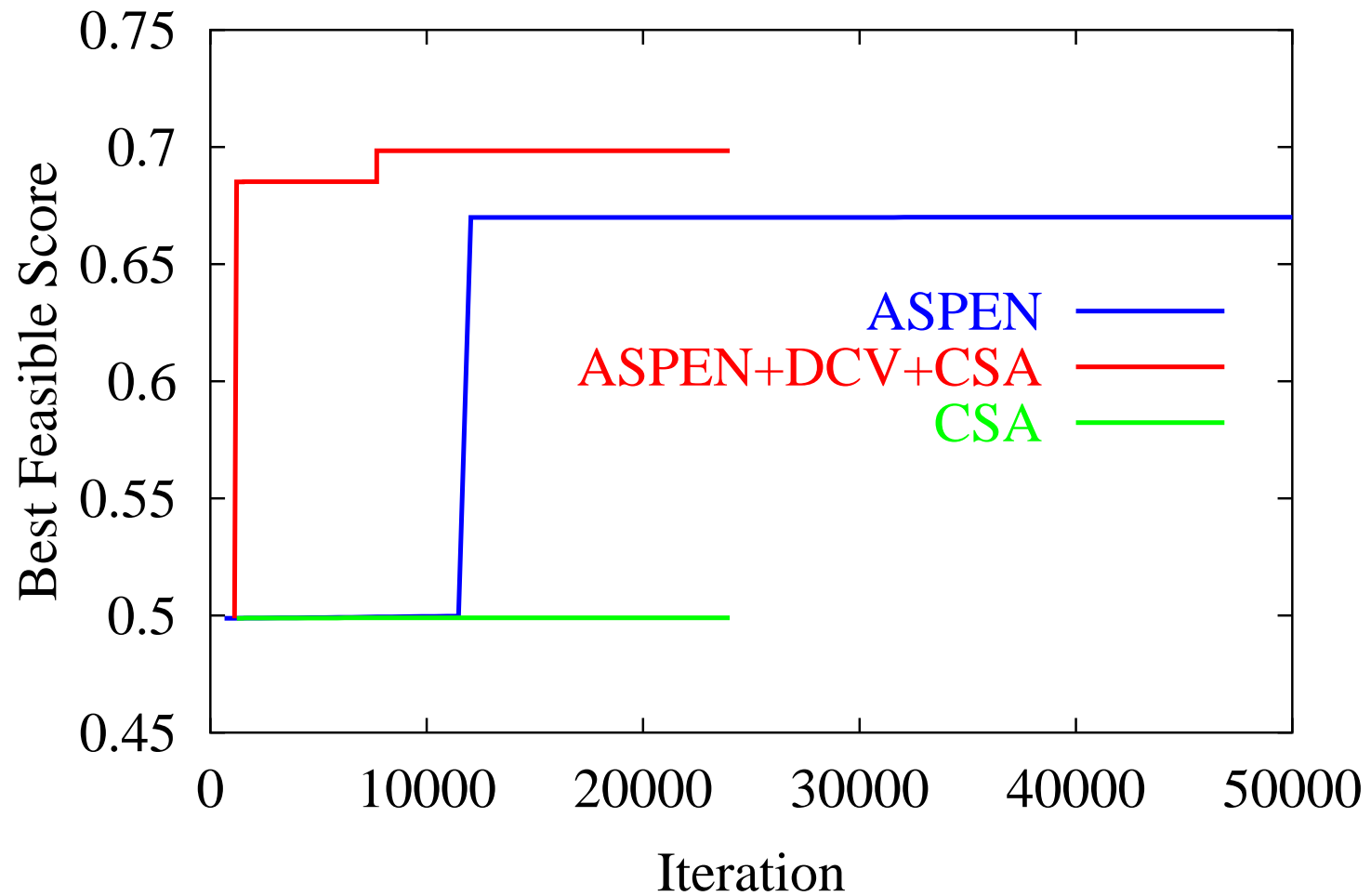
Search Progress on an 8-Orbit Problem

- Conflicts vs. Iteration:



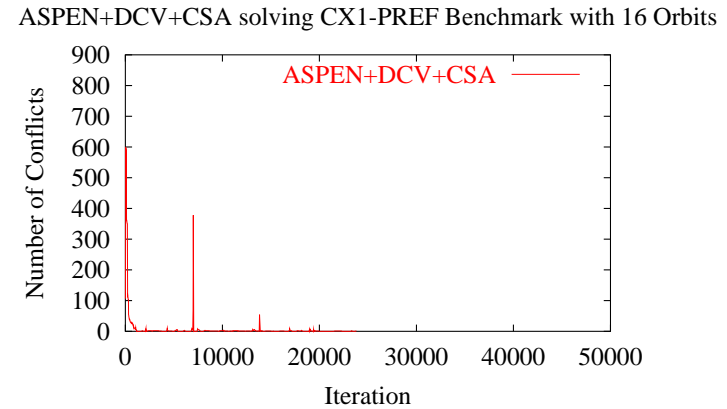
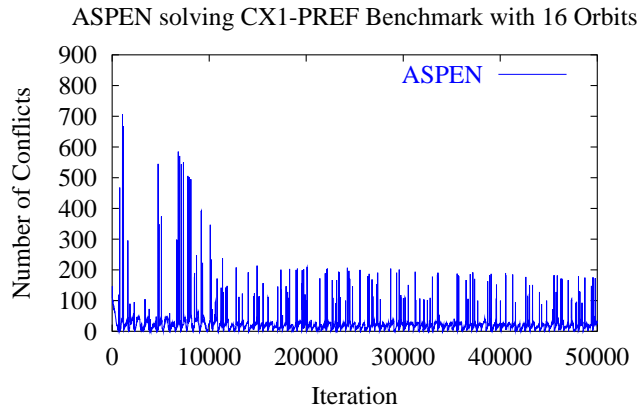
- Score vs. Iteration:



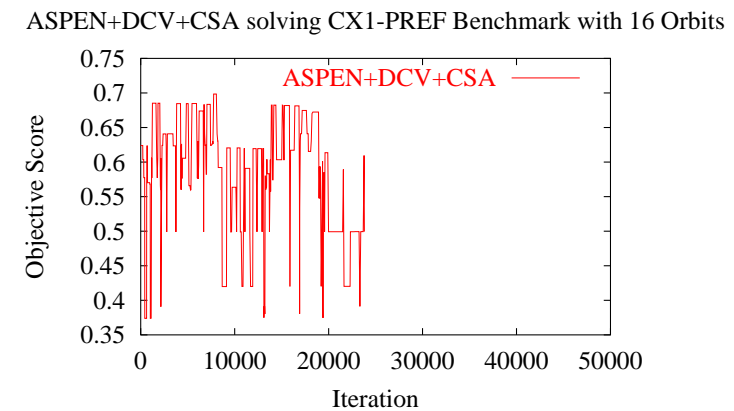
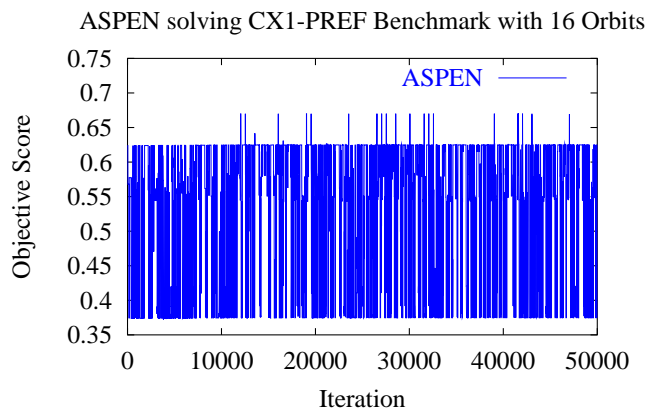
Best Feasible Solution on a 16-Orbit Problem

Search Progress on a 16-Orbit Problem

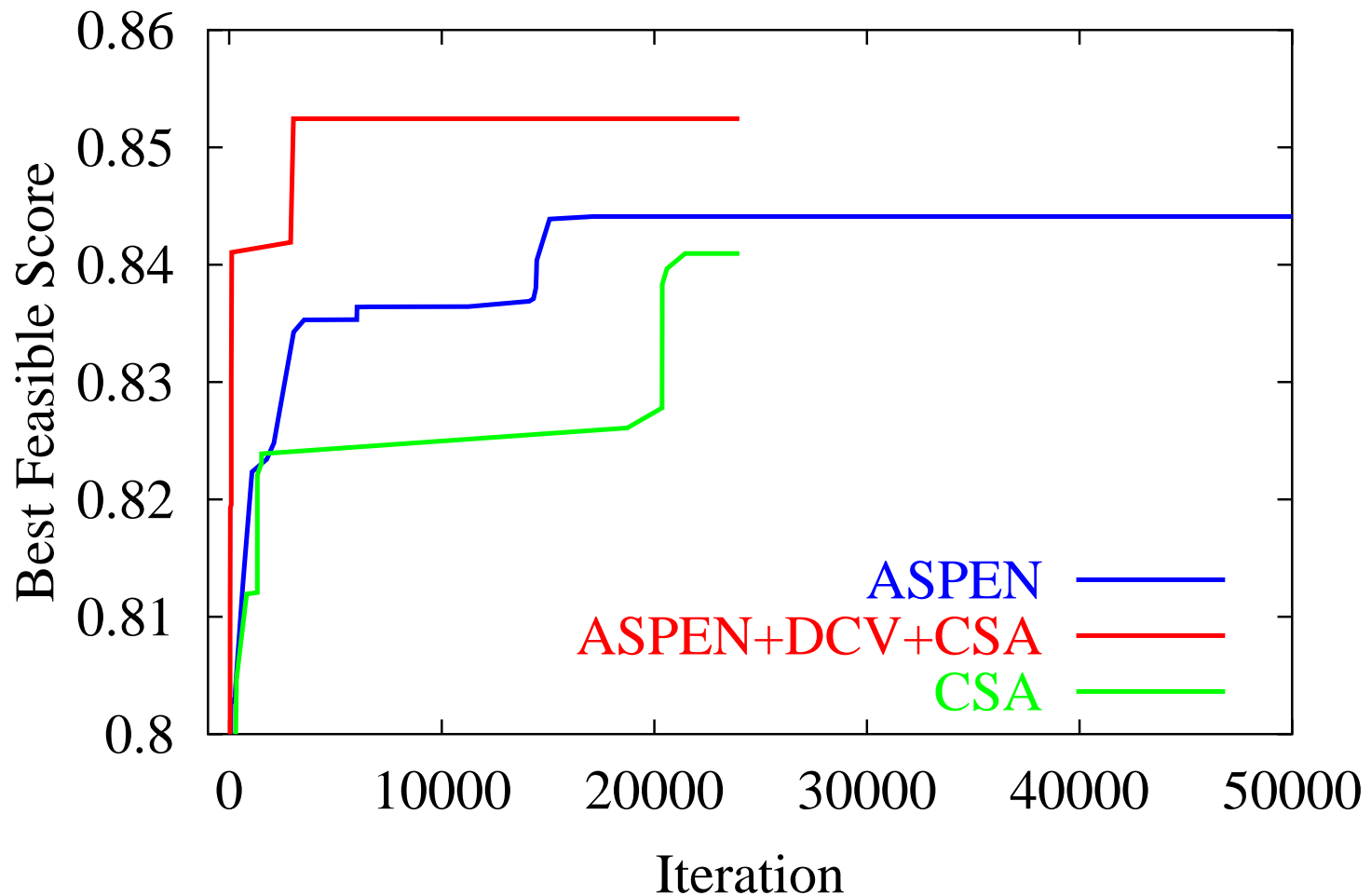
- Conflicts vs. Iteration:



- Score vs. Iteration:

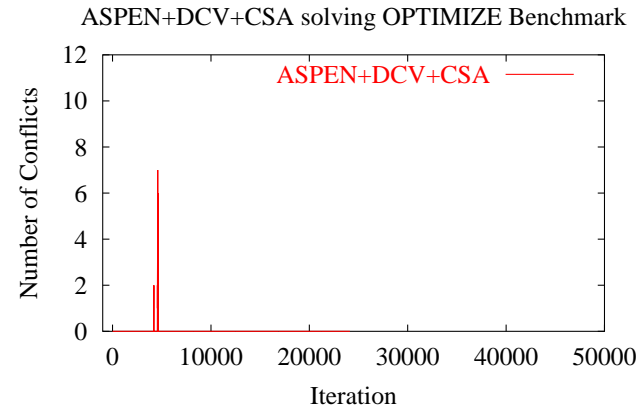
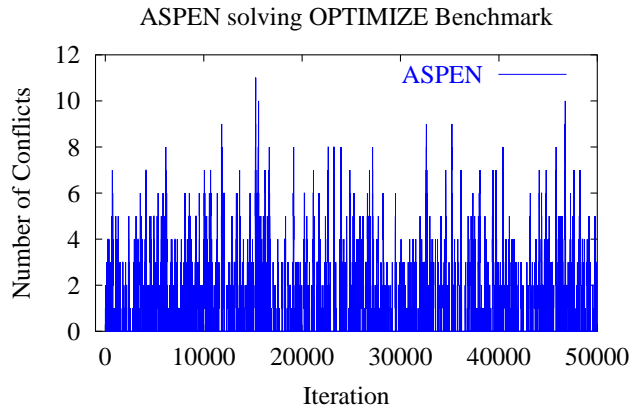


Best Feasible Solution on OPTIMIZE Benchmark

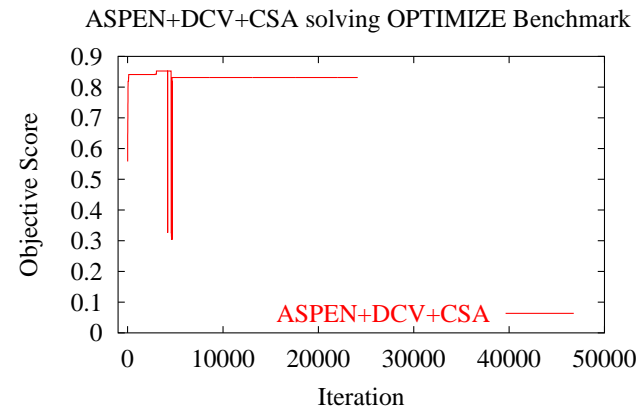
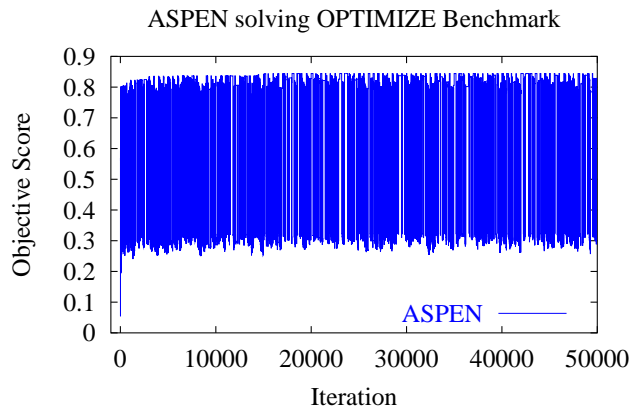


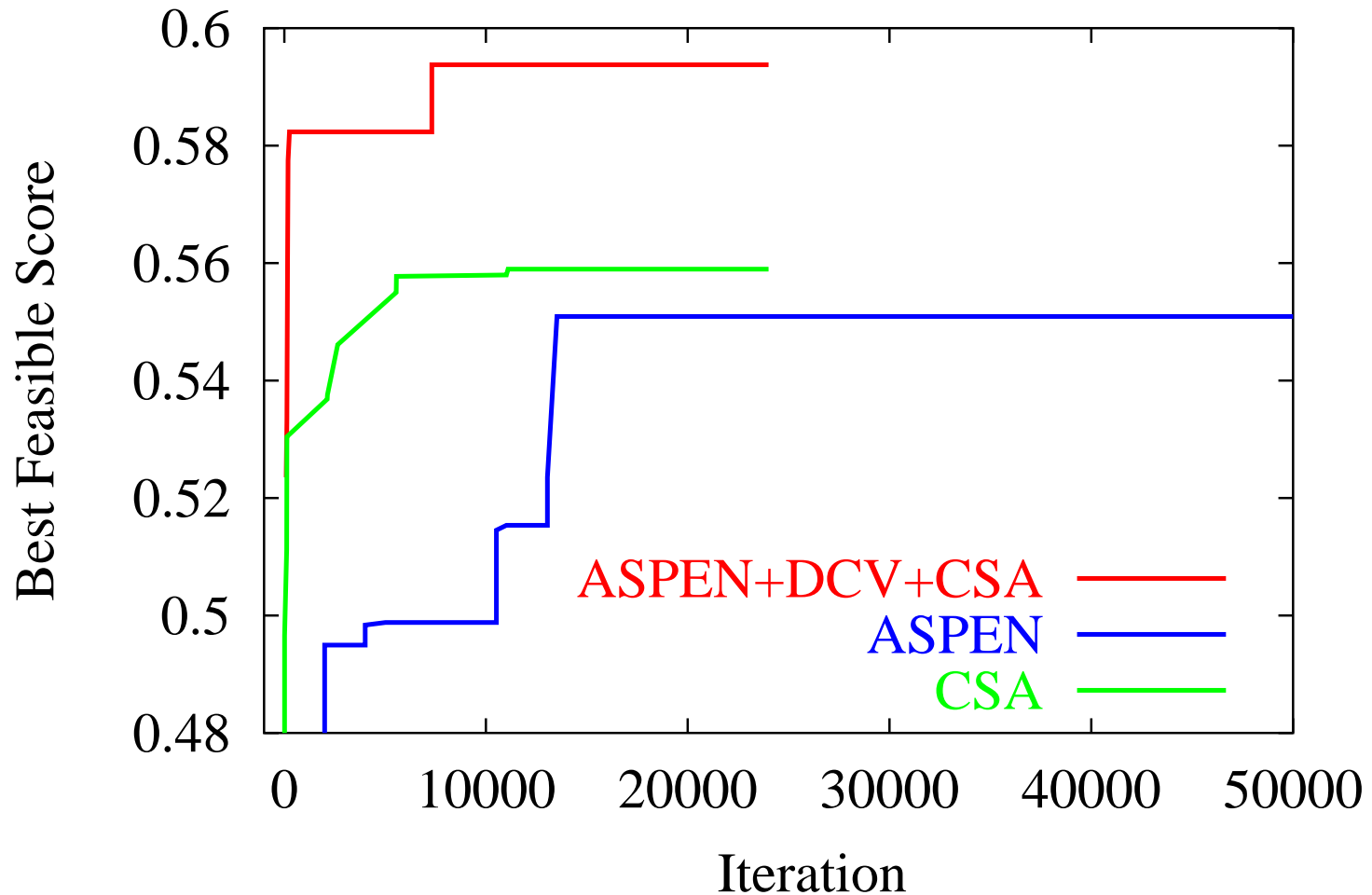
Search Progress on OPTIMIZE Benchmark

- Conflicts vs. Iteration:



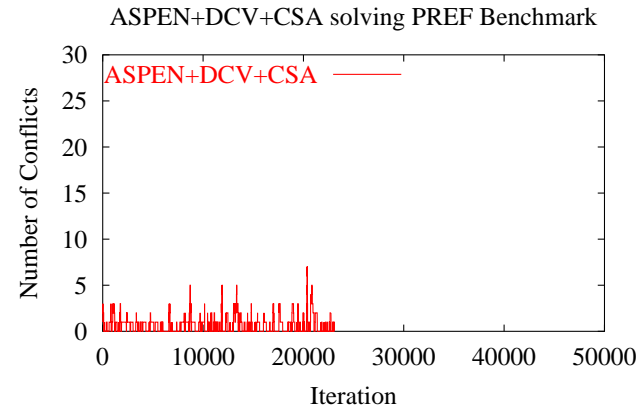
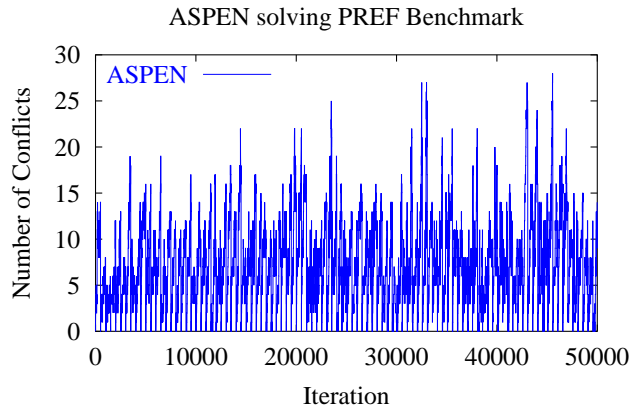
- Score vs. Iteration:



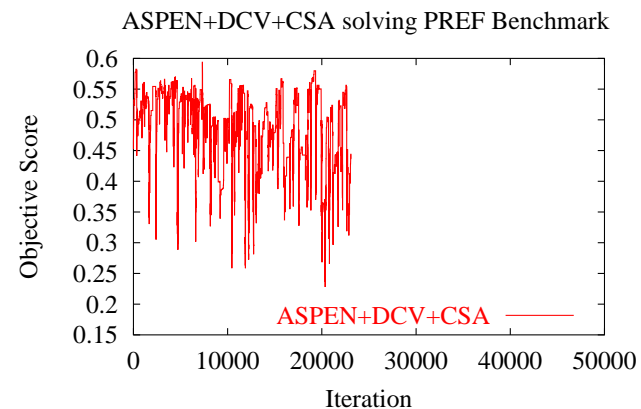
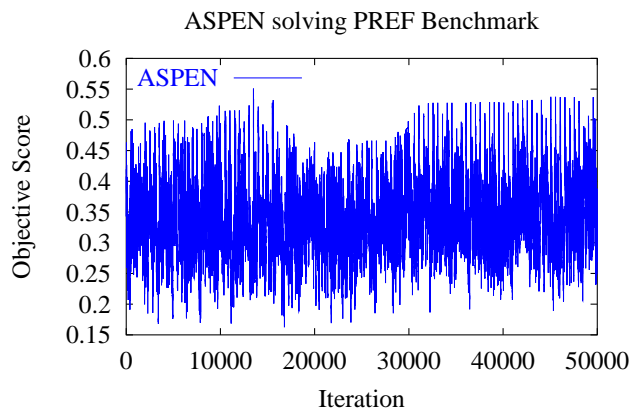
Best Feasible Solution on PREF Benchmark

Search Progress on PREF Benchmark

- Conflicts vs. Iteration:



- Score vs. Iteration:



Conclusions

- Extension of calculus of variations in continuous space to discrete space
- Partitioning general necessary conditions into distributed necessary conditions
- Relying on theory of Lagrange multipliers for discrete constrained optimization
- Significant reduction in the base of the exponential complexity
- Significant improvement in search times with equal or better quality in planning and scheduling problems as compared to those of ASPEN