

Solving Multistage Stochastic Linear Programs on the Computational Grid

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Overview

- Multi-stage stochastic linear programs (MSLP) are **difficult**.
 - They are cast as large-scale optimization problems.
 - There is no viable software tools for solving large-scale MSLP instances.
- Grid is a very **powerful** computational platform but needs to be used wisely.
- This research focus on implementing parallel nested decomposition algorithm on a computational Grid.
 - We discuss the challenges and propose the approaches.
- We also study the value of MSLP as we can do comprehensive numerical testings on large-scale MSLP instances.

Outline

- Stochastic Linear Program
 - Linear Program vs. Stochastic Linear Program
 - Multi-stage Stochastic Linear Program
 - Nested Decomposition Algorithm
- Distributed Computing
 - Grid Computing
 - Condor & MW
- CDF Framework
- Research Challenges
- Value of Multistage Stochastic Linear Program
- Future Research

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Linear Program v.s Stochastic Linear Program

Linear Program

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax = b, \\ & x \geq 0, \\ & c \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m. \end{aligned}$$

Linear Program v.s Stochastic Linear Program

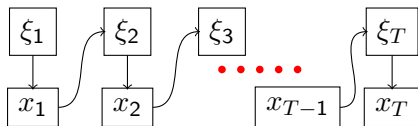
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- All functions are linear.
- Does not consider uncertainty in the model.
- Easy.

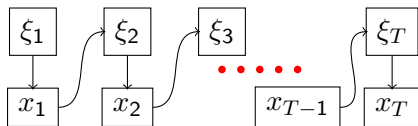
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- Not all decisions are made at the same time.
- There is **uncertainty!**



Linear Program v.s Stochastic Linear Program

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How to make a good decision (x_1) now by taking into account all future uncertainty?

Linear Program vs Stochastic Linear Program

Stochastic Linear Program

$$\begin{aligned} \min \quad & c_1^T x_1 + Q_1(x_1) \\ \text{s.t.} \quad & A_1 x_1 = b_1, \\ & x_1 \geq 0, \\ & c_1 \in \mathbb{R}^n, A_1 \in \mathbb{R}^{m \times n}, b_1 \in \mathbb{R}^m. \end{aligned}$$

where $Q_1(x_1)$ is the expected recourse function.

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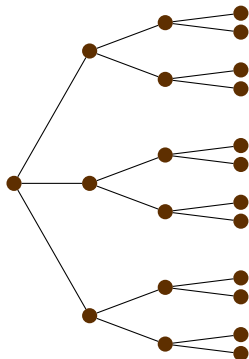
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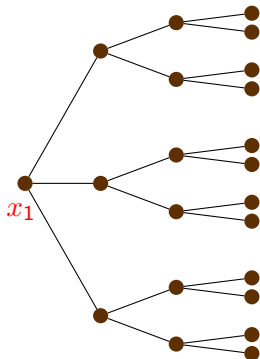
- $Q_1(x_1)$ measures the cost of making corrective actions on your initial decision x_1 , after a random events have taken place.

Multi-stage Scenario Tree



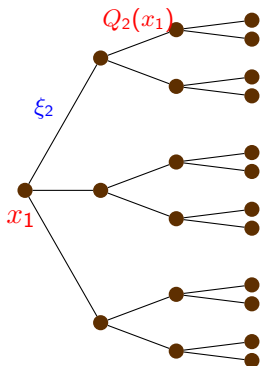
- \mathcal{N} : Set of nodes in the tree
- $\rho(n)$: Unique predecessor of node n in the tree
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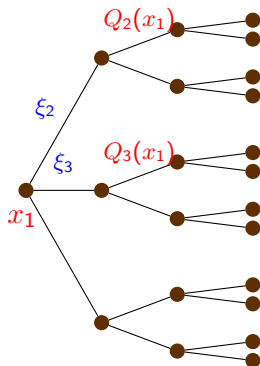
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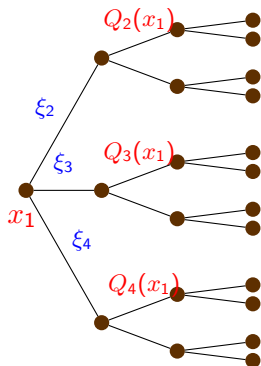
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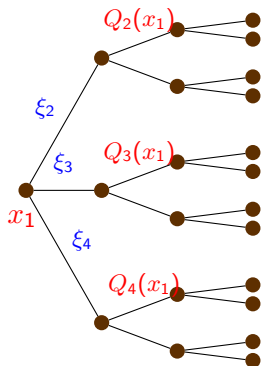
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Multi-stage Scenario Tree



$$Q_1(x_1) = \sum_{m=2}^4 \hat{p}_m Q_m(x_1)$$

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Multi-stage Stochastic Linear Program

Recursive Model

$$\begin{aligned} \mathbf{Z} = \min \quad & c_1^T x_1 + Q_1(x_1) \\ \text{s.t.} \quad & W_1 x_1 = h_1, \\ & x_1 \geq 0, \end{aligned}$$

where

$$Q_n(x_n) \stackrel{\text{def}}{=} \sum_{\tilde{n} \in \mathcal{S}(n)} \hat{p}_{\tilde{n}} Q_{\tilde{n}}(x_n), \quad \forall n \in \mathcal{N},$$

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$$Q_n(x_{\rho(n)}) \stackrel{\text{def}}{=} \min_{x_n \geq 0} \left\{ c_n^T x_n + Q_n(x_n) \mid W_n x_n = h_n - T_n x_{\rho(n)} \right\},$$

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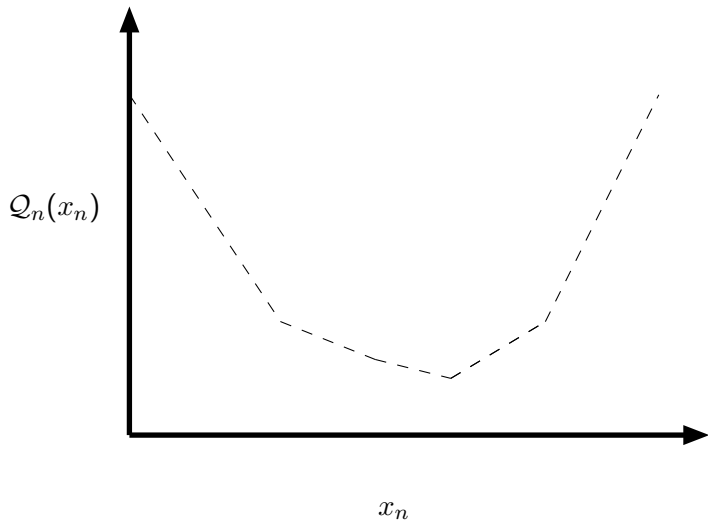
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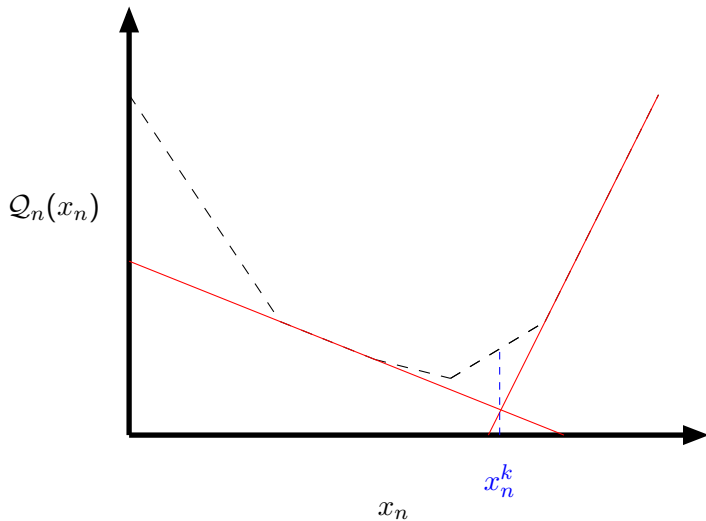
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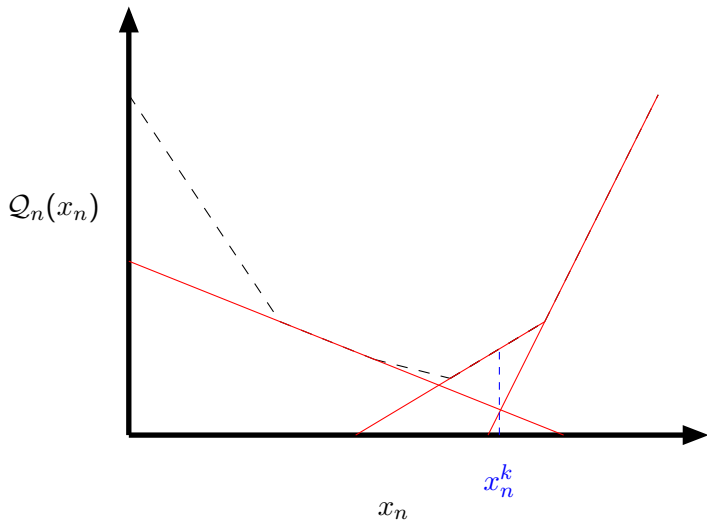
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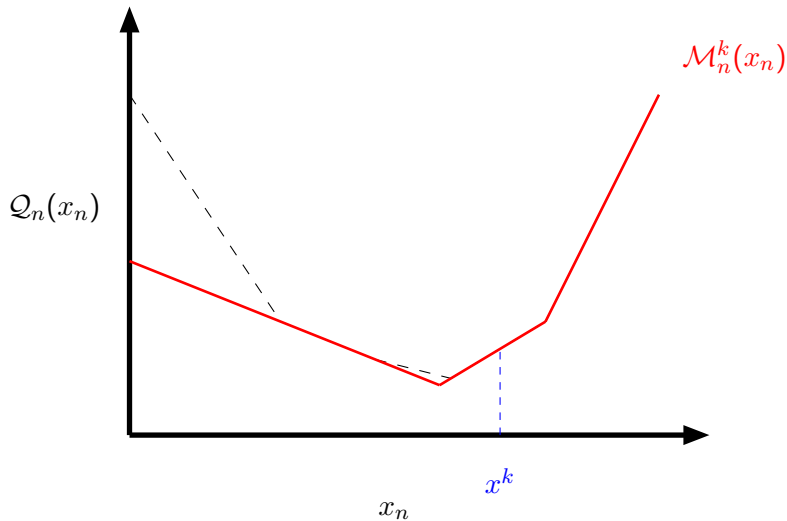
- Bad news: $Q_n(\cdot)$ is extremely difficult to evaluate;
- Good news: Evaluation of $Q_n(\cdot)$ can be broken down into smaller function evaluation $Q_{\tilde{n}}(\cdot)$.
- Better news: $Q_n(\cdot)$ is convex function. (So is $Q_{\tilde{n}}(\cdot)$)

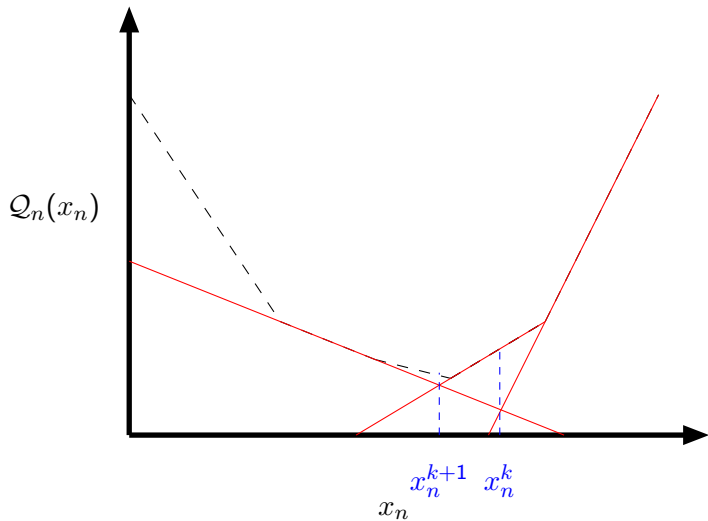
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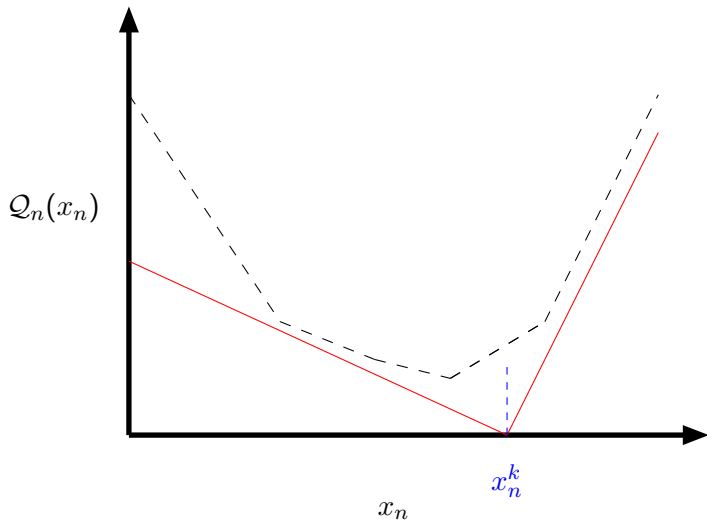


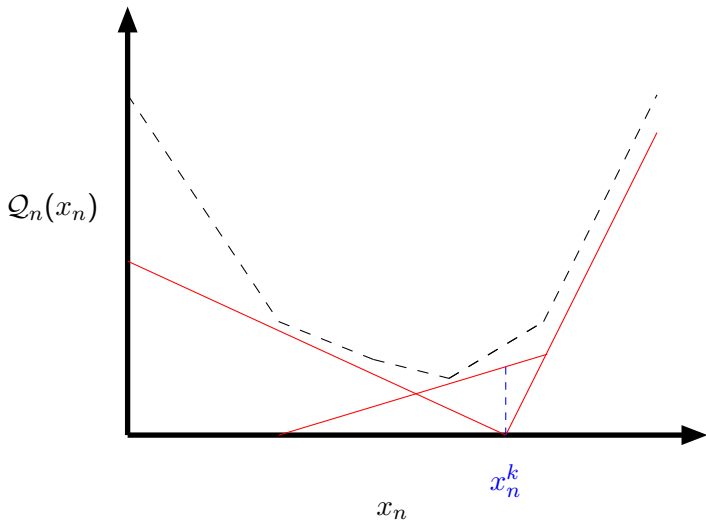
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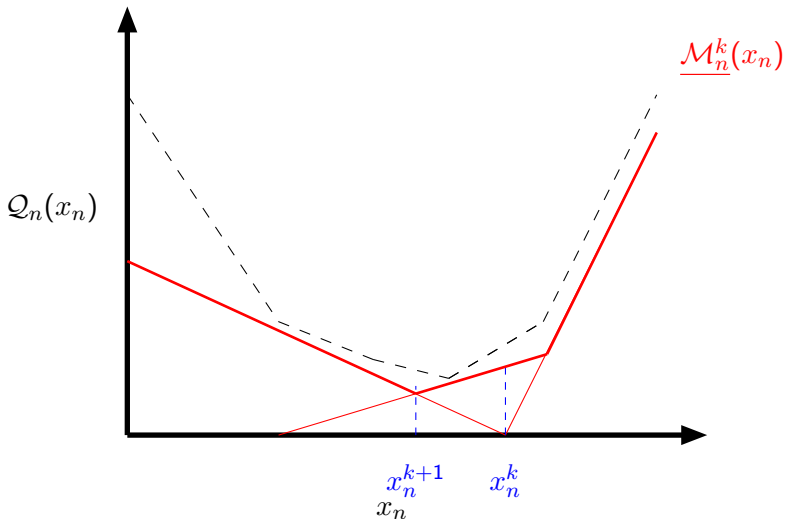
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Recourse Function Properties

Model function – lower bound to the True model

$LP_n(x_{\rho(n)}) :$

$$\begin{aligned} \mathcal{M}_n^l(x_{\rho(n)}) = \min \quad & c_n^T x_n + \sum_{j=1}^{C_n} \theta_{n,[j]} \\ \text{s.t.} \quad & W_n x_n = h_n - T_n x_{\rho(n)}, \\ & 0 \geq -dx_n + \delta, \quad \forall (d, \delta) \in \mathcal{D}_n^l \\ & \theta_{n,[j]} \geq -ex_n + \epsilon, \quad \forall (e, \epsilon) \in \mathcal{E}_{n,[j]}^l, \quad \forall j \in \{1, \dots, C_n\} \\ & x_n \geq 0 \quad , \quad \theta_{n,[j]} \geq -M, \quad \forall j \in \{1, \dots, C_n\} \end{aligned}$$

- LP_n is the master linear program to be solved on node n .

Nested Decomposition Algorithm

Main steps

Start from root node $n = 1$:

- ➊ Solve $LP_n(x_{\rho(n)})$. If infeasible, go to step 2, otherwise go to step 3.
- ➋ If $n = 1$, STOP. Otherwise, find feasibility cut. Go to step 4.
- ➌ Decide the direction (According to the sequencing method).
 - If *Forward*, record the primal solution as policy. Add nodes $m \in \mathcal{S}(n)$ into queue. Go to step 4.
 - If go *Backward*, record the simplex multiplier and find optimality cut. Add node $\rho(n)$ into queue and go to step 4.
- ➍ If stopping criteria meet, STOP. Otherwise get the next node from queue and return to step 1.

- A lot of freedom when choosing the directions.

Nested Decomposition Algorithm

Sequencing method

- Fast Forward Fast Backward (FFFB)
Makes complete passes through the tree. Change the direction as little as possible.
- Fast Forward (FF)
Computational work are focus at the latter stages. Always find the best model function.
- Fast Backward (FB)
Choose to go to the stage that requires the least amount of work. Try to find the best policy before function evaluation.
- Hybrid Methods

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Distributed Computing

Supercomputer

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 - Run mathematical operations on one data element at a time.

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Grid Computing

Grid Computing

Challenges

- Security
 - Who should be allowed to tap in?
- Interfaces
 - How should they tap in?
- Heterogeneous
 - Different hardware, operating systems, software...
- Dynamic
 - You don't know when one machine will leave the pool
 - You don't know when one machine will join the pool
 - Fault-Tolerance is a very important issue when designing the program
- Distributed
 - Machines may be very far apart \Rightarrow slow communication

Grid Computing

Tools

- Condor (<http://www.cs.wisc.edu/condor>)
 - User need not have an account or access to the machines
 - Machine owner specifies conditions under which jobs are allowed to run
 - Condor use matchmaking to schedule jobs among the pool
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 - Jobs can be check-pointed and migrated
- MW (<http://www.cs.wisc.edu/condor/MW>)
 - Master assigns tasks to the workers
 - Workers execute tasks and report results to the master
 - Workers need not to communicate with each other
 - Simple and Fault-Tolerant
 - A set of C++ abstract base classes

Grid Computing

Master-Worker (MW) Structure

- MWDriver
 - *get_userinfo()*
 - *setup_initial_tasks()*
 - *pack_worker_init_data()*
 - *act_on_completed_task()*
- MWTask
 - *pack_work()*
 - *unpack_work()*
 - *pack_results()*
 - *unpack_results()*
- MWWorker
 - *unpack_init_data()*
 - *execute_task()*

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- 2 Support different sequencing mechanisms
 - FFFB, FF, FB, hybrid
- 3 Allow asynchronous algorithm behaviors
 - Partial evaluation of $Q_n(\cdot)$
- 4 Be efficient with the MW-Grid Framework
 - Buffering, aggregating evaluations into reasonable-sized tasks (computational units)

CDF Framework – Record Node Status

- Iteration Counter ν_n
- Child Counter $\phi_n^{\nu_n}$
- Cut Counter $\psi_n^{\nu_n}$
- CDF Status: $ST_n = (\text{COLOR}, \text{DIRECTION}, \text{FLAG})$

COLOR

- **Red**: Job is completed
 - **Green**: Job is under process
-

DIRECTION

- \rightarrow Forward: Forward job is under process or information will be passed from parent
 - \leftarrow Backward: Backward job is under process or information will be passed from children
-

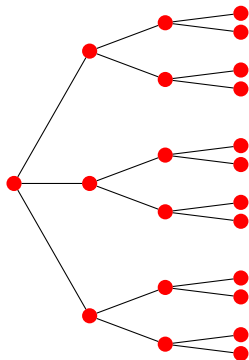
FLAG

- * Star: True model is obtained ($M_n^l(x_{\rho(n)}) = Q_n(x_{\rho(n)})$)
- \emptyset Null: True model is not obtained ($M_n^l(x_{\rho(n)}) < Q_n(x_{\rho(n)})$)

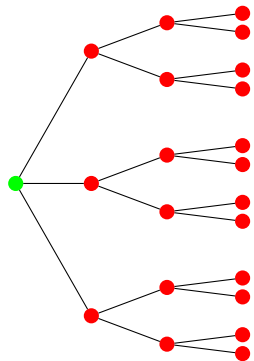
CDF Framework – Trigger Signals

- Start
 - To children: “Here is a policy, start to evaluate your recourse function.”
- Update
 - To children: “Here is a policy, update my model function.”
- Restart
 - To parent: “Give me a new policy.”
- Done
 - To parent: “Model function is not a true model, but we are done.”
- End
 - To parent: “Model function is a true model, we are done.”
- Terminate
 - To siblings: “Terminate, do not evaluate the recourse function any more.”

CDF Framework – Example 1 (FFFB)

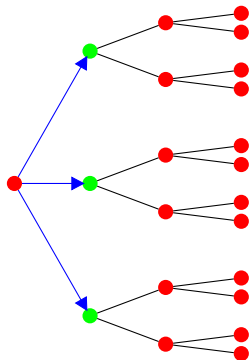


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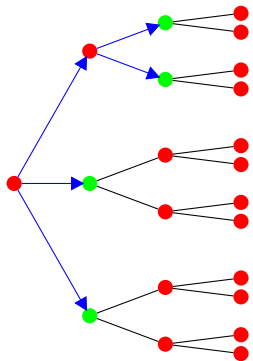
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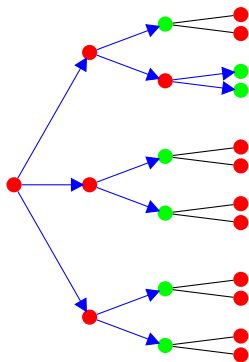
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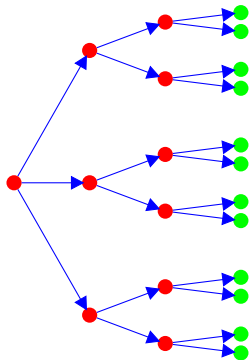
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- $n \in \mathcal{S}(2)$: Start

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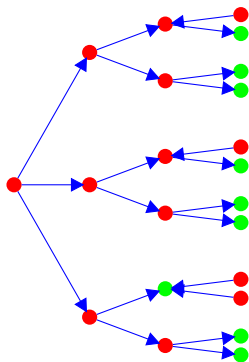
- $n = 1$: Start
- $n \in \mathcal{S}(1)$: Start
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- $n \in \mathcal{S}(3) \cup \mathcal{S}(4)$: Start
- $n \in \mathcal{S}(6)$: Update

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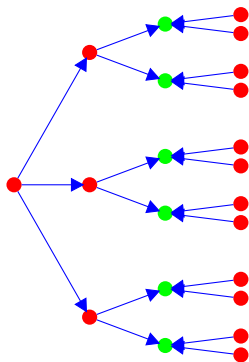
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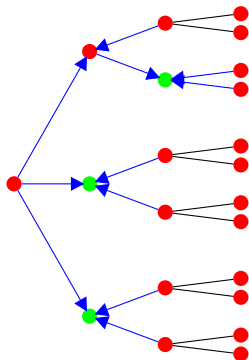
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- $n = \rho(19)$: Done

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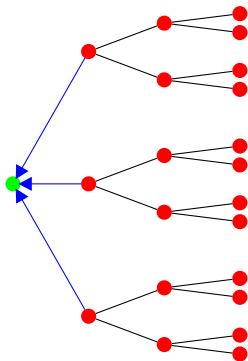
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- $n \in \mathcal{S}(3) \cup \mathcal{S}(4)$: Start
- $n \in \mathcal{S}(6)$: Update
- \vdots
- $n = \rho(19)$: Done
- \vdots

CDF Framework – Example 1 (FFFB)



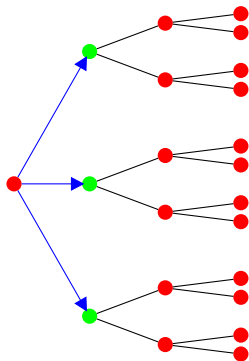
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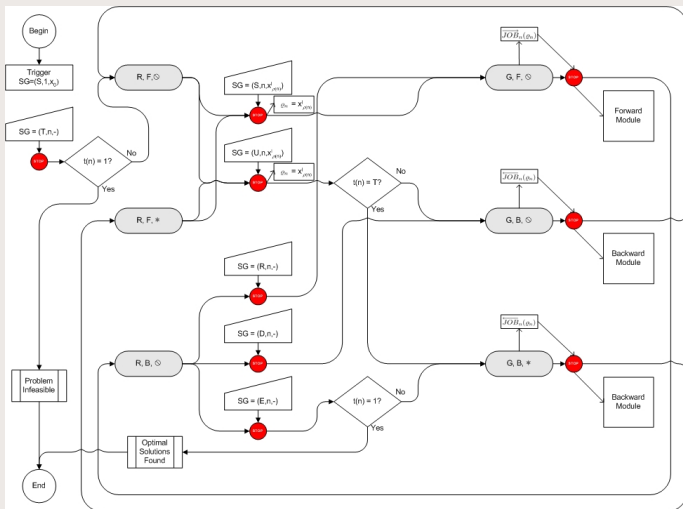
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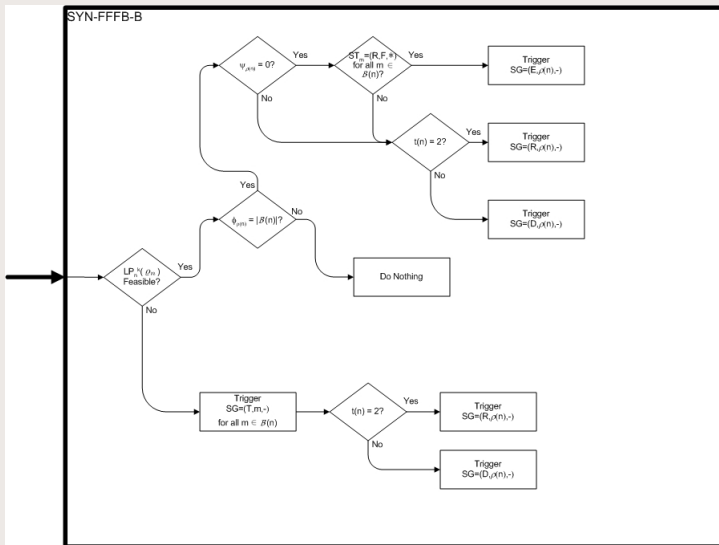
CDF Framework

CDF State Evolving Procedure

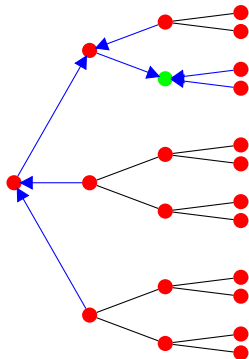


CDF Framework

Signal Triggering Module SYN-FFFB-B



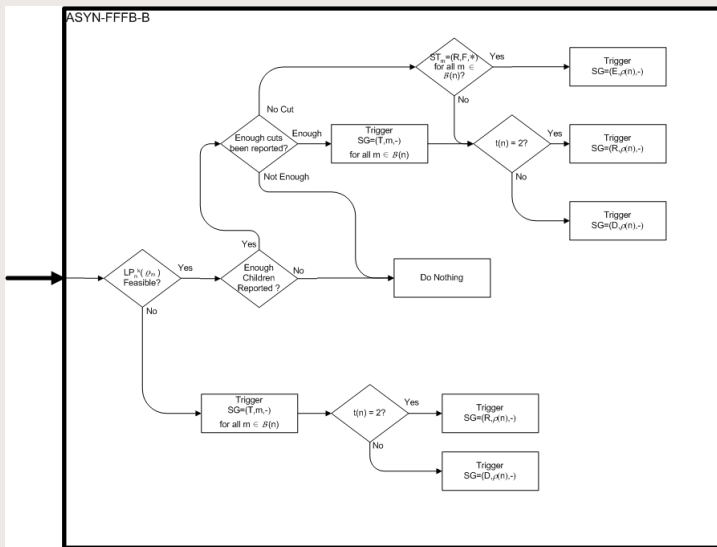
CDF Framework



Synchronicity is
Bad
in the Grid

CDF Framework (Asynchronous)

Signal Triggering Module ASYN-FFFB-B



CDF Framework (Asynchronous)

Asynchronicity Level

- Enough children α_1 .
- Enough cuts α_2 .

$\phi_{\rho(n)}^{\nu_{\rho(n)}} = \mathcal{B}(\rho(n)) $, $\psi_{\rho(n)}^{\nu_{\rho(n)}} = 0$	No Cut
$\phi_{\rho(n)}^{\nu_{\rho(n)}} \neq \mathcal{B}(\rho(n)) $, $\psi_{\rho(n)}^{\nu_{\rho(n)}} = 0$	Not Enough
$\phi_{\rho(n)}^{\nu_{\rho(n)}} = \mathcal{B}(\rho(n)) $, $0 < \psi_{\rho(n)}^{\nu_{\rho(n)}} < \alpha_2 \Gamma_{\rho(n)}$	Enough
$\phi_{\rho(n)}^{\nu_{\rho(n)}} \neq \mathcal{B}(\rho(n)) $, $0 < \psi_{\rho(n)}^{\nu_{\rho(n)}} < \alpha_2 \Gamma_{\rho(n)}$	Not Enough
$\phi_{\rho(n)}^{\nu_{\rho(n)}} = \mathcal{B}(\rho(n)) $, $\psi_{\rho(n)}^{\nu_{\rho(n)}} \geq \alpha_2 \Gamma_{\rho(n)}$	Enough
$\phi_{\rho(n)}^{\nu_{\rho(n)}} \neq \mathcal{B}(\rho(n)) $, $\psi_{\rho(n)}^{\nu_{\rho(n)}} \geq \alpha_2 \Gamma_{\rho(n)}$	Enough

Table: The criteria for enough cutting plain information.

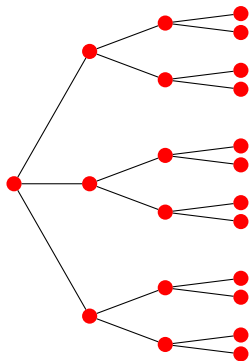
CDF Framework (with buffering)

Purpose: To obtain a reasonable task (computational unit) size.

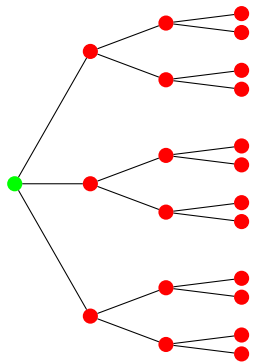
Buffering

- Buffer
 - Temporary storage room for jobs
- new COLOR – Yellow
 - Create jobs on the node, and add the job into the buffer
- new Signal – Go
 - Aggregate the jobs in the buffer and start to execute the task in Grid

CDF Framework – Example 2 (buffer size = 3)

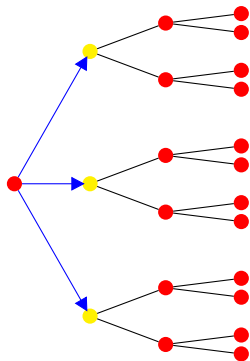


CDF Framework – Example 2 (buffer size = 3)



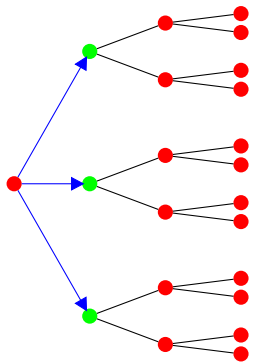
● $n = 1$: Go

CDF Framework – Example 2 (buffer size = 3)



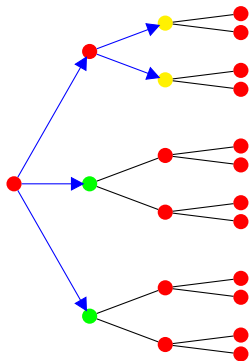
- $n = 1$: Go
- $n \in \mathcal{S}(1)$: Start

CDF Framework – Example 2 (buffer size = 3)



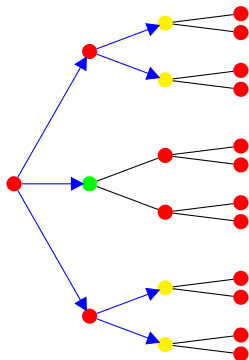
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CDF Framework – Example 2 (buffer size = 3)



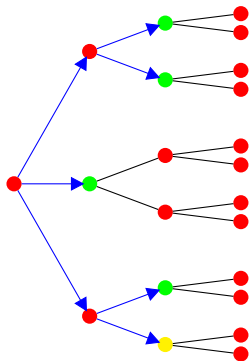
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CDF Framework – Example 2 (buffer size = 3)



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CDF Framework – Example 2 (buffer size = 3)



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- $n \in \mathcal{S}(1)$: Go
- $n \in \mathcal{S}(2)$: Start
- $n \in \mathcal{S}(4)$: Start
- n in buffer 1: Go

Outline

- Stochastic Linear Program
 - Linear Program vs. Stochastic Linear Program
 - Multi-stage Stochastic Linear Program
 - Nested Decomposition Algorithm
- Distributed Computing
 - Grid Computing
 - Condor & MW
- CDF Framework
- Research Challenges
- Value of Multistage Stochastic Linear Program
- Future Research

Research Challenges

- How to ensure effective algorithm performance?
- How to efficiently utilize the Grid resource?
- How to manage the large amount of data?

Algorithmic Challenges

Challenge: To determine the proper level of asynchronicity level

Algorithmic Challenges

Challenge: To determine the proper level of asynchronicity level

Asynchronicity Level

- High level:
 - High utilization of the resources
 - Less accurate recourse function evaluation at each iteration
 - More iterations required
- Low level:
 - More accurate recourse function evaluation at each iteration
 - Lower overall parallel performance

Algorithmic Challenges

Challenge: To determine the proper level of asynchronicity level

Asynchronicity Level

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Proposal: Dynamic asynchronicity level

- Stage-dependent (later stage \Rightarrow lower asynchronicity level)
- Iteration-dependent (later iteration \Rightarrow lower asynchronicity level)

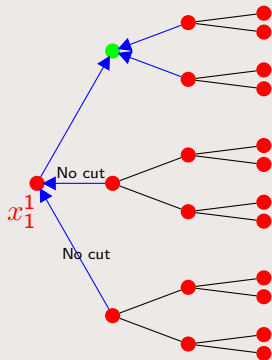
Algorithmic Challenges

Challenge: To ensure non-blocking behavior of the algorithm

Algorithmic Challenges

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Sequencing Method



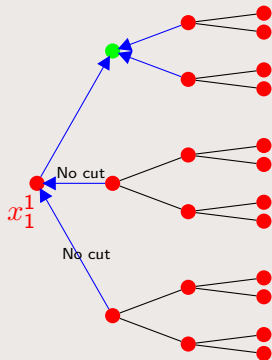
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- $ST_4 = (R, F, \emptyset)$

Algorithmic Challenges

Challenge: To ensure non-blocking behavior of the algorithm

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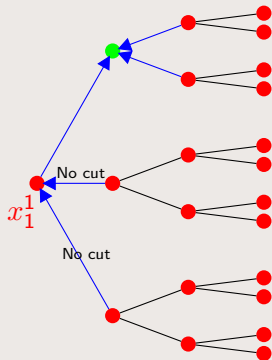


- $ST_3 = (R, F, \emptyset)$
- $ST_4 = (R, F, \emptyset)$
- If using FFFB, nothing can be done regardless of the asynchronicity level

Algorithmic Challenges

Challenge: To ensure non-blocking behavior of the algorithm

Sequencing Method



- $ST_3 = (R, F, \emptyset)$
- $ST_4 = (R, F, \emptyset)$
- If using FFFB, nothing can be done regardless of the asynchronicity level
- Potential work: continue evaluate $Q_3(x_1^1)$ and $Q_4(x_1^1)$

Algorithmic Challenges

Challenge: To ensure non-blocking behavior of the algorithm

Sequencing Method

- Algorithm may be blocking even though the asynchronicity level is set to high.
- More flexibility is preferred.

Algorithmic Challenges

Challenge: To ensure non-blocking behavior of the algorithm

Sequencing Method

- Algorithm may be blocking even though the asynchronicity level is set to high.
- More flexibility is preferred.

Proposal: Dynamic double layer sequencing protocol

- First layer: main iteration, suggest FFFB
- Second layer: fine tune, (whenever resource is available)

Grid Resource Utilization Challenges

Challenge: To limit the negative effects of both contention and starvation

Grid Resource Utilization Challenges

Challenge: To limit the negative effects of both contention and starvation

Buffer size

Too small:

- Workers report results frequently
- Contention occurs

Too big:

- Can not create enough tasks to meet the demand.
- Starvation occurs

Grid Resource Utilization Challenges

Challenge: To limit the negative effects of both contention and starvation

Buffer size

Too small:

- Workers report results frequently
- Contention occurs

Too big:

- Can not create enough tasks to meet the demand.
- Starvation occurs

Proposal: Dynamic tasking scheme with node aggregation

- Dynamic tasking based on stages, LP size, and # available workers
- Aggregating nodes to increase task size

Large Data Management Challenges

Challenge: To handle the massive amounts of cuts that the algorithm generated

Large Data Management Challenges

Challenge: To handle the massive amounts of cuts that the algorithm generated

Large amount of data – Cuts

- Required memory to store the cuts may be huge
 - For example: 27,000 nodes in period $T - 1$, each node has 20 cuts, $x_n \in \mathbb{R}^{100}$, requires $\geq 400\text{MB}$ to store cuts.

Large Data Management Challenges

Challenge: To handle the massive amounts of cuts that the algorithm generated

Large amount of data – Cuts

- We can not store cuts on the workers as we do not have control over workers, and do not know when the worker will be leaving;
- Master memorizes all the cuts, and will be very busy handling these cuts as the number increases.
- We must do our best to compress or reduce the amount of data.

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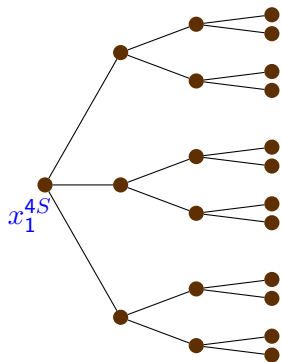
Proposal: Cut Management

- Cut Hashing: To quickly sort and locate identical cuts
- Cut Sharing: To allow information sharing among nodes;
- Cut Purging: To reduce the number of inactive or loose cuts;
- Cut Aggregation: To generate aggregated cuts by clustering the nodes.

Outline

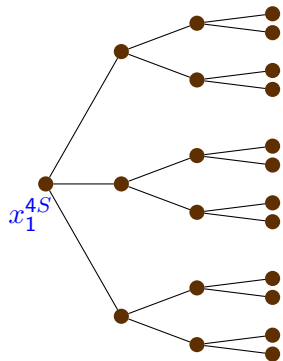
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Value of MSLP



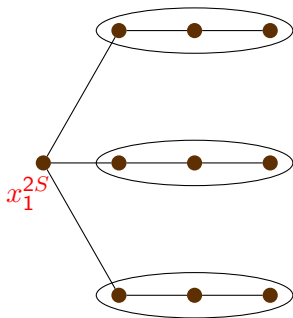
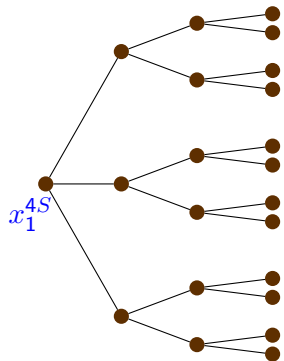
Value of MSLP

$$v^{4S} = c_1^T x_1^{4S} + Q_1(x_1^{4S})$$



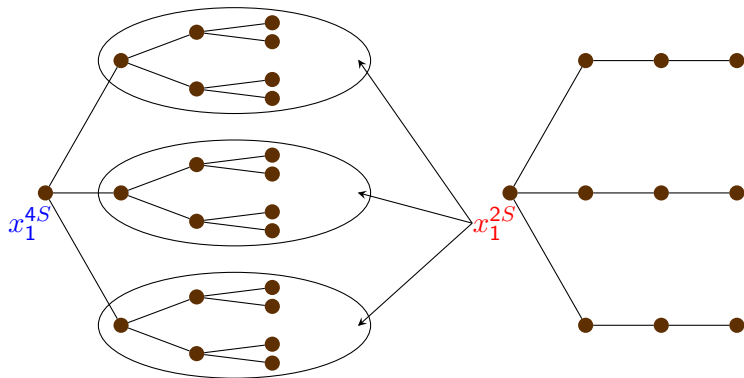
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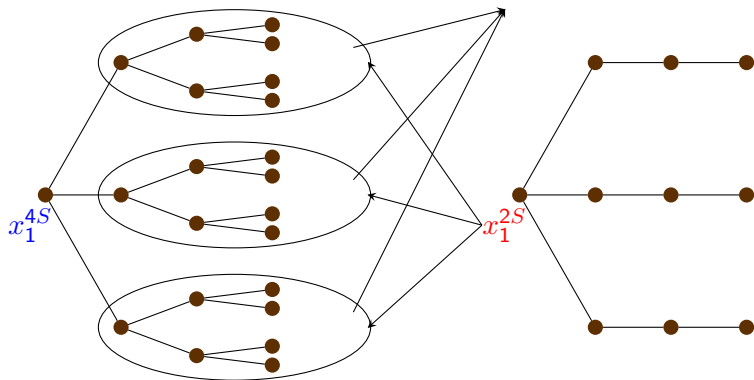
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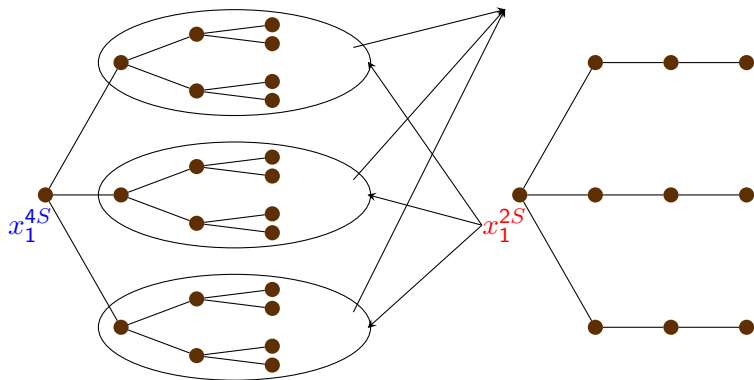
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Value of MSLP

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$$v^{2S} = c_1^T x_1^{2S} + Q_1(x_1^{2S})$$



•

$$VMS_{4S}^{2S} = v^{2S} - v^{4S} \geq 0$$

Value of MSLP

Test Problems

- Asset Management Problem (Blomvall and Shapiro [2004])
- Network Planning Problem (Sen, Doverspike and Cosares [1994])
- Enterprise-wide Optimization Problem (EWO-AP project)
- Dynamic Vehicle Allocation Problem (Powell [1988])
- More?

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Accomplishments

- 1 Defined a set of consistent notations
- 2 Laying out challenges for Grid computing implementation.
- 3 Developed a *CDF framework* that enables an easy implementation of parallel nested decomposition algorithm
- 4 Extended the *CDF framework* to an asynchronous version with buffering
- 5 Created two large scale test problem instances (Asset Management and Network Planning)
- 6 Implemented node aggregation
- 7 Created a Cut-Management class in the code that enables cut hashing

Things To Do

- 1 Implement the *dynamic asynchronicity level* (Algorithmic Challenge)
- 2 Implement the *double layer sequencing protocol* (Algorithmic Challenge)
- 3 Implement the *dynamic tasking scheme* (Grid Resource Utilization Challenge)
- 4 Increase functions in Cut-Management including *cut sharing purging*, and *aggregation* (Large Data Management Challenge)
- 5 Create other large-scale MSLP instances (SMPS files)
- 6 Study the value of MSLP

Road Map

- Clean up the current code, add Cut Management functions, create more instances. (4-6 weeks)
- Test dynamic asynchronicity, sequencing, tasking. Prepare to run problem on larger Grid. (8-10 weeks)
 - Keep all results for further VMS analysis.
- Run larger computational problems, study VMS (8-10 weeks)
- Thesis writing (n months)