

# Stochastic Programming

## Lecture 12

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# Today's Class

- 1 More Methods for Solving 2SLPs
- 2 Regularized Decomposition
- 3 C/C++ - CPLEX Example

# Outline

- 1 More Methods for Solving 2SLPs
- 2 Regularized Decomposition
- 3 C/C++ - CPLEX Example

# More Methods for Solving 2SLPs

So far we have discussed the L-shaped method and several extensions including

- Multi-cut L-shaped method
- Full decomposability
- Bunching
- Inner Linearization
- Extreme point methods
- Special cases of recourse (simple recourse, network flow)

Today we will discuss:

- Regularized decomposition
- A CPLEX Example using C/C++ and the callable library

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# Regularized Decomposition

A common problem with the L-shaped method is that early iterations do not produce useful optimality cuts.

*Regularized Decomposition* provides a means for dampening variation in the first stage solution using a quadratic penalty term (Ruszczynski, 1986).

# Regularized Decomposition

## Algorithm:

**Step 0:** Set  $r = \nu = 0$ ,  $s_k = 0$  for all  $k = 1, \dots, K$ . Select  $a^1$ , a feasible solution.

**Step 1:** Set  $\nu = \nu + 1$ . Solve the regularized master:

$$\begin{aligned} \min z &= cx + \sum_{k=1}^K \theta_k + \alpha(x - a^\nu)^2 \\ \text{s.t. } Ax &= b \\ D_\ell &\geq d_\ell, \quad \ell = 1, \dots, r, \\ E_{\ell(k)}x + \theta_k &\geq e_{\ell(k)}, \quad \ell(k) = 1, \dots, s_k, \\ x &\geq 0, \theta \in \mathcal{R}. \end{aligned}$$

Let  $(x^\nu, \theta^\nu)$  be an optimal solution. If  $cx^\nu + e\theta^\nu = ca^\nu + Q(a^\nu)$  stop with  $a^\nu$  optimal.

# Regularized Decomposition

**Step 2:** Solve Phase 1 LPs for  $k = 1, \dots, K$ . If a feasibility cut is generated set  $a^{v+1} = a^v$  (called a *null infeasible step*) and return to Step 1.

**Step 3:** Solve subproblems for  $k = 1, \dots, K$ . If stopping criteria is not satisfied ( $\theta_k < p_k(\pi_k)(h_k - T_k x^v)$  for some  $k$ ) then generate an optimality cut. Set  $s_k = s_k + 1$ . Otherwise continue.

**Step 4:** If  $\theta_k \leq p_k(\pi_k)(h_k - T_k x^v)$  for all  $k$  then set  $a^{v+1} = x^v$  (called an *exact serious step*). Go to Step 1.

**Step 5:** If  $cx^v + Q(x^v) \leq ca^v + Q(a^v)$  then  $a^{v+1} = x^v$  (called an *approximate serious step*). Go to Step 1. Else set  $a^{v+1} = a^v$  (null feasible step) and go to Step 1.



# Regularized Decomposition

Convergence of regularized decomposition was established by Ruszczyński (1986)

Lemma 1 (B&L Ch 6, Section 6.1).

$$e^T \theta^v \leq \eta(x^v, \theta^v, a^v) \leq Q(a^v).$$

Proof Sketch:

The first inequality follows from  $\|x^\mu - a^v\|^2 \geq 0$ .

The second inequality follows from the fact that  $a^v$  is always feasible. The solution  $(a^v, \hat{\theta})$  where  $\hat{\theta}_k = p_k Q_k(a^v)$ ,  $k = 1, \dots, K$  satisfies all optimality cuts since  $\theta_k$  is a lower bound on  $p_k Q_k(\cdot)$ . It follows that  $\eta(x^v, \theta^v, a^v) \leq \eta(x^v, \hat{\theta}^v, a^v) = Q(a^v)$ .

# Regularized Decomposition

Lemma 2 (B&L Ch 6, Section 6.1).

*If the regularized decomposition algorithm stops at Step 1, then  $a^v$  solves the original problem.*

Proof Sketch:

By Lemma 1 and the optimality criterion,  $e\theta^v = Q(a^v)$ , and it follows  $e\theta^v = \eta(x^v, \theta^v, a^v)$ , which implies  $\|x^v - a^v\|^2 = 0$  and therefore  $x^v = a^v$ . Thus,  $a^v$  solves the regularized master and the unregularized master which means  $a^v$  solves the original problem.

# Regularized Decomposition

Lemma 3 (B&L Ch 6, Section 6.1).

*If there is a null step at iteration  $\nu$ , then*

$$\eta(x^{\nu+1}, \theta^{\nu+1}, a^{\nu+1}) > \eta(x^{\nu}, \theta^{\nu}, a^{\nu})$$

Proof Sketch: Because the regularized master problem is strictly convex it has a unique optimal solution. A null step at iteration  $\nu$  may be either a null feasible step or a null infeasible step. In the first case a cut is generated that renders  $x^{\nu}$  infeasible. In the second case a cut renders  $x^{\nu}, \theta^{\nu}$  infeasible. Thus the objective function necessarily increases.

# Regularized Decomposition

Lemmas 4-5 establishes finite convergence as the number of serious and approximate serious steps are finite. Lemmas 1 - 5 are used to prove the main result...

Theorem 8 (B&L Ch 6, Section 6.1).

*If the original problem has a solution, then the algorithm stops after a finite number of iterations. Otherwise, it generates a sequence of feasible points  $a^\nu$  such that  $Q(a^\nu)$  tends to  $-\infty$  as  $\nu \rightarrow \infty$ .*

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# C/C++ - CPLEX Example

- ILOG CPLEX comes with a callable C/C++ library that includes simplex, network simplex, dual simplex, interior point, quadratice, and MIP solvers
- Using the callable library requires some understanding of C/C++ and the CPLEX functions used to build, solve, modify, and extract information from LPs