Brief Introduction to Stochastic Programming (and Financial Modeling Applications)

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OUTLINE

- What is SP? – "Definition"
- Basic Concepts – Terminology
- Common modeling forms/approaches of SP
- Need and Value of SP
- Overview of solution methods
- Sample Applications (emphasis on Finance)
- Active research domains
- Information sources

Traditional Perceptions:

Uncertainty gives rise to Risk
Risk is “bad” – should be avoided when possible
✡Uncertainty is “bad”

BUT Uncertainties are inevitable (often exogenous)

Risk & Uncertainty should be managed,
but can not be totally eliminated

Even if risk can be eliminated, is this always a preferable strategy?
At what cost? Sacrifice of upside potential? Flexibility?

Traditional Perceptions:

"Predicting the future … is hard (next to impossible)".

BUT can uncertainty about the future be ignored?

Costs can be substantial.
Extreme events are bound to occur – Their effects can be catastrophic.

Themes:

Risk Management is a BIG business $$

Managing Risk does not mean eliminating risk.

OR/MS provide powerful tools to support improved risk management.

Key tools: Stochastic Modeling, Optimization, Derivative Pricing.

"Definition":

Stochastic programming is a framework for modeling optimization problems that involve uncertainty. Whereas deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. When the parameters are known only within certain bounds, one approach to tackling such problems is called robust optimization. Here the goal is to find a solution which is feasible for all such data and optimal in some sense. Stochastic programming models are similar in style but take advantage of the fact that ***probability distributions*** governing the data are known or can be estimated. The goal here is to find some policy that is feasible for all (or almost all) the possible data instances and maximizes the expectation of some function of the decisions and the random variables. More generally, such models are formulated, solved analytically or numerically, and analyzed in order to provide useful information to a decision-maker.

"COSP information site"

Common Perception ("Reputation" of SP):

interesting, potentially useful, nice theory

BUT …

conceptually difficult, impractical, computationally demanding

Undeserved today, and much more in the future:

Significant algorithmic & theoretical developments

Large-scale computational implementations

Exploitation of high-performance computing capabilities

Many practical applications – track record

Improved understanding of models

<u>SP provides decision support tools to</u>:

Account for uncertainty, Explore/Exploit/Reveal the value of flexibility

Overview:

- Stochastic optimization
  - Traditional
    - Small problems
    - Impractical
  - Current
    - Integrate with large-scale optimization (stochastic programming)
    - Practical examples
    - Expanding rapidly
    - Integration of financial and operation considerations

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

LP with random parameters (in constraints)

$$\min_{x \in \mathbb{R}^n_+} \{cx : \; Ax = b, \; Tx \geq h \}$$

Assumptions:

– real value of (T, h) is not known:
unknown which instance of model occurs

– uncertainty is expressed by
probability distribution, e.g. "scenarios"

$$\Pr\{(T, h) = (T^s, h^s)\} = p_s, \quad s = 1, \dots, S$$

– distribution known: data, experts, ...
"deterministic LP is degenerate case"

Stochastic LP:

– Decide on x here-and-now,
without knowing the real value of (T, h),
but knowing its probability distribution

– $Tx \geq h$ is interpreted as a goal constraint,
to be specified more precisely

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Approaches:

(1) Fat solution

Replace $Tx \geq h$ by $T^s x \geq h^s$, $s = 1, \ldots, S$
Constraint to be satisfied in all scenarios

Advantage: deterministic LP model

Disadvantage:
too conservative / expensive / restrictive.
Often no feasible solution exists!

(2) Expected value

Replace $Tx \geq h$ by $\bar{T}x \geq \bar{h}$,
with $\bar{T} = \sum_s p_s T^s$ and $\bar{h} = \sum_s p_s h^s$.

Advantage: simple model again:
deterministic LP

Disadvantage: no care taken of risk:
$T^s x \geq h^s$ only for some scenarios.

Alternative:
– use more conservative values than $(\bar{T}, \bar{h})$
– apply sensitivity analysis
Still poor model of decision under
uncertainty

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

(3) Scenario analysis

For every scenario (T^s, h^s), $s = 1, \ldots, S$, solve

$$\min_{x \in \mathbb{R}^n_+} \{cx : \ Ax = b, \ T^s x \geq h^s \}$$

$\longrightarrow$ scenario solutions x^s

Find an overall solution by
"looking at the scenario solutions"

Advantage:
– Each scenario problem is an LP
– Improvement over EV approach ...

Very popular approach

Disadvantage: see example (later)

BUT solutions are different for each scenario
… which one to implement?

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

(4) Chance constraint

Replace $Tx \geq h$ by

$$\Pr\{Tx \geq h\} \geq \alpha$$

for some prescribed reliability level
$\alpha \in (1/2, 1)$.
(α to be determined by problem owner)

Advantage: Risk is taken care of explicitly:

$$\text{risk} := \Pr\{Tx \not\geq h\}$$

$1 - \alpha$ is maximal acceptable risk.

Disadvantage:
discr. distr. $\longrightarrow$ mixed-integer LP model
(In general: possibly non-convex model)

(5) Two-stage recourse model

Introduce explicitly corrective actions
(in LP framework).
Replace $Tx \geq h$ by

$$Tx + Wy \geq h$$

where y is the decision vector of a
second-stage LP problem,
value y depends on the realization of (T, h).

Penalize corrective actions
(called recourse actions in SLP)

Minimize total expected costs

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Recourse model (discrete distributions)

$$\begin{array}{llllll}
\min\limits_{x,\ y^s} & cx & + \sum\limits_{s=1}^{S} p_s\, qy^s & & & \\
\text{s.t.} & Ax & & = & b & \\
& T^s x & + \ W y^s & \geq & h^s & \forall\ s \\
& x \geq 0, & \ y^s \geq 0\ \forall\ s & & &
\end{array}$$

with q unit penalty costs.
Objective: cx + expected recourse costs

Advantage:

– Risk is taken care of explicitly:
  risk $\longrightarrow$ expected recourse costs

– large-scale LP model

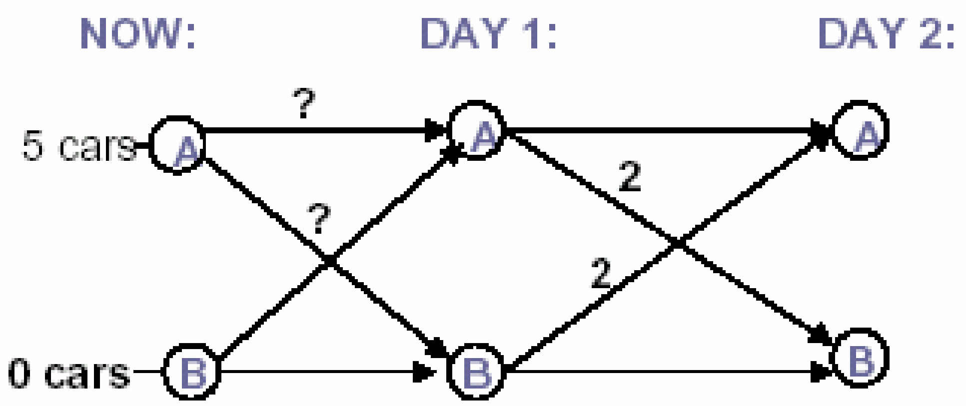
Disadvantage: too large to solve

10 independent random variables
5 realizations each $\longrightarrow S = 5^{10} \approx 10^7$
A is $m_1 \times n$, W is $m \times p$
$\longrightarrow$ LP with $(n + pS)$ variables,
$(m_1 + mS)$ constraints

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Vehicle allocation example

- Decision:
  - How to position empty freight cars?



DEMAND:

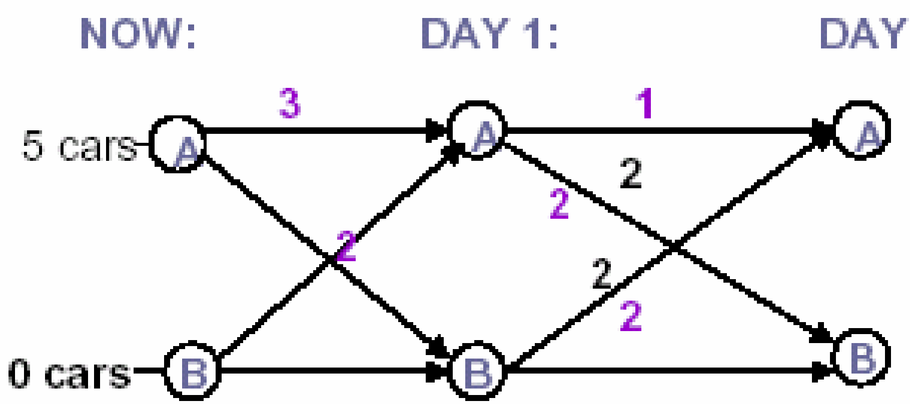
DAY 1: B to A:Mean Value=2
DAY 1: A to B:Mean Value=2

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Vehicle allocation – Mean Value Solution

Parameters: COST: 0.5 per empty car from A to B
REVENUE: 1.5 per full car from B to A, 1 from A to B

- **Maximize:** Revenue-Cost
  - » MOVE TWO EMPTY CARS FROM A to B



RESULT: Net 2: A to B; Net 2: B to A
TOTAL(*MV*) = 4

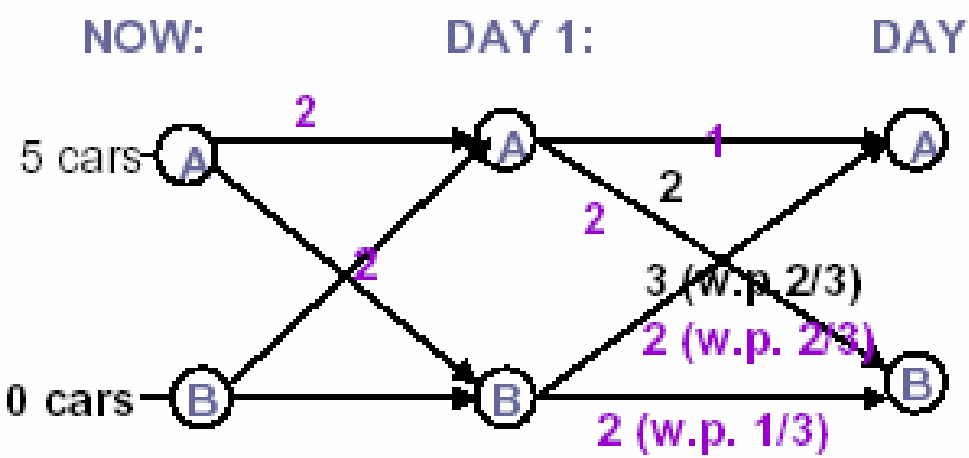
Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Expectation of Mean Value Model

Suppose: Demand is Random (Expectation from A to B=2)

- 0 from A to B with prob. 1/3
- 3 from A to B with prob. 2/3

- **Find: Expected (Revenue-Cost)**
  - » MOVE Two EMPTY CARS FROM A to B



Expected Value:

Net 2: A to B;

Net 2: B to A (w.p. 2/3)

-1: B to A (w.p. 1/3)

TOTAL (*EMV*): 3

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Stochastic Program

- **ASSUME:** Random demand on AB and BA
- **GOAL:** maximize **expected** profits
  - (risk neutral)
- **DECISIONS:** x_{ij} - empty from i to j
  - $y_{ij}(s)$ - full from i to j in scenario s **(RECOURSE)**
  - (prob. p(s))
- **FORMULATION:**

$$
\begin{array}{llllll}
\text{Max} & -0.5xAB + \Sigma_{s=s1,s2}\, p(s)\ (1.5\ yAB(s) + 1.5\ yBA(s)) & & & & \\
\text{s.t.} & xAB \quad +xAA & & & = 5 & \text{(Initial)} \\
 & -xAB & & + yBA(s) & <= 0 & \text{(Limit BA)} \\
 & -xAA & + yAB(s) & & <= 0 & \text{(Limit AB)} \\
 & & yBA(s) <= DBA(s) & & & \text{(Demand BA)} \\
 & & + yAB(s) <= DAB(s) & & & \text{(Demand AB)} \\
 & xAA,\ XAB,\ yAA(s),\ yAB\ (s) >= 0 & & & &
\end{array}
$$

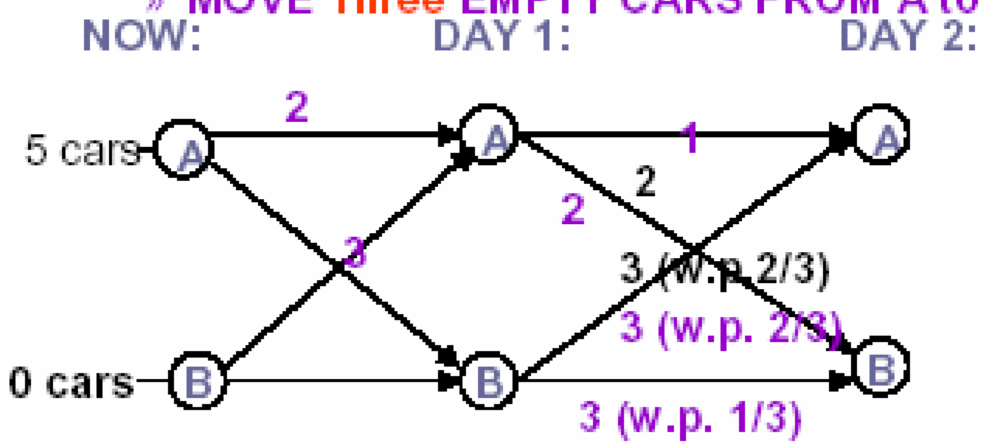
Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Stochastic Programming Solution

Suppose: Demand is Random (as before)

GOAL: A solution to obtain highest expected value

- Maximize: Expected (Revenue-Cost)
  - » MOVE Three EMPTY CARS FROM A to B



Expected Value:

Net 2: A to B;

Net 3: B to A (w.p. 2/3)

-1.5 : B to A (w.p. 1/3)

TOTAL (*RP*): 3.5

RP=Recourse Problem

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Information and Model Value

- INFORMATION VALUE:
  - FIND Expected Value with Perfect Information or Wait-and-See (WS) solution:
    - Know demand: if 3, send 3 from A to B; If 0, send 0 from A to B:
    - Earn: 2 (AtoB) + (2/3) (3) + (1/3)0= 4 = WS
  - Expected Value of Perfect Information (EVPI):
    - EVPI = WS - RP = 4 - 3.5 = 0.5
    - Value of knowing future demand precisely
- MODEL VALUE:
  - FIND EMV, RP
  - Value of the Stochastic Solution (VSS):
    - VSS = RP - EMV=3.5 - 3 = 0.5
    - Value of using the correct optimization model

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Model & Information Value

- EVPI and VSS:
  - ALWAYS >= 0 (WS >= RP>= EMV)
  - OFTEN DIFFERENT (WS=RP but RP > EMV and vice versa)
  - FIT CIRCUMSTANCES:
    - COST TO GATHER INFORMATION
    - COST TO BUILD MODEL AND SOLVE PROBLEM
- MEAN VALUE PROBLEMS:
  - MV IS OPTIMISTIC (MV=4 BUT EMV=3, RP=3.5)
    - ALWAYS TRUE IF CONVEX AND RANDOM
    - CONSTRAINT PARAMETERS
  - VSS LARGER FOR SKEWED DISTRIBUTIONS/COSTS

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

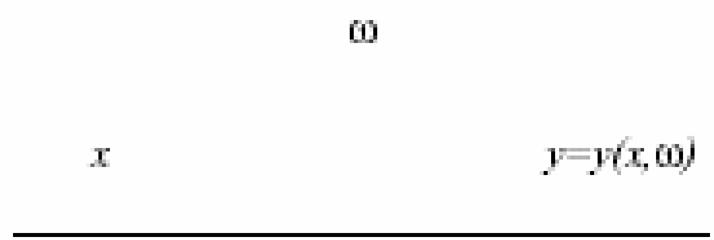
Fundamental Concepts

Scenario Tree (Discrete representation of uncertainty)
SP Recourse Models
Non-anticipativity

Two-stage recourse model

Idea:

- allow infeasibilities w.r.t. random constraints
- correct them later, pay for corrections
- all in LP framework



Replace $T(\omega)x = h(\omega)$ by

$$T(\omega)x + Wy = h(\omega)$$

where $y = y(x, \omega)$ is a recourse action for

- decision x and
- realization ω

W is $m \times p$ recourse (technology) matrix

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Minimize costs of recourse actions:
$y^* = y^*(x, \omega)$ is a solution (?!) of the second-stage LP problem

$$v(x, \omega) := \min_{y \in \mathbb{R}^p_+} \{qy : Wy = h(\omega) - T(\omega)x\}$$

where q is the unit recourse cost vector

$v(x, \omega)$ is the second-stage value function

Compute $v(x, \omega)$ for all $\omega \in \Omega \longrightarrow$

$Q(x) := E_\omega v(x, \omega)$

the expected recourse costs of the decision x

Minimize total expected costs $cx + Q(x)$

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Recourse model (canonical form)

$$\min\left\{cx + Q(x) : Ax = b,\ x \in \mathbb{R}^n_+\right\}$$

$$Q(x) = E_\omega v(h(\omega) - T(\omega)x)$$

$$v(z) = \min\left\{qy : Wy = z,\ y \in \mathbb{R}^p_+\right\}$$

Special case: $\Omega = \{\omega^1, \dots, \omega^S\}$, prob. p_s
notation: $(T(\omega^s), h(\omega^s)) = (T^s, h^s)$

$$\begin{array}{llcccccll}
\min & cx & + & p_1 \cdot qy^1 & + & \dots & + & p_S \cdot qy^S & \\
\text{s.t.} & Ax & & & & & & & = b \\
 & T^1x & + & Wy^1 & & & & & = h^1 \\
 & \vdots & & & & \ddots & & & \vdots \\
 & T^Sx & & & & & + & Wy^S & = h^S \\
 & x \geq 0 & & y^1 \geq 0 & & & & y^S \geq 0 &
\end{array}$$

Large-scale LP, size $(m_1 + mS) \times (n + pS)$,
with special structure

Any distribution: approximate by finite one
$\longrightarrow$ solve recourse problems as large-scale LP

In general, not possible since S astronomical

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

"Conclusions" for recourse models:

– flexible model (LP framework)

– explicit modeling of risk (quantitative)

– specification of (q, W) may be non-trivial

– concept not easy (problem owners, cf. CC)

Nice model, but can it be solved?

THEORY:

– convex objective (see later),
  linear constraints $\longrightarrow$ convex model

– nice theory (KKT), many good algorithms

Answer: YES

PRACTICE:

Function evaluations / gradients of
$Q(x) = E_\omega v(x, \omega)$ very expensive.
For given x

– solve 2nd-stage LP for each $\omega \in \Omega$

– calculate E_ω (r-dim. integral)

Answer: NO, except in special cases

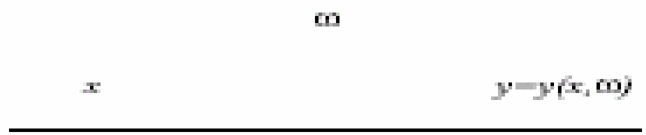
– finite distribution, small S

– 2nd-stage LP nice:
  $\longrightarrow$ special recourse structure (q, W)

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Multi-stage recourse

Recall two-stage model



NOW: decide on x

– ω only known in distribution

. . . observe ω

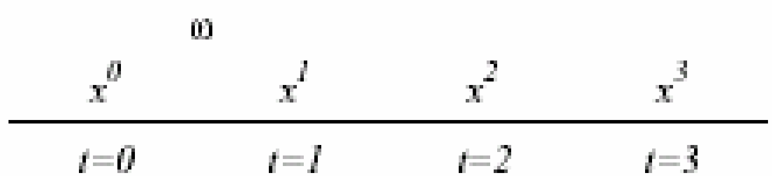
LATER: decide on recourse action $y(x, \omega)$

– $y(x, \omega)$ is optimal solution of 2nd-stage LP

– costs $v(x, \omega) \longrightarrow$ EVF $Q(x) = \mathsf{E}_\omega [v(x, \omega)]$

Essential: 2 stages $\sim \omega$ revealed all at once

– more than 2 periods possible



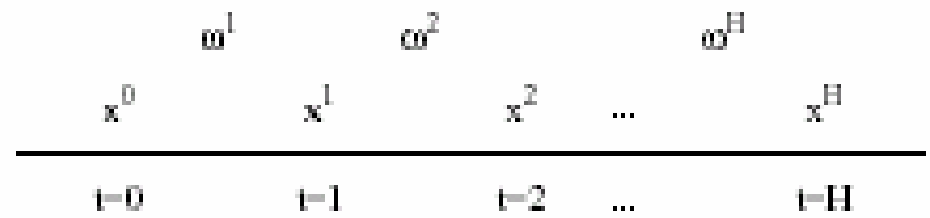
(see LN 3.2.3: Multi-period prod. planning)

Either

– correct model

– approximation of MULTI-STAGE

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)



Multi-stage: $H + 1 > 2$ stages
(H is time horizon)

- decision–observation–decision. . .
  . . . observation–decision
- $\omega = (\omega^1, \dots, \omega^H)$ revealed
  at H different moments in time
  e.g. monthly interest rate
- $\omega^t \sim F_{\omega^t|\omega^{t-1}}$, $\Omega^t \subset \mathbb{R}^{r_t}$, $\quad t = 1, \dots, H$
- x^t depends on $(x^0, \dots, x^{t-1})$
  and observations $(\omega^1, \dots, \omega^t)$

At each stage

NEW INFORMATION $\longrightarrow$ DECISION

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Assumptions

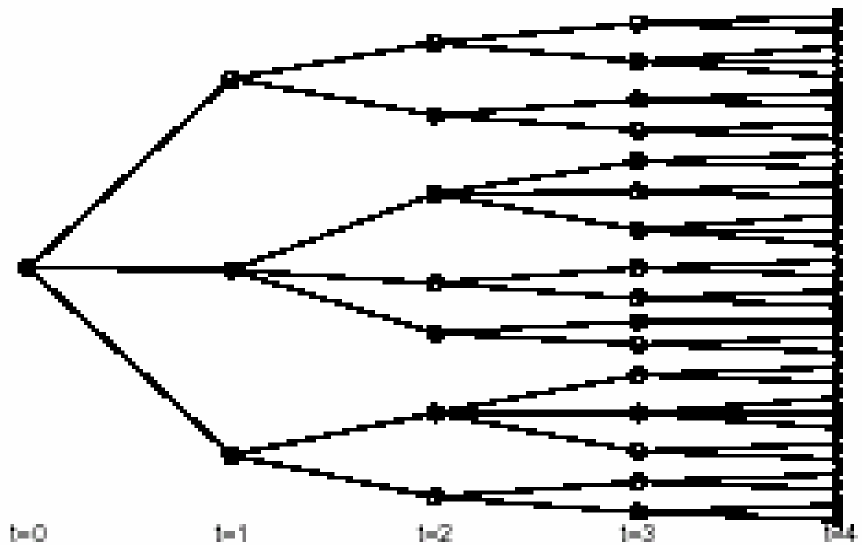
- discrete time t
- finite # stages

  now: $t = 0$, time horizon: $t = H$
- ω^t discrete random vector, $t = 1, \ldots, H$

Uncertainty represented by

SCENARIOS $\bar{\omega} = (\bar{\omega}^1, \bar{\omega}^2, \ldots, \bar{\omega}^H)$

$\longrightarrow$ SCENARIO TREE (...)



34 scenarios (paths in tree)

In general: indexed $s = 1, \ldots, S$

5 stages, decision at each node $\circ$

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Compact formulation multi-stage recourse

$$\min_{x^0 \geq 0} \left\{ cx^0 + Q^1(x^0) : Ax^0 = b \right\}$$

with, for $t = 1, \ldots, H-1$

$$Q^t(x^{t-1}) := E_{\omega^t}\left[v^t(x^{t-1}, \omega^t) \right]$$

$$v^t(x^{t-1}, \omega^t) :=$$

$$\min_{x^t \geq 0} \left\{ q^t x^t + Q^{t+1}(x^t) : W^t x^t = h^t - T^t x^{t-1} \right\}$$

where $q^t := q^t(\omega^t)$, $h^t := h^t(\omega^t)$, $T^t := T^t(\omega^t)$

and $Q^H(x^{H-1}) = 0$ $(\ldots)$

$\longrightarrow$ recursion

Assumptions

– complete recourse

– sufficiently expensive recourse

– $E_{\omega^t}\left[|\omega^t| \right] < +\infty$

$\longrightarrow$ Q^t finite for all t

Source: Maarten van der Vlerk (http://mally.eco.rug.nl/lnmb/lnmb.html)

Solution Approaches

- PRINCIPLES:
  - DISCRETIZATION LEADS TO MATHEMATICAL PROGRAM BUT LARGE-SCALE
  - USE STANDARD METHODS BUT EXPLOIT STRUCTURE
- DIRECT METHODS
  - TAKE ADVANTAGE OF SPARSITY STRUCTURE
    - SOME EFFICIENCIES
  - USE SIMILAR SUBPROBLEM STRUCTURE
    - GREATER EFFICIENCY

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Classes of SP Solution Algorithms

- Sparsity Structure Advantage
  - PARTITIONING
  - BASIS FACTORIZATION
  - INTERIOR POINT FACTORIZATION
- Similar/Small Problem Advantage
  - DP APPROACHES: DECOMPOSITION
    - BENDERS, L-SHAPED (VAN SLYKE – WETS)
    - DANTZIG-WOLFE (PRIMAL VERSION)
    - REGULARIZED (RUSZCZYNSKI)
    - VARIOUS SAMPLING SCHEMES (HIGLE/SEN Stochastic Decomposition, Abridge Nested Decomposition)
  - LAGRANGIAN METHODS

Source: John R. Birge (http://users.iems.nwu.edu/~jrbirge/html/talks/talks.html)

Sample Applications of SP

- Finance (later)
- SCM, Logistics, Distribution, Transportation
- Production Planning
- Capacity Planning
- Energy (power plant management, unit commitment)
- Natural Resources Management

  Forestry, Fisheries, Agriculture, Lakes
- Yield/Revenue Management
- Risk Management

SP & Finance

Financial Modeling is a particularly fertile domain for SP.

A very active research field – significant contributions,
Continual advancements, important practical applications

Some of the Reasons:

Continual stream of challenging/important problems
Sophistication of sector – rich underlying background, receptiveness
Volatility – obvious impact of uncertainties
High availability of data
Validation potential - benchmarking
$$ and high stakes
Suitability of problems for SP models:
Liquid markets – recourse flexibilities
Diversity of instruments/securities (hedging instruments)

Representative SP Applications in Finance

- **Portfolio management**
  Cash management, Fixed-income securities, MBS, International
- **Asset and Liability Management**
  Pension funds, Insurance contracts, Personal finance
- **Financial Risk Management**
- **Design of Financial Products**
- **Real Options (Integer SP)**

Two Finalists for the Edelman Prize of Best Achievement in MS:

- 1993, Russel-Yasuda-Kasai Model (Insurance), W.T. Ziemba, et al.
- 1999, Towers-Perrin Model (Global Asset Mgmt.), J.M. Mulvey, et al.

Active Research Domains

Applications (Increasing application base and extensions)
Exploitation of Computational GRIDS
Scenario Generation Procedures (& Scenario Reduction Techniques)
Approximation Schemes & Sampling-based Methods
Modeling Tools
Bounding Methods
Output Analysis
Development of Alternative/Sophisticated Risk Measures
Financial Risk Management
Specialized Algorithms
Stochastic Integer Programming

WWW Resources on SP

- The Committee on Stochastic Programming (COSP – MPS)
  "Stochastic Programming Community Homepage" http//stoprog.org
- Optimization Technology Center, Argonne National Lab
  http://www-fp.mcs.anl.gov/otc/Guide/OptWeb/continuous/constrained/stochastic/
  NEOS Server for Optimization: http://www-neos.mcs.anl.gov/
- IBM Research Group in Stochastic Programming
  http://www.research.ibm.com/stopro/
- Stochastic Optimization Research Group,
  Georgia Institute of Technology http://www.isye.gatech.edu/so/
- The MORE Institute, University of Arizona
  http://tucson.sie.arizona.edu/MORE/

Groups:

- Centre for Financial Research, Judge Institute of Management, Cambridge University
  http://www-cfr.jims.cam.ac.uk/
- Risk Management and Financial Engineering Lab, University of Florida
  http://www.ise.ufl.edu/rmfe/
- HERMES European Center of Excellence on Computational Finance and Economics, University of Cyprus
  http://www.hermes.ucy.ac.cy
- Centre for Analysis of Risk and Optimisation Modelling Application (CARISMA), Brunel University
  http://carisma.brunel.ac.uk/
- Other (Un. St. Gallen, Un. Vienna, ETH-Zurich, Un. Karlsruhe, Erasmus Univ., etc.)

http://mally.eco.rug.nl (Maarten van der Vlerk, Univ. of Groningen,
– bibliographic database & other links)

http://iems.northwestern.edu/~jrbirge/ (John R. Birge, Northwestern Univ.)

SP & Financial Modeling Books/Volumes:

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P. Kall, S.W. Wallace, *Stochastic Programming*, Wiley, 1994.
Available for free: www.unizh.ch/ior/Pages/Deutsch/Mitglieder/Kall/bib/ka-wal-94.pdf

A. Prékopa, *Stochastic Programming*, Kluwer, 1995.

A Ruszczyński, A. Shapiro, *Stochastic Programming*, Series "Handbooks in Operations Research and Management Science", Vol. 10, Elsevier, 2003.

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- "Financial Modeling & Risk Management" – 2 volumes?, H. Vladimirou (ed.)
- Vol. 100 (2000), J.R. Birge, C. Edirisinghe, W.T. Ziemba (eds.)
- Vol. 85 (1999), R.J-B Wets, W.T. Ziemba, (eds.)
- Vol. 64 (1996), S.W. Wallace, J. Higle, S. Sen (eds.)

SP & Financial Modeling Books/Volumes: (cont.)

S.A. Zenios (ed.), *Financial Optimization*, Cambridge University Press, 1993.

W.T. Ziemba, J.M. Mulvey, *Worldwide Asset and Liability Modeling*, Cambridge University Press, 1998.

J. Dupačová, J. Hurt, V. Stépan, *Stochastic Modeling in Economics and Finance*, Kluwer, 2002.

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