

Stability of two- and multistage stochastic programs

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PARAOPT VIII, Cairo, Egypt, November 29, 2005



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Multistage stochastic programs

Let $\xi = \{\xi_t\}_{t=1}^T$ be an \mathbb{R}^d -valued discrete-time stochastic data process defined on some probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and with ξ_1 deterministic. The stochastic decision x_t at period t is assumed to be measurable with respect to $\mathcal{F}_t := \sigma(\xi_1, \dots, \xi_t)$ (**nonanticipativity**).

Multistage stochastic program:

$$\min \left\{ \mathbb{E} \left[\sum_{t=1}^T \langle b_t(\xi_t), x_t \rangle \right] \left| \begin{array}{l} x_t \in X_t, \\ x_t \text{ is } \mathcal{F}_t \text{ - measurable, } t = 1, \dots, T, \\ A_{t,0}x_t + A_{t,1}(\xi_t)x_{t-1} = h_t(\xi_t), t = 2, \dots, T \end{array} \right. \right\}$$

where X_t are nonempty and polyhedral set, $A_{t,0}$ are fixed matrices and $b_t(\cdot)$, $h_t(\cdot)$ and $A_{t,1}(\cdot)$ possibly depend affinely linearly on ξ_t , where ξ varies in a polyhedral set Ξ .

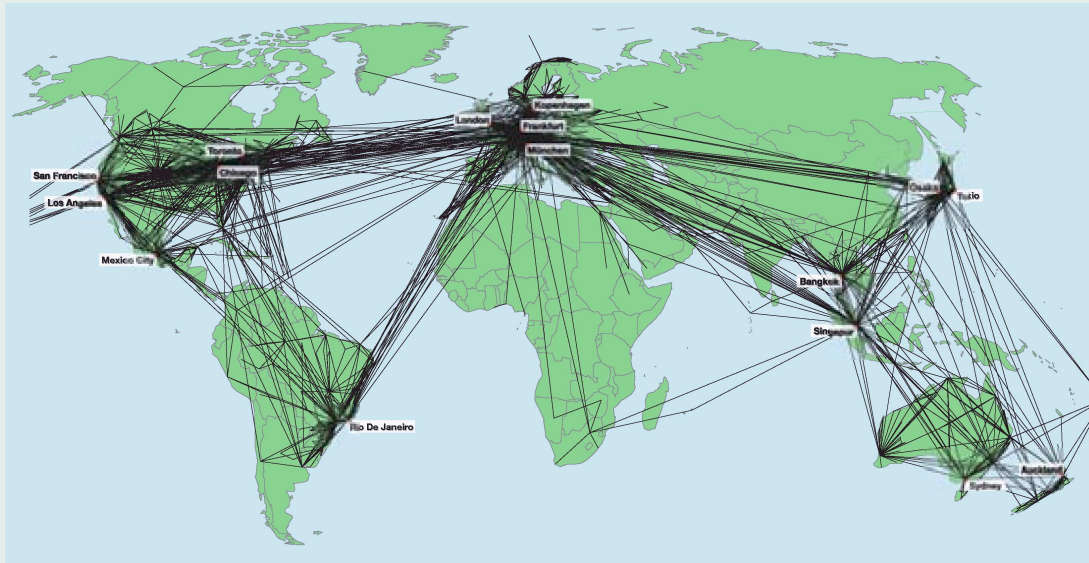
The model is **(multiperiod) two-stage** if $\mathcal{F}_t = \mathcal{F}$, $t = 2, \dots, T$.

Stability of such models is not known so far (cf. the survey by Römisch 03).

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Application: Airline Revenue Management

Origin&Destination (O&D) Revenue Management has become a standard instrument in airline industry. It considers the entire **airline network** and determines **protection levels** for all **origin destination itineraries**, fare classes, points of sale and data collection points (dcp's) of the booking horizon. Our model incorporates the **stochastic nature of the passenger behaviour** and represents a **multi-stage stochastic program** where its **stages** refer to the dcp's.



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To have the multistage stochastic program well defined, we assume $x_t \in L_{r'}(\Omega, \mathcal{F}_t, \mathbb{P}; \mathbb{R}^{m_t})$ and $\xi_t \in L_r(\Omega, \mathcal{F}_t, \mathbb{P}; \mathbb{R}^d)$, where $r \geq 1$ and

$$r' := \begin{cases} \frac{r}{r-1} & , \text{ if only costs are random} \\ r & , \text{ if only right-hand sides are random} \\ r = 2 & , \text{ if only costs and right-hand sides are random} \\ \infty & , \text{ if all technology matrices are random and } r = T. \end{cases}$$

Then **nonanticipativity** may be expressed as

$$x \in \mathcal{N}_{na}$$

$$\mathcal{N}_{na} = \{x \in \times_{t=1}^T L_{r'}(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^{m_t}) : x_t = \mathbb{E}[x_t | \mathcal{F}_t], \forall t\},$$

i.e., as a subspace constraint, by using the conditional expectations $\mathbb{E}[\cdot | \mathcal{F}_t]$ with respect to the σ -fields \mathcal{F}_t .

For $T = 2$ we have $\mathcal{N}_{na} = \mathbb{R}^{m_1} \times L_{r'}(\Omega, \mathcal{F}, P; \mathbb{R}^{m_2})$.

→ **infinite-dimensional optimization problem**

Dynamic programming

Theorem: (Evstigneev 76, Rockafellar/Wets 76)

Under weak assumptions the multistage stochastic program is equivalent to the (first-stage) convex minimization problem

$$\min_{\Xi} \left\{ \int_{\Xi} f(x_1, \xi) P(d\xi) : x_1 \in X_1 \right\},$$

where f is an integrand on $\mathbb{R}^{m_1} \times \Xi$ given by

$$f(x_1, \xi) := \langle b_1(\xi_1), x_1 \rangle + \Phi_2(x_1, \xi^2),$$

$$\Phi_t(x_1, \dots, x_{t-1}, \xi^t) := \inf \left\{ \langle b_t(\xi_t), x_t \rangle + \mathbb{E} [\Phi_{t+1}(x_1, \dots, x_t, \xi^{t+1}) | \mathcal{F}_t] : \right. \\ \left. x_t \in X_t, A_{t,0}x_t + A_{t,1}x_{t-1} = h_t(\xi_t) \right\}$$

for $t = 2, \dots, T$, where $\Phi_{T+1}(x_1, \dots, x_T, \xi^{T+1}) := 0$.

→ The integrand f depends on the probability measure \mathbb{P} in a nonlinear way !

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Quantitative Stability

Let us introduce some notations. Let F denote the objective function defined on $L_r(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^s) \times L_{r'}(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^m) \rightarrow \mathbb{R}$ by $F(\xi, x) := \mathbb{E}[\sum_{t=1}^T \langle b_t(\xi_t), x_t \rangle]$, let

$$\mathcal{X}_t(x_{t-1}; \xi_t) := \{x_t \in X_t | A_{t,0}x_t + A_{t,1}(\xi_t)x_{t-1} = h_t(\xi_t)\}$$

denote the t -th feasibility set for every $t = 2, \dots, T$ and

$$\mathcal{X}(\xi) := \{x \in \times_{t=1}^T L_{r'}(\Omega, \mathcal{F}_t, \mathbb{P}; \mathbb{R}^{m_t}) | x_1 \in X_1, x_t \in \mathcal{X}_t(x_{t-1}; \xi_t)\}$$

the set of feasible elements with input ξ .

Then the multistage stochastic program may be rewritten as

$$\min\{F(\xi, x) : x \in \mathcal{X}(\xi)\}.$$

Let $v(\xi)$ denote its optimal value and, for any $\alpha \geq 0$,

$$l_\alpha(F(\xi, \cdot)) := \{x \in \mathcal{X}(\xi) : F(\xi, x) \leq v(\xi) + \alpha\}$$

denote the α -level set of the stochastic program with input ξ .

The following conditions are imposed:

(A1) There exists a $\delta > 0$ such that for any $\tilde{\xi} \in L_r(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^s)$ with $\|\tilde{\xi} - \xi\|_r \leq \delta$, any $t = 2, \dots, T$ and any $x_1 \in X_1$, $x_\tau \in \mathcal{X}_\tau(x_{\tau-1}; \tilde{\xi}_\tau)$, $\tau = 2, \dots, t-1$, the set $\mathcal{X}_t(x_{t-1}; \tilde{\xi}_t)$ is nonempty (**relatively complete recourse locally around ξ**).

(A2) The optimal value $v(\xi)$ is finite and the objective function F is **level-bounded locally uniformly at ξ** , i.e., for some $\alpha > 0$ there exists a $\delta > 0$ and a bounded subset B of $L_{r'}(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^m)$ such that $l_\alpha(F(\tilde{\xi}, \cdot))$ is nonempty and contained in B for all $\tilde{\xi} \in L_r(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^s)$ with $\|\tilde{\xi} - \xi\|_r \leq \delta$.

(A3) $\xi \in L_r(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^s)$ for some $r \geq 1$.

Norm in L_r : $\|\xi\|_r := \left(\sum_{t=1}^T \mathbb{E}[\|\xi_t\|^r] \right)^{\frac{1}{r}}$

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Theorem:

Let (A1), (A2) and (A3) be satisfied and X_1 be bounded. Then there exist positive constants L , α and δ such that

$$|v(\xi) - v(\tilde{\xi})| \leq L(\|\xi - \tilde{\xi}\|_r + D_f(\xi, \tilde{\xi}))$$

holds for all $\tilde{\xi} \in L_r(\Omega, \mathcal{F}, \mathbb{P}; \mathbb{R}^s)$ with $\|\tilde{\xi} - \xi\|_r \leq \delta$.

Here, $D_f(\xi, \tilde{\xi})$ denotes the **filtration distance** of ξ and $\tilde{\xi}$ defined by

$$D_f(\xi, \tilde{\xi}) := \sup_{\varepsilon \in (0, \alpha]} \inf_{\substack{x \in I_\varepsilon(F(\xi, \cdot)) \\ \tilde{x} \in I_\varepsilon(F(\tilde{\xi}, \cdot))}} \sum_{t=2}^{T-1} \max\{\|x_t - \mathbb{E}[x_t | \tilde{\mathcal{F}}_t]\|_{r'}, \|\tilde{x}_t - \mathbb{E}[\tilde{x}_t | \mathcal{F}_t]\|_{r'}\}$$

where $\mathcal{F}_t = \sigma(\xi_1, \dots, \xi_t)$ and $\tilde{\mathcal{F}}_t = \sigma(\tilde{\xi}_1, \dots, \tilde{\xi}_t)$, $t = 2, \dots, T-1$.

Note that the **filtration distance vanishes** for **multiperiod two-stage stochastic programs** !

If solutions exist, the filtration distance is of the simplified form

$$D_f(\xi, \tilde{\xi}) = \inf_{\substack{x \in l_0(F(\xi, \cdot)) \\ \tilde{x} \in l_0(F(\tilde{\xi}, \cdot))}} \sum_{t=2}^{T-1} \max\{\|x_t - \mathbb{E}[x_t | \tilde{\mathcal{F}}_t]\|_{r'}, \|\tilde{x}_t - \mathbb{E}[\tilde{x}_t | \mathcal{F}_t]\|_{r'}\}.$$

For example, solutions exist if Ω is finite or if $1 < r' < \infty$ implying that the spaces $L_{r'}$ are finite-dimensional or reflexive Banach spaces (hence, the level sets are compact or weakly sequentially compact).

Remark:

The continuity property of infima in the Theorem can be supplemented by a **quantitative stability property** of the set $S(\xi)$ of first stage solutions. Namely, there exists a constant $\hat{L} > 0$ such that

$$\sup_{x \in S(\tilde{\xi})} d(x, S(\xi)) \leq \Psi_\xi^{-1}(\hat{L}(\|\xi - \tilde{\xi}\|_r + D_f(\xi, \tilde{\xi}))),$$

where $\Psi_\xi(\tau) := \inf\{\mathbb{E}[f(x_1, \xi)] - v(\xi) : d(x_1, S(\xi)) \geq \tau, x_1 \in X_1\}$ with $\Psi_\xi^{-1}(\alpha) := \sup\{\tau \in \mathbb{R}_+ : \Psi_\xi(\tau) \leq \alpha\}$ ($\alpha \in \mathbb{R}_+$) is the **growth function** of the original problem near its solution set $S(\xi)$.

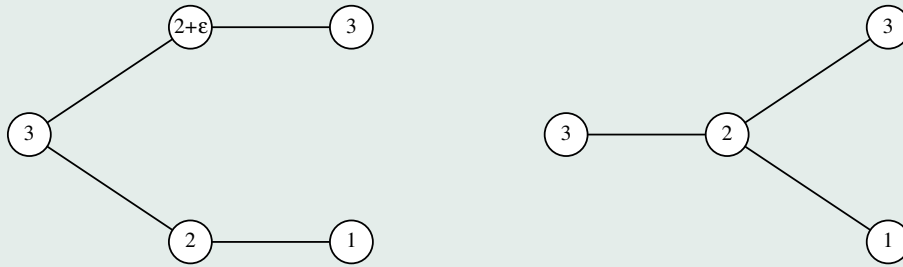
The following example shows that the filtration distance D_f is indispensable for the stability result to hold.

Example: (Optimal purchase under uncertainty)

The decisions x_t correspond to the amounts to be purchased at each time period with uncertain prices are ξ_t , $t = 1, \dots, T$, and such that a prescribed amount a is achieved at the end of a given time horizon. The problem is of the form

$$\min \left\{ \mathbb{E} \left[\sum_{t=1}^T \xi_t x_t \right] \left| \begin{array}{l} (x_t, s_t) \in X_t = \mathbb{R}_+^2, \\ (x_t, s_t) \text{ is } (\xi_1, \dots, \xi_t)\text{-measurable,} \\ s_t - s_{t-1} = x_t, \quad t = 2, \dots, T, \\ s_1 = 0, s_T = a. \end{array} \right. \right\},$$

where the state variable s_t corresponds to the amount at time t . Let $T := 3$ and ξ_ε denote the stochastic price process having the two scenarios $\xi_\varepsilon^1 = (3, 2 + \varepsilon, 3)$ ($\varepsilon \in (0, 1)$) and $\xi_\varepsilon^2 = (3, 2, 1)$ each endowed with probability $\frac{1}{2}$. Let $\tilde{\xi}$ denote the approximation of ξ_ε given by the two scenarios $\tilde{\xi}^1 = (3, 2, 3)$ and $\tilde{\xi}^2 = (3, 2, 1)$ with the same probabilities $\frac{1}{2}$.



Scenario trees for ξ_ε (left) and $\tilde{\xi}$

We obtain

$$v(\xi_\varepsilon) = \frac{1}{2}((2 + \varepsilon)a + a) = \frac{3 + \varepsilon}{2}a$$

$$v(\tilde{\xi}) = 2a, \quad \text{but}$$

$$\|\xi_\varepsilon - \tilde{\xi}\|_1 \leq \frac{1}{2}(0 + \varepsilon + 0) + \frac{1}{2}(0 + 0 + 0) = \frac{\varepsilon}{2}.$$

Hence, the multistage stochastic purchasing model is **not stable** with respect to $\|\cdot\|_1$.

However, the estimate for $|v(\xi) - v(\tilde{\xi})|$ in the stability theorem is valid with $L = 1$ since $D_f(\xi, \tilde{\xi}) = \frac{a}{2}$.

Conclusions

The stability result has important consequences for the construction of **scenario trees** ξ_{tr} as approximations of the original process ξ . The tree ξ_{tr} should be selected such that

$$\|\xi - \xi_{\text{tr}}\|_r \quad \text{and} \quad D_f(\xi, \xi_{\text{tr}})$$

are **smaller** than some **tolerance**. This problem may be solved for ξ having scenarios ξ^i and probabilities p_i , $i = 1, \dots, N$.

Application: **Airline revenue management** (continued)

Let ξ^i be **passenger demand scenarios** for a single flight (LH400, A340-300) with $d = 14$ fare classes and the booking time horizon with $T = 18$ obtained by (re)sampling from historical data ($N=300$). An implementation of a **(forward) tree construction** leads to the following scenario tree with 150 scenarios, 1190 nodes and branching at all $t = 1, \dots, 18$.

