

Multiperiod Risk Functionals in stochastic programming

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Multistage stochastic programs

Let $\{\xi_t\}_{t=1}^T$ be a 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 optimization model:

$$\min \left\{ \mathbb{E} \left[\sum_{t=1}^T \langle b_t(\xi_t), x_t \rangle \right] \left| \begin{array}{l} x_t \in X_t, t = 1, \dots, T, A_{1,0}x_1 = h_1(\xi_1), \\ x_t \text{ is } \mathcal{F}_t \text{ - measurable, } t = 1, \dots, T, \\ A_{t,0}x_t + A_{t,1}x_{t-1} = h_t(\xi_t), t = 2, \dots, T \end{array} \right. \right\}$$

where the sets X_t , $t = 1, \dots, T$, are polyhedral cones, the vectors $b_t(\cdot)$ and $h_t(\cdot)$ depend affine linearly on ξ_t .

If the process $\{\xi_t\}_{t=1}^T$ has a finite number of scenarios, they exhibit a **scenario tree** structure.

Typical applications: Power production planning, revenue and portfolio management models.

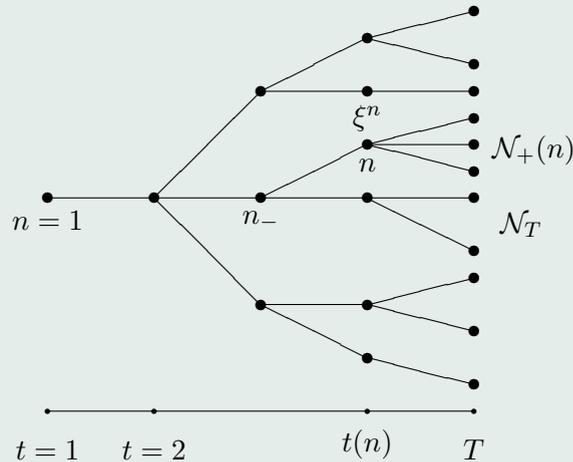
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Data process approximation by scenario trees

The process $\{\xi_t\}_{t=1}^T$ is approximated by a process forming a **scenario tree** being based on a finite set $\mathcal{N} \subset \mathbb{N}$ of nodes.



Scenario tree with $T = 5$, $N = 22$ and 11 leaves

$n = 1$ **root node**, n_- unique **predecessor** of node n , $\text{path}(n) = \{1, \dots, n_-, n\}$, $t(n) := |\text{path}(n)|$, $\mathcal{N}_+(n)$ set of **successors** to n , $\mathcal{N}_T := \{n \in \mathcal{N} : \mathcal{N}_+(n) = \emptyset\}$ set of **leaves**, $\text{path}(n)$, $n \in \mathcal{N}_T$, **scenario** with (given) probability π^n , $\pi^n := \sum_{\nu \in \mathcal{N}_+(n)} \pi^\nu$ **probability of node n** , ξ^n realization of $\xi_{t(n)}$.

Tree representation of the optimization model

$$\min \left\{ \sum_{n \in \mathcal{N}} \pi^n \langle b_{t(n)}(\xi^n), x^n \rangle \mid \begin{array}{l} x^n \in X_{t(n)}, n \in \mathcal{N}, A_{1,0}x^1 = h_1(\xi^1) \\ A_{t(n),0}x^n + A_{t(n),1}x^{n-} = h_{t(n)}(\xi^n), n \in \mathcal{N} \end{array} \right\}$$

How to solve the optimization model ?

- Standard software (e.g., CPLEX)
- Decomposition methods for (very) large scale models
(Ruszczynski/Shapiro (Eds.): Stochastic Programming, Handbook, 2003)

Open question:

How to model and incorporate risk into multiperiod models ?

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Risk functionals

Let z be a real random variable on some probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Assume that $z = z(x)$ is the revenue depending on a decision x in some stochastic optimization model. The **traditional objective** of such models consists in **maximizing the expected revenue**, i.e.,

$$\max_x \mathbb{E}[z(x)].$$

However, the revenue $z(x)$ of some or many decisions x might have **fat tails**, in particular, to the left. Looking only at the expectation of z hides any tail information.

Examples of risk functionals:

Upper semivariance:

$$sV_+(z) := \mathbb{E}[(\mathbb{E}[z] - z)_+^2] = \mathbb{E}[\max\{\mathbb{E}[z] - z, 0\}^2]$$

Value-at-Risk:

$$VaR_p(z) := -\inf\{r \in \mathbb{R} : \mathbb{P}(z \leq r) \geq p\} \quad (p \in (0, 1))$$

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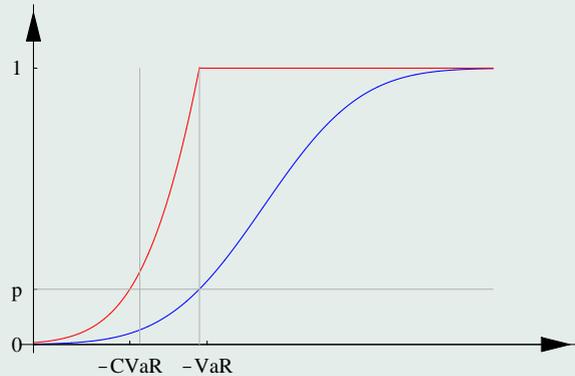
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Conditional Value-at-risk:

$CVaR_p(z) :=$ mean of the tail distribution function F_p

where $F_p(t) := \begin{cases} 1 & t \geq -VaR_p(z), \\ \frac{F(t)}{p} & t < -VaR_p(z) \end{cases}$ and

$F(t) := \mathbb{P}(\{z \leq t\})$ is the distribution function of z .



$VaR_p(z)$ and $CVaR_p(z)$ for a continuously distributed z

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Axiomatic characterization of risk:

Let $\mathcal{Z} = L_p(\Omega, \mathcal{F}, \mathbb{P})$ for $1 \leq p \leq +\infty$. A mapping $\mathcal{A} : \mathcal{Z} \rightarrow \mathbb{R}$ is called **acceptability functional** if it is **concave** on \mathcal{Z} and satisfies the following two conditions for all $z, \tilde{z} \in \mathcal{Z}$:

- (i) If $z \leq \tilde{z}$, then $\mathcal{A}(z) \leq \mathcal{A}(\tilde{z})$ (**monotonicity**).
- (ii) For each $r \in \mathbb{R}$ and $z \in \mathcal{Z}$ we have $\mathcal{A}(z + r) = \mathcal{A}(z) + r$ (**translation equivariance**).

An acceptability functional \mathcal{A} is called **positively homogeneous** if $\mathcal{A}(\lambda z) = \lambda \mathcal{A}(z)$ holds for all $\lambda \geq 0$ and $z \in \mathcal{Z}$.

\mathcal{A} is called **strict** if $\mathcal{A}(z) \leq \mathbb{E}[z]$ for each $z \in \mathcal{Z}$.

Given an acceptability functional \mathcal{A} , the mapping $\rho := -\mathcal{A}$ is called a **convex risk functional**. ρ is called a **coherent risk functional** if \mathcal{A} is positively homogeneous.

Conditional risk mappings

Let $\mathcal{G} \subset \mathcal{F}$ be σ -fields and $\mathcal{Y} := L_p(\Omega, \mathcal{G}, \mathbb{P})$ be the corresponding subspace of \mathcal{Z} .

A mapping $\mathcal{A} : \mathcal{Z} \rightarrow \mathcal{Y}$ is called **conditional acceptability mapping** or **acceptability mapping with observable information \mathcal{G}** if it satisfies the following conditions for all $z, \tilde{z} \in \mathcal{Z}$:

- (i) $\mathcal{A}(\lambda z + (1 - \lambda)\tilde{z}) \geq \lambda\mathcal{A}(z) + (1 - \lambda)\mathcal{A}(\tilde{z})$ for all $\lambda \in [0, 1]$
(((pointwise) concavity))
- (ii) If $z \leq \tilde{z}$, then $\mathcal{A}(z) \leq \mathcal{A}(\tilde{z})$ (**monotonicity**).
- (iii) If $\tilde{z} \in \mathcal{Y}$, we have $\mathcal{A}(z + \tilde{z}) = \mathcal{A}(z) + \tilde{z}$ (**(predictable) translation equivariance**).

Notation: $\mathcal{A}(\cdot, \mathcal{G})$ or $\mathcal{A}_{\mathcal{F}|\mathcal{G}}$.

The mapping $\rho = \rho_{\mathcal{F}|\mathcal{G}} := -\mathcal{A}_{\mathcal{F}|\mathcal{G}}$ is called **conditional convex risk mapping**.

Multiperiod risk functionals

Let a filtration of σ -fields \mathcal{F}_t , $t = 1, \dots, T$, and (real) random variables $\{z_t\}_{t=1}^T$ with $z_t \in L_p(\Omega, \mathcal{F}_t, \mathbb{P})$, $1 \leq p \leq +\infty$, be given. Then it may become necessary to measure their risk by multiperiod functionals. We assume $\mathcal{F}_t \subseteq \mathcal{F}_{t+1} \subseteq \mathcal{F}$ and $\mathcal{F}_1 = \{\emptyset, \Omega\}$, i.e. z_1 is deterministic.

A functional $\mathcal{A} : \mathcal{Z} = \times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P}) \rightarrow \overline{\mathbb{R}}$ is called **multiperiod acceptability functional** if it is **concave** and satisfies the following two conditions for all $z, \tilde{z} \in \times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$:

(i) If $z_t \leq \tilde{z}_t$, $t = 1, \dots, T$, then $\mathcal{A}(z_1, \dots, z_T) \leq \mathcal{A}(\tilde{z}_1, \dots, \tilde{z}_T)$ (**monotonicity**),

(ii) If $\tilde{z}_t \in L_p(\Omega, \mathcal{F}_{t-1}, \mathbb{P})$, then $\mathcal{A}(z_1, \dots, z_t + \tilde{z}_t, \dots, z_T) = \mathbb{E}[\tilde{z}_t] + \mathcal{A}(z_1, \dots, z_T)$ (**(predictable) translation equivariance**).

Notation: $\mathcal{A}(z_1, \dots, z_T; \mathcal{F}_1, \dots, \mathcal{F}_T)$.

The mapping $\rho := -\mathcal{A}$ is called a **multiperiod convex risk functional**.

Dual representations and properties

Let \mathcal{Z}^* denote the topological dual of \mathcal{Z} for $p \in [1, +\infty)$, i.e., $\mathcal{Z}^* := \times_{t=1}^T L_{p'}(\Omega, \mathcal{F}_t, \mathbb{P})$ with $\frac{1}{p} + \frac{1}{p'} = 1$, and let

$$\langle z^*, z \rangle = \sum_{t=1}^T \mathbb{E}[z_t^* z_t]$$

be the dual pairing between \mathcal{Z}^* and \mathcal{Z} .

An acceptability functional \mathcal{A} is called **proper** if $\mathcal{A}(z) < +\infty$ for all $z \in \mathcal{Z}$ and its domain $\text{dom}(\mathcal{A}) := \{Z \in \mathcal{Z} : \mathcal{A}(z) > -\infty\}$ is nonempty. If \mathcal{A} is proper and upper semicontinuous, its domain is closed and convex.

The conjugate $\mathcal{A}^* : \mathcal{Z}^* \rightarrow \overline{\mathbb{R}}$ of \mathcal{A} is given by

$$\mathcal{A}^*(z^*) := \inf_{z \in \mathcal{Z}} \{\langle z^*, z \rangle - \mathcal{A}(z)\}.$$

The Fenchel-Moreau theorem of convex analysis then implies the representation

$$\mathcal{A}(z) = \inf_{z^* \in \mathcal{Z}^*} \{\langle z^*, z \rangle - \mathcal{A}^*(z^*)\}$$

if \mathcal{A} is proper and upper semicontinuous.

Theorem:

Let $\mathcal{A} : \mathcal{Z} \rightarrow \overline{\mathbb{R}}$ be a proper multiperiod acceptability functional. Then the representation

$$\mathcal{A}(z) = \inf_{z^* \in \mathcal{Z}^*} \left\{ \sum_{t=1}^T \mathbb{E}[z_t^* z_t] - \mathcal{A}^*(z^*) : z_t^* \geq 0, \mathbb{E}[z_t^* | \mathcal{F}_{t-1}] = 1, \right. \\ \left. t = 2, \dots, T \right\}$$

is valid for every $z \in \mathcal{Z}$ if \mathcal{A} is **upper semicontinuous**.

Conversely, if \mathcal{A} can be represented in the above form for some function $\mathcal{A}^* : \mathcal{Z}^* \rightarrow \overline{\mathbb{R}}$, then \mathcal{A} is an upper semicontinuous multiperiod acceptability functional.

Moreover, \mathcal{A} is **locally Lipschitz continuous**, **superdifferentiable** and **Hadamard directionally differentiable** on $\text{int dom}(\mathcal{A})$. Its directional derivative at $\bar{z} \in \text{int dom}(\mathcal{A})$ satisfies

$$\mathcal{A}'(\bar{z}, z) = \inf_{z^* \in \partial \mathcal{A}(\bar{z})} \langle z^*, z \rangle, \quad \forall z \in \mathcal{Z}, \\ \partial \mathcal{A}(\bar{z}) = \{z^* \in \mathcal{Z}^* : \mathcal{A}(z) \leq \mathcal{A}(\bar{z}) + \langle z^*, z - \bar{z} \rangle, \quad \forall z \in \mathcal{Z}\}.$$

Multiperiod polyhedral risk functionals

It is a natural idea to introduce **acceptability and risk functionals** as optimal values of certain stochastic programs.

Definition:

A multiperiod acceptability functional \mathcal{A} on $\times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$ is called **polyhedral** if there are $k_t \in \mathbb{N}$, $c_t \in \mathbb{R}^{k_t}$, $t = 1, \dots, T$, $w_{t\tau} \in \mathbb{R}^{k_{t-\tau}}$, $t = 1, \dots, T$, $\tau = 0, \dots, t-1$, a polyhedral set Y_1 and polyhedral cones $Y_t \subset \mathbb{R}^{k_t}$, $t = 2, \dots, T$, such that

$$\mathcal{A}(z) = -\inf \left\{ \mathbb{E} \left[\sum_{t=1}^T \langle c_t, y_t \rangle \right] \left| \begin{array}{l} y_t \in L_p(\Omega, \mathcal{F}_t, \mathbb{P}; \mathbb{R}^{k_t}), y_t \in Y_t \\ \sum_{\tau=0}^{t-1} \langle w_{t,\tau}, y_{t-\tau} \rangle = z_t, t = 1, \dots, T \end{array} \right. \right\}.$$

A mapping $\rho := -\mathcal{A}$ is called **multiperiod polyhedral risk functional**.

Remark: A convex combination of the expectation and of a multiperiod polyhedral acceptability functional is again a multiperiod polyhedral acceptability functional.

Polyhedral risk functionals preserve **linearity and decomposition structures** of optimization models. (Eichhorn/Römisch, SIAM J. Optim. 05)

Theorem:

Let \mathcal{A} be a functional on $\times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$ ($p \in [1, +\infty)$) having the form in the previous definition. Assume

(i) complete recourse: $\langle w_{t,0}, Y_t \rangle = \mathbb{R}$, $t = 2, \dots, T$,

(ii) dual feasibility: $\left\{ u \in \mathbb{R}^T : c_t + \sum_{\nu=t}^T u_\nu w_{\nu, \nu-t} \in -Y_t^* \right\} \neq \emptyset$,

where the sets Y_t^* are the (polyhedral) polar cones of Y_t .

Then \mathcal{A} is finite, continuous and concave on $\times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$ and the following **dual representation** holds whenever $\frac{1}{p} + \frac{1}{p'} = 1$:

$$\mathcal{A}(z) = \inf \left\{ \begin{array}{l} \mathbb{E} \left[\sum_{t=1}^T z_t^* z_t \right] \\ - \inf_{y_1 \in Y_1} \left\langle c_1 + \sum_{\nu=1}^T \mathbb{E} [z_\nu^*] w_{\nu, \nu-1}, y_1 \right\rangle \end{array} \middle| \begin{array}{l} z_t^* \in L_{p'}(\Omega, \mathcal{F}_t, \mathbb{P}) \\ c_t + \sum_{\nu=t+1}^T \mathbb{E} [z_\nu^* | \mathcal{F}_t] w_{\nu, \nu-t} \in -Y_t^* \end{array} \right\}.$$

Idea: Determine the parameters k_t , c_t , $w_{t\tau}$ and Y_t such that

$$c_1 + \sum_{t=2}^T w_{t,t-1} \mathbb{E}[z_t^*] \in -Y_1^* \Rightarrow \mathbb{E}[z_2^*] = 1,$$

$$c_t + \sum_{\tau=t+1}^T w_{\tau,\tau-t} \mathbb{E}[z_\tau^* | \mathcal{F}_t] \in -Y_t^* \Rightarrow \mathbb{E}[z_{t+1}^* | \mathcal{F}_t] = 1 \text{ and } z_t^* \geq 0$$

$$c_T + w_{T,0} z_T^* \in -Y_T^* \Rightarrow z_T^* \geq 0.$$

We assume $k_1 \geq 2$, $k_t \geq 3$, $t = 2, \dots, T-1$, and $k_T \geq 2$.

Furthermore, let the sets Y_t be of the form

$$Y_1 = \mathbb{R} \times \hat{Y}_1, Y_t = \mathbb{R} \times \mathbb{R}_+ \times \hat{Y}_t, t = 2, \dots, T-1, Y_T = \mathbb{R}_+ \times \hat{Y}_T,$$

where \hat{Y}_1 is polyhedral and the sets \hat{Y}_t , $t = 2, \dots, T$, are polyhedral cones. Finally, we set

$$c_1 = (-1, \hat{c}_1), c_t = (-1, 0, \hat{c}_t), t = 2, \dots, T-1, c_T = (0, \hat{c}_T),$$

$$w_{1,1} = (1, \hat{w}_{1,1}), w_{t,t} = (0, \hat{w}_{t,t}), t = 2, \dots, T, w_{T,1} = (1, \hat{w}_{T,1}),$$

$$w_{t,1} = (0, 1, \hat{w}_{t,1}), w_{t,1} = (1, 0, \hat{w}_{t,1}), w_{t,\tau} = (0, 0, \hat{w}_{t,\tau}), \tau =$$

$$2, \dots, T-t, t = 1, \dots, T-1.$$

Corollary:

Let \mathcal{A} be a functional on $\times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$ ($p \in [1, +\infty)$) with parameters chosen as above. Assume **complete recourse** and **dual feasibility**. Then \mathcal{A} is a finite, continuous and multiperiod acceptability functional having the representation

$$\mathcal{A}(z) = \inf \left\{ \sum_{t=1}^T \mathbb{E}[z_t^* z_t] - \inf_{\hat{y}_1 \in \hat{Y}_1} \langle \bar{c}_1, \hat{y}_1 \rangle \mid z_t^* \in L_{p'}(\Omega, \mathcal{F}_t, \mathbb{P}), z_t^* \geq 0, \right. \\ \left. \mathbb{E}[z_t^* | \mathcal{F}_{t-1}] = 1, \bar{c}_t + \hat{w}_{t,1} z_t^* + \epsilon \in -\hat{Y}_t^*, t = 2, \dots, T \right\},$$

where $\bar{c}_1 := \hat{c}_1 + \sum_{t=2}^T \hat{w}_{t,t-1} \in Y_1$, $\bar{c}_t := \hat{c}_t + \sum_{\tau=t+1}^T \hat{w}_{\tau,\tau-t}$, $t = 2, \dots, T-1$, $\bar{c}_T := \hat{c}_T$.

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Example: (value-of-information approach)

Let $k_t = 3$ for $t = 1, \dots, T$, $\bar{c}_1 = (0, 0)$, $\hat{Y}_1 = \mathbb{R}_+ \times \mathbb{R}_+$, $\bar{c}_t = \frac{1}{\alpha_t}$, $\hat{w}_{t,0} = -1$ and $\hat{Y}_t = \mathbb{R}_+$, $t = 1, \dots, T - 1$, $\bar{c}_T = (0, \frac{1}{\alpha_T})$, $\hat{Y}_T = \mathbb{R}_+ \times \mathbb{R}_+$ and $\hat{w}_{T,1} = (0, -1)$, where $\alpha_t \in (0, 1)$. Then we obtain the following acceptability functional

$$\mathcal{A}(z) = \inf \left\{ \sum_{t=2}^T \mathbb{E}[z_t^* z_t] : z_t^* \in L_{p'}(\Omega, \mathcal{F}_t, \mathbb{P}), \mathbb{E}[z_t^* | \mathcal{F}_{t-1}] = 1, z_t^* \in [0, \frac{1}{\alpha_t}], t = 2, \dots, T \right\}.$$

$$\mathcal{A}(z) = \mathbb{E} \left[\sum_{t=2}^T \inf \left\{ z_t^* z_t : \mathbb{E}[z_t^* | \mathcal{F}_{t-1}] = 1, z_t^* \in [0, \frac{1}{\alpha_t}] \right\} \right]$$

$$\rho(z) = \mathbb{E} \left[\sum_{t=2}^T AVaR_{\alpha_t}(z_t, \mathcal{F}_{t-1}) \right]$$

Iterated conditional risk mappings

Let $\mathcal{A}_{\mathcal{F}_t|\mathcal{F}_{t-1}}$, $t = 2, \dots, T$, be conditional acceptability mappings and we define an acceptability functional \mathcal{A} on $\times_{t=1}^T L_p(\Omega, \mathcal{F}_t, \mathbb{P})$

$$\begin{aligned}\mathcal{A}(z) &:= z_1 + \mathcal{A}_{\mathcal{F}_2|\mathcal{F}_1} \left[z_2 + \dots + \mathcal{A}_{\mathcal{F}_{T-1}|\mathcal{F}_{T-2}} [z_{T-1} + \mathcal{A}_{\mathcal{F}_T|\mathcal{F}_{T-1}}(z_T)] \right] \\ &= \mathcal{A}_{\mathcal{F}_2|\mathcal{F}_1} \circ \dots \circ \mathcal{A}_{\mathcal{F}_{T-1}|\mathcal{F}_{T-2}} \circ \mathcal{A}_{\mathcal{F}_T|\mathcal{F}_{T-1}}(z_1 + \dots + z_T),\end{aligned}$$

where the latter representation is a consequence of the (predictable) translation equivariance.

Example: (polyhedral conditional acceptability mappings)

$$\mathcal{A}_{\mathcal{F}_t|\mathcal{F}_{t-1}}(z) = - \inf \left\{ \langle c_1, y_1 \rangle + \mathbb{E}[\langle c_2, y_2 \rangle | \mathcal{F}_{t-1}] : y_1 \in L_p(\Omega, \mathcal{F}_{t-1}, \mathbb{P}), \right. \\ \left. y_1 \in Y_1, y_2 \in L_p(\Omega, \mathcal{F}_t, \mathbb{P}), y_2 \in Y_2, \langle w_1, y_1 \rangle + \langle w_2, y_2 \rangle = z \right\}$$

and select the parameters such that $\mathcal{A}_{\mathcal{F}_t|\mathcal{F}_{t-1}}$ is a conditional acceptability mapping.