SPS Newsletter

The Newsletter of the Stochastic Programming Society

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Chair's Column

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Dear Colleagues,

Welcome to the fourth newsletter of the Stochastic Programming Society and our last newsletter during my term as Chair of the Committee on Stochastic Programming (COSP).

I would like to begin by highlighting notable awards and honors earned by our members and by researchers in closely related fields since our last newsletter:

- Amy M. Cohn was named INFORMS Fellow, for contributions to improving healthcare delivery; for providing experiential learning opportunities in healthcare to Operations Research students; and for her leadership and service to INFORMS and the profession.

- David L. Woodruff was named INFORMS Fellow, for contributions to the theory and practice of stochastic optimization, the development of high-quality open source software, and service to the operations research community.
- Zuo-Jun (Max) Shen and his co-authors earned the INFORMS Daniel H. Wagner Prize for Excellence in the Practice of Advanced Analytics and Operations Research for their work at JD.com to improve fulfillment efficiency with data-driven integrated assortment planning and inventory allocation.
- Adam Elmachtoub won the INFORMS Donald P. Gaver, Jr. Early Career Award for Excellence in Operations Research for outstanding research contributions at the interface of operations research, machine learning, and optimization; for the creativity and impact of his research collaborations within both the private and public sectors; and for his outstanding contributions to the education and mentoring of students.
- Anatoli Juditsky and Arkadi Nemirovski earned the Frederick W. Lanchester Prize for their book "Statistical Inference via Convex Optimization" which provides a modern perspective on the connection between convex optimization and high-dimensional statistics, commonly used in machine learning.
- David Shmoys won the George E. Kimball Medal in recognition of distinguished service to INFORMS and to the profession of operations research and the management sciences. He was also awarded the Philip McCord Morse Lectureship Award in recognition of his pioneering contribution to the field of operations research and the management sciences.
- Jim Dai earned the John von Neumann Theory Prize for his fundamental and sustained contributions to stochastic systems theory, most prominently for his seminal work on stochastic network stability and heavy traffic diffusion approximations.
- Barry L. Nelson was awarded the Saul Gass Expository Writing Award for his clear and concise writing.
- Alice E. Smith was inducted into the National Academies of Engineering (NAE) for advancements in computational intelligence as applied to modeling and optimization of complex systems.

Please join me in congratulating our colleagues! And please let me know about any recognitions I missed which deserve highlighting on our social media.

In a few weeks, many of us will be reuniting again at the International Conference on Stochastic Programming (ICSP) chaired by Vincent Leclère in Paris, see here: https://icsp2025.org. At the conference, we have a very exciting program carefully curated by an all-star scientific committee chaired by Andrzej Ruszczyński.

Since our last newsletter, we sadly lost Roger J-B Wets, a pioneer of stochastic programming whose foundational work has profoundly shaped our field. His impact will endure through his papers, books, students, collaborators, and lasting influence on our community. In this newsletter, we include memorial columns for Roger J-B Wets, Werner Römisch, and Gautam Mitra. They will all be dearly missed. At ICSP, we will have a dedicated session in their memory.

The upcoming ICSP will mark the end of our term for the current COSP (which includes Merve Bodur, Giorgio Consigli, Vincent Leclère, Bernardo Pagnoncelli, Ward Romeijnders, Wim van Ackooij, Wolfram Wiesemann, Haoxiang Yang, and myself). Therefore, I would like to highlight some of the initiatives that we have completed during our term, which I hope will help our community in various ways.

1. To help elevate the work of our community, we have launched 2 new prizes/awards for our society, to be awarded at each ICSP, to add to the current student paper prize. These are:
   (a) An early-career/junior researcher prize targeted at researchers in our community within 7 years of their highest degree. The prize will be named after Roger J-B Wets, who we sadly lost this year. His family has generously offered to support this prize in perpetuity in honor of his memory. The first iteration of the junior prize already happened this year and the winner(s) will be announced at ICSP.
   (b) An impact prize, for an optimization under uncertainty solution that is deployed, with emphasis placed on quantifiable impact (e.g., money saved, lives saved), on how innovative the application is, and on how challenging it was to deploy it (e.g., technical or political difficulties that had to be overcome).

We have drafted associated changes to the by-laws, adding two articles about these prizes, which will be voted on at ICSP. These draft by-laws can be found here: https://www.dropbox.com/scl/fi/90h32al3o4ai4o5nnex4y/The-Committee-on-Stochastic-Programming-Bylaws-Revised-July2025.docx?rlkey=xp143gilm04ccf8aum7w1xecy&dl=0. To arrive at these two awards and at the specifics of the by-laws, we interviewed over 15 members of our community who either currently hold or have held in the past leadership roles in our community. This helped us narrow it down to 3 candidate awards (junior researcher prize, impact prize, and best video competition). We then solicited your feedback through an online survey and also live at the last SPS Business Meeting at ISMP 2024. Based on this feedback, we further narrowed it down to the junior prize and the impact prize, drafted the associated by-laws and sent them out to many of our members for feedback before finalizing them. I am grateful to Ward Romeijnders, Vincent Leclère, Haoxiang Wang, and Wim van Ackooij for co-leading this initiative with me.

2. We have updated the by-laws for the Dupačová-Prékopa Best Student Paper Prize in Stochastic Programming based on the recommendations of this year's Best Student Paper Prize Committee and issues they faced in evaluating submissions. First, the original by-laws required the student(s) to be the first author(s). However, in our community, many groups follow alphabetical author order, creating ambiguity as to whether students who did most of the work on a paper are eligible for the award. The new by-laws make it clear that what matters is that the student should have been the main contributor (rather than requiring them to be the first author). Second, the original by-laws gave the impression that a single senior co-author (the student's advisor) is allowed. We now clarify that multiple senior co-authors are allowed. Finally, we clarify who the entrants/winners are (in case of multiple student authors) and we ensure that all co-authors must sign the letter stating that the eligibility criteria are met. After making the changes, we also checked back with the Best Student Paper Prize Committee and they confirmed that the changes we made address their concerns. The proposed by-law changes can be found here: https://www.dropbox.com/scl/fi/90h32al3o4ai4o5nnex4y/The-Committee-on-Stochastic-Programming-Bylaws-Revised-July2025.docx?rlkey=xp143gilm04ccf8aum7w1xecy&dl=0 and will be voted on at the upcoming ICSP in Paris.

3. We launched a new, more modern, better-structured, and easier-to-maintain SPS website, see here: https://www.stoprog.org. You will note that we also have a new logo which is more modern than the original one but is similar in spirit. A huge thank you to Wolfram Wiesemann, our webmaster, for leading this initiative and to Bernardo Pagnoncelli, our treasurer, for managing its financials.

4. We migrated our mailing list to a new system as the original one had many issues, which significantly delayed the publication of messages. With the new system, messages can be approved immediately. A big thank you to Wolfram Wiesemann for helping me with the migration.

5. We published two issues of the SPS Newsletter corresponding to the two years of our term: one in July 2024 and the other in July 2025. Special thanks to Giorgio Consigli and Haoxiang Yang, who thoughtfully curated and edited these newsletters.

6. During our term, we ran three series of the SPS Seminar Series, corresponding to a total of 26 talks (27 speakers), 3 of which were tutorials, and 6 of which were from junior researchers. We also created a dedicated mailing list and website for the series, see here: https://sites.google.com/view/sps-seminar-series/. All talks were recorded and are available on our SPS YouTube channel, see here: https://www.youtube.com/@stochasticprogrammingsocie3357. A huge thank you to Merve Bodur and Giorgio Consigli for organizing and hosting this important initiative and to Wim van Ackooij for maintaining the YouTube channel.

7. We continue to maintain our LinkedIn (https://www.linkedin.com/groups/13799735/) and Twitter (https://twitter.com/stoprogsociety) pages: a big thank you to Bernardo Pagnoncelli and Merve Bodur, respectively!

If you have any thoughts/ideas/questions on the above initiatives or ideas of other initiatives you would like us to push, please let me know by email at: phebe.vayanos@usc.edu and I will make sure to transmit them to the new COSP.

At ICSP, we will be announcing the winners of the Dupačová-Prékopa best student paper prize. Finalists are Maria Carolina Bazotte, Mengmeng Li, Haoming Shen, Tianyu Wang, and Xian Yu. We will also be announcing the winners of the inaugural Roger J-B Wets Junior Researcher Best Paper Prize in Stochastic Programming. Finalists are Rui Gao and Bradley Sturt. Congratulations to the finalists!

During the SPS Business Meeting at ICSP, we will be sharing with you more about the above initiatives, voting on the new by-laws, conducting the COSP elections (electronically for the first time!), and sharing with you the possible locations of the next ICSP in 2028!

I hope you are all having a wonderful summer and I look forward to seeing all of you at ICSP in a few weeks.

Best Wishes,
Phebe

SPS Virtual Seminar Series: Season III & IV

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on behalf of COSP

The Stochastic Programming Society proudly continues its Virtual Seminar Series, a tradition that began in 2020 to bring together a global community passionate about decision-making under uncertainty. As always, we aim to highlight recent breakthroughs, foster collaboration across disciplines, and provide inclusive opportunities for researchers at all career stages. The bi-weekly seminars are launched on September 13 through December 6 in 2024, then resumed on January 17 and concluded on May 9 in 2025.

2024-2025 Seminar Highlights

This year's lineup featured a diverse set of leading researchers pushing the frontiers of stochastic and robust optimization:

- Stan Uryasev opened the 2024-2025 series by introducing the Risk Quadrangle framework, which links optimization, risk management, and statistical estimation.
- Jeff Linderoth introduced probing-enhanced stochastic programming and a specialized branch-and-bound method.
- Karmel Shehadeh proposed a trade-off robust optimization model bridging optimism and conservatism in data-driven decisions.
- Melvyn Sim presented a unified framework for models that integrate robust optimization and robust satisficing paradigms.
- Siqian Shen introduced a trust-aware distributionally robust optimization framework informed by data from multiple sources.
- Angelos Georghiou proposed a robust, decentralized approach for multi-agent decision-making, minimizing communication and promoting privacy.
- Bernardo Costa presented duality and bounding techniques for risk-averse multistage stochastic programs.

- Susan Hunter discussed two-stage stochastic multi-objective linear programs, including properties and solution methods.
- Alois Pichler focused on fundamental results on stochastic dominance partial orders with applications across different fields.
- The series concluded with Haofeng Zhang and Adam Elmachtoub, who co-presented theoretical insights into integrated estimation-optimization.

Tutorials and Junior Research Spotlight

We continued to invest in accessibility and inclusiveness with tutorial sessions and a dedicated junior speaker spotlight:

- Francesca Maggioni and Utsav Sadana delivered tutorials on bounding methods for multistage stochastic programs and the emerging field of contextual optimization, respectively.
- Junior researchers Di Zhang, Bianca Marin Moreno, Maria Bazotte, and Haoyun Deng tackled cutting-edge topics including sampling-based progressive hedging, convex/concave utility reinforcement learning, two-stage stochastic programs with decision-dependent probability distribution, and ReLU Lagrangian cuts for stochastic mixed-integer programming.

To view talk recordings, please visit the SPS YouTube channel (`https://www.youtube.com/@stochasticprogrammingsocie3357`), and to register for future events, please check out the SPS Seminar Series Website (`https://sites.google.com/view/sps-seminar-series/`). Looking forward to seeing you next time for more discovery and dialogue!

The ICSP XVI Dupačová-Prékopa Student Paper Prize

Activated Benders Decomposition with Locally Pareto-Optimal Cuts

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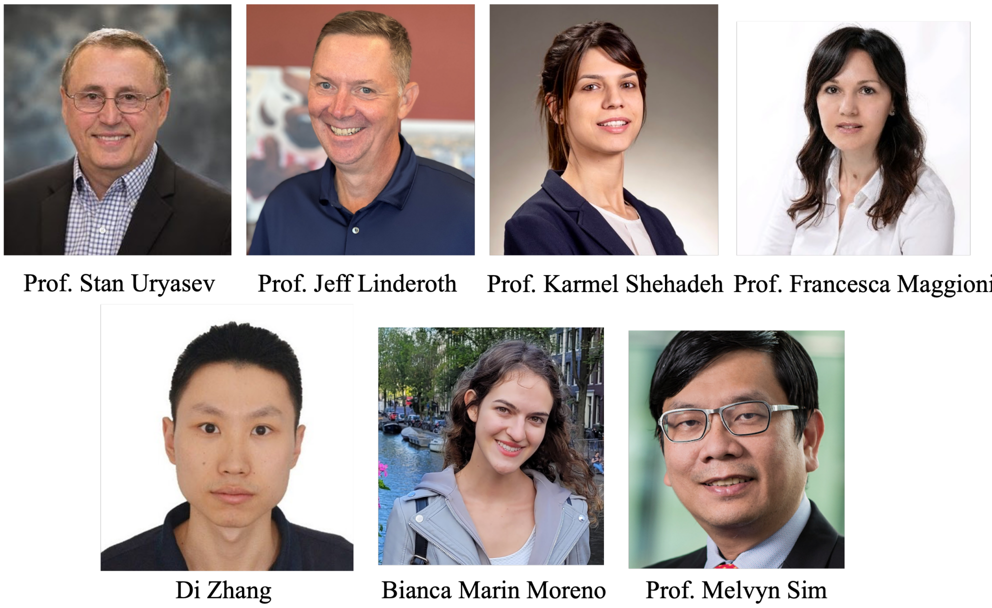
The 2023 Dupačová-Prékopa Best Student Paper Finalist was awarded to Kayla Kummerlowe (née Cummings) at ICSP XVI for the paper "Activated Benders Decomposition with Locally Pareto-Optimal Cuts," co-authored with Alexandre Jacquillat and Vikrant Vaze, preprint in INFORMS Journal on Computing. Kummerlowe completed the work during her time as a PhD student at Massachusetts Institute of Technology. Below is a summary of this paper.

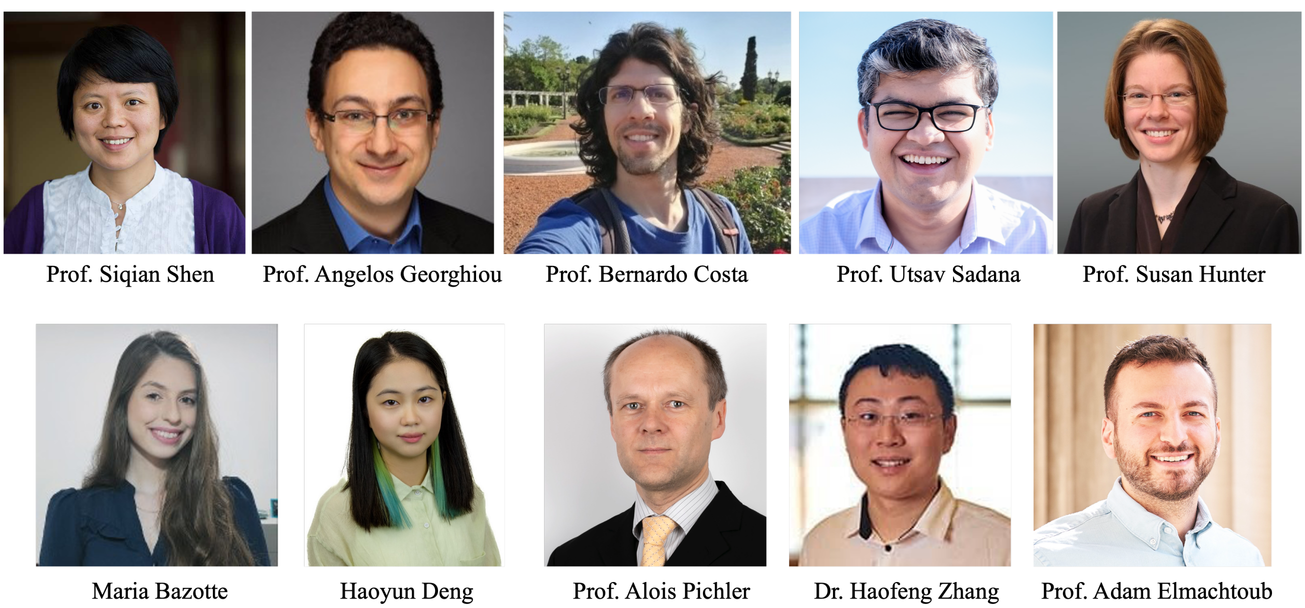
We contribute an exact *activated Benders decomposition (ABD)* algorithm for two-stage stochastic mixed-binary optimization with a nested block-angular structure. Compared to Benders decomposition (BD), ABD exploits linking constraints between first-stage and second-stage decisions to solve smaller, "activated" subproblems at each iteration, by fixing variables and eliminating redundant constraints. In facility location, network design, and unit commitment, the activated problems are induced by the selected facilities, arcs, and plants. Using a primal-dual approach, the ABD scheme lifts the activated solution into the full dual space to retrieve optimality and feasibility cuts. The algorithm circumvents exponentially large subproblems without sacrificing exactness: we prove that it converges finitely to an optimal solution.

We present ABD for a generic two-stage mixed-binary optimization problem with continuous recourse and linking constraints, referred to as $(2MBO)$. Let $\boldsymbol{c} \in \mathbb{R}^{k+n}$, $\boldsymbol{f} \in \mathbb{R}^{p}$, $\boldsymbol{A} \in \mathbb{R}^{m_1\times(k+n)}$, $\boldsymbol{G} \in \mathbb{R}^{m_2\times(k+n)}$, $\boldsymbol{H} \in \mathbb{R}^{m_2\times p}$, $\boldsymbol{b} \in \mathbb{R}^{m_1}$ and $\boldsymbol{t} \in \mathbb{R}^{m_2}$. Let $\boldsymbol{x} \in \{0,1\}^k \times \mathbb{R}^n_+$ and $\boldsymbol{y} \in \mathbb{R}^p_+$ be first- and second-stage variables.

$$(2MBO) \quad \min \left\{ \boldsymbol{c}^\top \boldsymbol{x} + \boldsymbol{f}^\top \boldsymbol{y} \ : \ \boldsymbol{x} \in \mathcal{X},\ \boldsymbol{y} \in \mathcal{P}(\boldsymbol{x}) \right\}, \tag{1}$$



Presenters in the SPS Seminar Series in Season III, Fall 2024.



Presenters in the SPS Seminar Series in Season IV, Spring 2025.

with $\mathcal{X} = \{\boldsymbol{x} \in \{0,1\}^k \times \mathbb{R}^n_+ \,:\, \boldsymbol{A}\boldsymbol{x} \geq \boldsymbol{b}\}$ and $\mathcal{P}(\boldsymbol{x}) = \{\boldsymbol{y} \in \mathbb{R}^p_+ \,:\, \boldsymbol{H}\boldsymbol{y} \geq \boldsymbol{t} - \boldsymbol{G}\boldsymbol{x}\}$.

Let $\mathcal{D} = \{\boldsymbol{\pi} \in \mathbb{R}^{m_2}_+ \,:\, \boldsymbol{\pi}^\top \boldsymbol{H} \leq \boldsymbol{f}^\top\}$ denote the dual second-stage polyhedron, and $\{\widehat{\boldsymbol{\pi}}^u : u \in \mathcal{U}\}$ and $\{\widehat{\boldsymbol{r}}^v : v \in \mathcal{V}\}$ denote its extreme points and extreme rays. The Benders reformulation of $(2MBO)$ is

$$\min \left\{ \boldsymbol{c}^\top \boldsymbol{x} + \theta \,:\, \boldsymbol{x} \in \mathcal{X},\ (\boldsymbol{x}, \theta) \in \mathcal{F}(\mathcal{U}, \mathcal{V}) \right\}, \quad (2)$$

$$\text{with} \quad \mathcal{F}(\mathcal{U}, \mathcal{V}) = \{(\boldsymbol{x}, \theta) \in \mathbb{R}^{k+n+1} : \theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \widehat{\boldsymbol{\pi}}^u, \forall u \in \mathcal{U}; \; 0 \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \widehat{\boldsymbol{r}}^v, \forall v \in \mathcal{V}\}.$$

Let $\mathcal{MP}(\mathcal{U}', \mathcal{V}')$ denote the BD main problem, which produces a first-stage solution $\boldsymbol{x} \in \mathcal{X}$; and let $\mathcal{SP}(\boldsymbol{x})$ denote the subproblem. If the subproblem admits a direction of unboundedness $\boldsymbol{r}^v,\ v \in \mathcal{V}$ (an optimal solution $\boldsymbol{\pi}^u,\ u \in \mathcal{U}$), then it generates a feasibility (optimality) cut.

We define *activation* constraints as linking constraints between first- and second-stage variables, indexed as $\mathcal{J}^A$, with $\mathcal{J}^O$ indexing other constraints. *Activated* constraints are simply activation constraints with a non-zero right-hand side based on $\boldsymbol{x}$, indexed by $\mathcal{J}^A(\boldsymbol{x}) \subseteq \mathcal{J}^A$. A deactivated constraint fixes all variables with nonzero coefficients to zero. We define *activation* variables—indexed as $\mathcal{Q}^A$—as those that can be deactivated for some first-stage solution, and *deactivated* variables as those that are forced to zero by $\boldsymbol{x}$. Let $\mathcal{Q}^A(\boldsymbol{x}) \subseteq \mathcal{Q}^A$ index the activated variables, and let $\mathcal{Q}^O$ index the other variables. Finally, we define an *invisible* constraint as a non-activation constraint that consists solely of deactivated variables. We assume that invisible constraints are always satisfied; we store other, *visible*, constraints in $\mathcal{J}^O(\boldsymbol{x})$. The *activated subproblem* projects the subproblem into the primal subspace spanned by activated variables and the dual subspace spanned by activated and visible constraints. Fixing $\boldsymbol{x} \in \text{conv}(\mathcal{X})$, the activated subproblem is

$$\overline{\mathcal{SP}}(\boldsymbol{x}) : \quad \max_{\boldsymbol{\pi} \in \overline{\mathcal{D}}(\boldsymbol{x})} \sum_{j \in \mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x})} \pi_j \left(t_j - \boldsymbol{g}_j^\top \boldsymbol{x} \right), \quad (3)$$

$$\text{with } \overline{\mathcal{D}}(\boldsymbol{x}) = \Big\{ \boldsymbol{\pi} \in \mathbb{R}_+^{|\mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x})|} : \sum_{j \in \mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x})} h_{ji} \pi_j \leq f_i, \quad \forall i \in \mathcal{Q}^A(\boldsymbol{x}) \cup \mathcal{Q}^O \Big\}. \quad (4)$$

The solution of $\overline{\mathcal{SP}}(\boldsymbol{x})$ does not include the dual prices of the omitted (deactivated and invisible) constraints, which cannot be assumed to have zero duals. Thus, we lift any solution of the activated subproblem into the full-dimensional dual space, by using a linear-time primal-dual approach to map extreme points and extreme rays of the activated polyhedron into extreme points and extreme rays of the full polyhedron, while preserving optimality and unboundedness.

First, Lemma 1 maps any feasible solution of the full subproblem into one of the activated subproblems. The crown jewel of our primal-dual approach, Lemma 2 identifies a linear-time *dual transformation*. This transformation maps any (optimal) extreme point of the activated dual subproblem into an (optimal) extreme point of the full dual subproblem, exploiting the fact that *any* feasible lifting procedure preserves optimality due to the zero-cost coefficients posed by the deactivated constraints.

Lemma 1. *Let $\boldsymbol{x} \in \mathcal{X}$ and $\widehat{\boldsymbol{\pi}} \in \mathcal{D}$. Then $proj(\widehat{\boldsymbol{\pi}}) \in \overline{\mathcal{D}}(\boldsymbol{x})$, where $proj(\cdot)$ denotes the projection of $\widehat{\boldsymbol{\pi}}$ in the dual subspace spanned by the activated and visible constraints:*

$$proj(\widehat{\boldsymbol{\pi}}) := (\widehat{\pi}_j)_{j \in \mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x})}. \quad (5)$$

Lemma 2. *Let $\mathcal{Z}_U = \{(\boldsymbol{x}, \boldsymbol{\pi}) \,:\, \boldsymbol{x} \in \mathcal{X},\ \boldsymbol{\pi} \in \overline{\mathcal{D}}(\boldsymbol{x})\}$. Let $\Phi^U : \mathcal{Z}_U \to \mathbb{R}^{m_2}_+$. For any $(\boldsymbol{x}, \boldsymbol{\pi}) \in \mathcal{Z}_U$, we define $\Phi^U_j(\boldsymbol{x}, \boldsymbol{\pi})$ as follows for each $j \in \{1, \ldots, m_2\}$:*

$$\Phi^U_j(\boldsymbol{x}, \boldsymbol{\pi}) = \begin{cases} \pi_j & \text{if } j \in \mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x}), \\ 0 & \text{if } j \in \mathcal{J}^O \setminus \mathcal{J}^O(\boldsymbol{x}), \\ \displaystyle \max_{\substack{i \in \mathcal{Q}^A \setminus \mathcal{Q}^A(\boldsymbol{x}) \\ \kappa(i) = j}} \frac{-1}{h_{ji}} \left(\sum_{k \in \mathcal{J}^A(\boldsymbol{x}) \cup \mathcal{J}^O(\boldsymbol{x})} h_{ki} \pi_k - f_i \right)^+ & \\ \qquad \text{if } j \in \mathcal{J}^A \setminus \mathcal{J}^A(\boldsymbol{x}). \end{cases} \quad (6)$$

Note that $\Phi^U(\boldsymbol{x}, \boldsymbol{\pi}) \in \mathcal{D}$ for all $(\boldsymbol{x}, \boldsymbol{\pi}) \in \mathcal{Z}_U$ and is an extreme point of $\mathcal{D}$ whenever $\boldsymbol{\pi}$ is an extreme point of $\overline{\mathcal{D}}(\boldsymbol{x})$. If $\overline{\mathcal{SP}}(\boldsymbol{x})$ admits an optimal solution $\boldsymbol{\pi} \in \overline{\mathcal{D}}(\boldsymbol{x})$, then $\overline{\mathcal{SP}}(\boldsymbol{x})$ and $\mathcal{SP}(\boldsymbol{x})$ achieve the same cost and $\Phi^U(\boldsymbol{x}, \boldsymbol{\pi})$ is an optimal solution of $\mathcal{SP}(\boldsymbol{x})$.

The full article provides an analogous Lemma for transformation Φ^V that maps any extreme ray of the activated dual polyhedron into one of the dual polyhedra and that preserves unboundedness. These Lemmas establish the equivalence of the activated and full subproblems: if one admits an optimal solution, so does the other; if one is unbounded, so is the other; and if one is infeasible, so is the other. Moreover, the dual and dual-ray transformations map extreme points and extreme rays of the activated dual polyhedron into extreme points and extreme rays of the full dual polyhedron. Specifically, if

$\{\boldsymbol{\pi}^u : u \in \overline{\mathcal{U}}(\boldsymbol{x})\}$ and $\{\boldsymbol{r}^v : v \in \overline{\mathcal{V}}(\boldsymbol{x})\}$ index the extreme points and extreme rays of $\overline{\mathcal{D}}(\boldsymbol{x})$ for any $\boldsymbol{x} \in \mathcal{X}$, we obtain:

$$\bigcup_{\boldsymbol{x}\in\mathcal{X}} \left\{\Phi^U(\boldsymbol{x},\boldsymbol{\pi}^u) : u \in \overline{\mathcal{U}}(\boldsymbol{x})\right\} \subseteq \{\widehat{\boldsymbol{\pi}}^u : u \in \mathcal{U}\} \quad (7)$$

$$\bigcup_{\boldsymbol{x}\in\mathcal{X}} \left\{\Phi^V(\boldsymbol{x},\boldsymbol{r}^v) : v \in \overline{\mathcal{V}}(\boldsymbol{x})\right\} \subseteq \{\widehat{\boldsymbol{r}}^v : v \in \mathcal{V}\}. \quad (8)$$

Whenever an incumbent solution $(\boldsymbol{x}^{(\tau)}, \theta^{(\tau)})$ is not optimal, the ABD generates an optimality or feasibility cut that separates it from the main problem's feasible region. Finiteness follows from the finite number of cuts (Equations (7)–(8)).

Theorem 1. *Activated Benders decomposition is an exact and finite algorithm for* (2*MBO*)*.*

We also augment the method from [2] to generate *locally Pareto-optimal (LPO) cuts* in a subspace including the incumbent first-stage decision. The LPO cuts can be generated via activated subproblems, retaining the computational benefits of the ABD algorithm. Together, the ABD algorithm and LPO cuts exploit the sparse first-stage structure and linking constraints to accelerate cut generation and to strengthen Benders cuts in "promising" regions. Given a core point $\boldsymbol{x}^0$ in the relative interior of the convex hull of the first-stage region $\mathcal{X}$, the *Pareto dual subproblem* seeks an optimal solution to the dual subproblem that also maximizes the dual objective in $\boldsymbol{x}^0$:

$$\mathcal{SP}^0(\boldsymbol{x};\boldsymbol{x}^0)$$
$$\max \left\{ \left(\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x}^0\right)^\top \boldsymbol{\pi} : \boldsymbol{\pi} \in \arg\max_{\widehat{\boldsymbol{\pi}}\in\mathcal{D}} \left(\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x}\right)^\top \widehat{\boldsymbol{\pi}} \right\}. \quad (9)$$

[2] showed that, if $\boldsymbol{\pi}^0$ solves $\mathcal{SP}^0(\boldsymbol{x};\boldsymbol{x}^0)$, then the cut $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}^0$ cannot be dominated by another cut $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}$ across the first-stage region $\mathcal{X}$.

Global Pareto-optimality requirements may dilute the local strength of the resource function approximation in an exponentially sized main problem. Additionally, generating Pareto-optimality cuts via an extra subproblem (Equation (9)) may diminish the computational benefits of ABD. We propose LPO cuts to strengthen optimality cuts in "promising" regions, and we generate them with activated subproblems. For any subset $\mathcal{K} \subseteq \{1,\ldots,k\}$, let $\mathcal{X}(\mathcal{K}) := \mathcal{X} \cap \{\boldsymbol{x} \in \mathbb{R}_+^{k+n} : x_i = 0, \forall i \in \mathcal{K}\}$ denote the first-stage region in which the binary variables in $\mathcal{K}$ are set to zero.

Definition 1. *Let* $\mathcal{K} \subseteq \{1,\ldots,k\}$*. Consider* $\boldsymbol{\pi}_1, \boldsymbol{\pi}_2 \in \mathcal{D}$*. A cut* $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_1$ *locally dominates another cut* $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_2$ *with respect to* $\mathcal{K}$ *if (a)* $(\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_1 \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_2$ *for all* $\boldsymbol{x} \in \mathcal{X}(\mathcal{K})$*, and (b)* $(\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_1 > (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}_2$ *for some* $\boldsymbol{x} \in \mathcal{X}(\mathcal{K})$*.*

Definition 2. *Let* $\mathcal{K} \subseteq \{1,\ldots,k\}$ *and* $\boldsymbol{\pi} \in \mathcal{D}$*. The cut* $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}$ *is locally Pareto-optimal with respect to* $\mathcal{K}$ *if there is no other cut that locally dominates it with respect to* $\mathcal{K}$*.*

Finally, we define a *local core point with respect to* $\mathcal{K}$ as a point in the relative interior of the convex hull of $\mathcal{X}(\mathcal{K})$. Instead of using a core point to generate a Pareto-optimal cut, our procedure uses a local core point to generate a locally Pareto-optimal cut.

Theorem 2. *Let* $\widehat{\boldsymbol{x}} \in \mathcal{X}$ *and define* $\mathcal{K} \subseteq \{1,\ldots,k\}$ *such that* $\widehat{\boldsymbol{x}} \in \mathcal{X}(\mathcal{K})$*. Let* $\boldsymbol{x}^0$ *be a local core point of* $\mathcal{X}$ *with respect to* $\mathcal{K}$*. Consider* $\boldsymbol{\pi}^0$*, an optimal solution of* $\mathcal{SP}^0(\widehat{\boldsymbol{x}};\boldsymbol{x}^0)$*. Then the optimality cut* $\theta \geq (\boldsymbol{t} - \boldsymbol{G}\boldsymbol{x})^\top \boldsymbol{\pi}^0$ *is locally Pareto-optimal with respect to* $\mathcal{K}$*.*

As with ABD, we apply a similar approach to generate locally Pareto-optimal cuts via an activated Pareto dual subproblem. The full article provides the linear-time lifting procedure for activated LPO cuts, using the activated Pareto dual subproblem. The full article also illustrates the benefits of the ABD algorithm and LPO cuts for solving large-scale paratransit itinerary planning instances, together with code and simulated data [1]. Benchmark algorithms exhibit limited scalability: off-the-shelf implementations only scale to small instances, and BD leaves large optimality gaps in medium instances with tens of thousands of itineraries and 10–50 scenarios. Together, the ABD algorithm and activated LPO cuts outperform the best BD benchmark in terms of solution quality (7–9% reduction in expected costs), solution guarantees (tight optimality and statistical bounds), and computational performance (speedups by one or two orders of magnitude). From a practical standpoint, our two-stage stochastic optimization approach can reduce paratransit operating costs by up to 3.5% without inducing service delays.

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The ICSP XVI Dupačová-Prékopa Student Paper Prize

General Feasibility Bounds for Sample Average Approximation via Vapnik–Chervonenkis Dimension

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The 2023 Dupačová-Prékopa Best Student Paper Finalist was awarded to Fengpei Li at ICSP XVI for the paper "General Feasibility Bounds for Sample Average Approximation via Vapnik–Chervonenkis Dimension," coauthored with Henry Lam, published in SIAM Journal on Optimization, 32(2): 1471–1497, 2022. Below is a summary of this paper.

This paper is among several recent works [1, 3] that follow up on the seminal work of [2], exploring the use of sample average approximation (SAA) for stochastic programming problems without assuming relatively complete recourse. In such setting, we consider stochastic programs of the form

$$\inf_{x\in X\subseteq\mathbb{R}^n} F(x) := \mathbb{E}[f(x,\xi)],$$

where $X \subseteq \mathbb{R}^n$ is the decision space and $\xi : \Omega \to \Xi \subseteq \mathbb{R}^r$ is a random vector defined on a complete probability space $(\Omega, \mathcal{F}, P)$. The extended real-valued function $f(\xi,\cdot) : X \to \mathbb{R}\cup\{+\infty\}$ is lower semicontinuous with the feasible set $\{x \in X : F(x) < +\infty\}$ assumed nonempty. As discussed in [2], the two-stage stochastic problems, where the objective is defined via a second-stage optimization problem:

$$f(x,\xi) = \inf_{y\in Y(x,\xi)} g_\xi(y),$$

is said to have relatively complete recourse (RCR), if for every decision $x \in X$ and almost every realization of ξ, the feasible set $Y(x,\xi)$ is nonempty, equivalently, $f(x,\cdot) < \infty$ almost surely $\forall x \in X$. When RCR assumption is violated, i.e., $\mathbb{P}(\{\xi \in \Xi : f(\xi,x) = +\infty\}) > 0$ for some $x \in X$, we are interested in quantifying $V(x^\star(\xi_{[N]}))$, a measure of feasibility for the SAA solution where

$$V(x) \triangleq P(\xi\in\Xi : x \notin \operatorname{dom} f_\xi \triangleq \{x\in X : f(\xi,x) < +\infty\}),$$

is the *violation probability* of a decision x and $x^\star(\xi_{[N]})$ is the solution of the SAA based on N I.I.D. samples $\xi_{[N]} \triangleq (\xi_1,\xi_2,\ldots,\xi_N)$ from $\mathbb{P}$, i.e., $\xi_{[N]} \sim \mathbb{P}^N \triangleq \underbrace{\mathbb{P}\times\mathbb{P}\times\cdots\times\mathbb{P}}_{N \text{ times}}$:

$$x^\star(\xi_{[N]}) = \arg\min_{x\in X} \frac{1}{N}\sum_{i=1}^{N} f(x,\xi_i).$$

In this paper, we employ probably approximately correct (PAC) learning, a framework for mathematical analysis in computational learning theory, to analyze the feasibility of SAA solutions. In this framework, the learner selects a hypothesis function from a specified class based on observed samples. The objective is to ensure that, with high probability ("probably"), the chosen hypothesis has a small generalization error ("approximately correct"). Consistent with prior research [1, 2], our analysis demonstrates exponential convergence $\mathbb{P}^N(V(x^*(\xi_{[N]})) > \epsilon)$ for any prespecified tolerance level ϵ. While prior works such as [2, 1] established exponential convergence by leveraging specific problem structures - such as properties of basic feasible solutions inherent to linear programming formulations [1] or the *chain-constrained domain* defined in [2] - and sometimes leaving certain constants implicit or unknown in the bound.

We use the Vapnik–Chervonenkis (VC) dimension as the measure of complexity for $\mathcal{H}$, a convenient but by no means exclusive choice within the PAC learning framework, to yield explicit feasibility bounds with readily computable constants dependent solely on problem parameters and VC dimension of $\mathcal{H} \triangleq \{H_x\}_{x\in X}$ where

$$H_x \triangleq \{\xi\in\Xi : f(\xi,x) < +\infty\},$$

while imposing no additional structural or regularity constraints. In particular, the main results can be summarized as:

$$\mathbb{P}^N\left(V(x^\star(\xi_{[N]})) > \epsilon\right) \;\le\; 2\exp\left(-\frac{N\epsilon}{4}\right)\left(\frac{12}{\epsilon}\right)^d \quad (1)$$

where d is the VC dimension $\mathcal{H}$. As a result, the method presented in this paper recovers previously established results on SAA feasibility and yields some previously unattainable results, including in two-stage stochastic programming with mixed-integer recourse and high-dimensional stochastic programming with low-dimensional structures, e.g., sparsity, low-rankness. The result (1) significantly simplifies the analysis; the primary challenge lies in bounding the VC dimension d_{VC} of $\mathcal{H}$, which is case-dependent, e.g., such as number of extreme rays of the polyhedral cone, finiteness properties, and the order of a *chain-constrained* domain.

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In Memoriam: Roger J-B Wets

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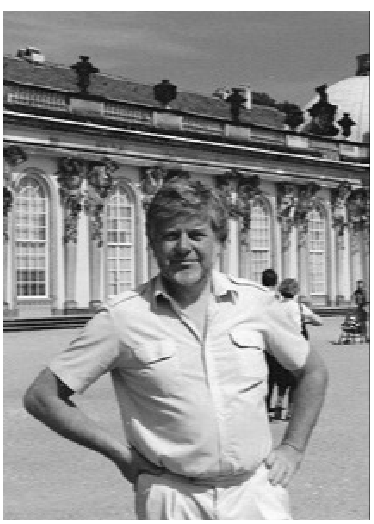
The stochastic programming community lost one of its giants on April 1, 2025. Distinguished Professor Roger J-B Wets (1937-2025) passed away in Davis, California, after a period of declining health. Originally from Belgium, Professor Wets came to Berkeley in the early 1960s for graduate studies under the guidance of George Dantzig and David Blackwell on pioneering work in stochastic programming.

After graduation, Professor Wets held positions at Boeing Scientific Research Labs, University of Chicago, and University of Kentucky. He was a leader at IIASA, Laxenburg, Austria (1980-1984; acting 1985-1987) and instrumental in the remarkable number of outstanding scholars from the East and the West passing through the institute. From 1984 to 2009, he was Professor and Distinguished Professor of Mathematics at University of California, Davis. After retirement, he remained active as Distinguished Research Professor of Mathematics and advised students until 2018. Professor Wets' fundamental contributions to stochastic programming, mathematical optimization, and variational analysis have been widely recognized. He was a Guggenheim Fellow, received the Dantzig and Lanchester prizes, and was awarded Doctor Honoris Causa by Universität Wien. He was recognized in 2004 as a Pioneer in the field by the Stochastic Programming Society.

Professor Wets developed the first algorithm directed specifically at two-stage stochastic optimization, the L-Shape Method, in 1969 with R. van Slyke. The method has been implemented in many software packages and remains a standard approach to such problems. In his earliest work, Professor Wets recognized the special kind of induced constraints that emerge naturally in multi-stage decision problems and coined the term. Later, he introduced the term nonanticipativity constraints in multi-stage stochastic optimization problems to describe the constraints that enforce the necessity of making decisions based only on the information available at the time of the decision. This breakthrough led to two 1976 papers (with R.T. Rockafellar) that established duality theory for stochastic programs and fundamental insight about the price of information. Professor Wets developed the Progressive Hedging Algorithm for multistage stochastic programs in 1991 (with Rockafellar), which is now implemented in the widely used software Pyomo.

Roger Wets' strong law of large numbers (developed with H. Attouch, Z. Artstein, and L. Korf in the 90s) gives the most versatile consistency theory for M-estimators. It relies on his even more fundamental work on approximation theory for optimization and variational problems: Professor Wets coined the term epi-convergence in 1980, which is now accepted as the "right" notion for approximating minimization problems; it ensures the convergence of optimal solutions and optimal values under the mildest possible assumptions. His contributions started in 1967 with a fundamental result about convergence and distances between convex cones as well as between their polars and include the first results on uniform approximations of sets and the convergence of measurable selections (both in 1981 with G. Salinetti), an Arzela-Ascoli Theorem for set-valued mappings (with A. Bagh in 1996), and a quantitative theory for epi-convergence (with Attouch in the 80s and early 90s). Many of Professor Wets' contributions are summarized and expanded in the seminal treatise, Variational Analysis (with Rockafellar in 1998).

Professor Wets will be greatly missed, especially for his kindness and generosity to all those aspiring researchers who sought his expert advice.



Roger J-B Wets

In Memoriam: Werner Römisch

A Pioneer of Stochastic Optimization

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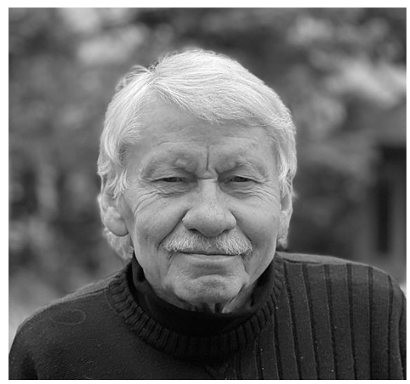

Werner Römisch (28.12.1947–7.6.2024)

On June 7 of last year, Werner Römisch, a pioneer in stochastic optimization, passed away at the age of 76. He was a highly esteemed member of our community whose fundamental contributions—particularly in the area of solution stability for stochastic optimization problems—have had a lasting impact on the development of our field. His lifetime achievements were honored in 2018 with the Khachiyan Prize of the INFORMS Optimization Society.

Werner Römisch was born in 1947 in Zwickau, East Germany. He studied mathematics at Humboldt University of Berlin (HUB), where he earned his doctorate in 1976. In 1993, he became Professor of Applied Mathematics at HUB. He was the co-author of 150 publications, including three books, served as an associate editor for several journals such as the SIAM Journal on Optimization, and was involved in more than 20 third-party funded research projects, nearly all of which were dedicated to applications of stochastic optimization in the energy sector. Furthermore, he supervised around 25 master's theses and 12 doctoral dissertations, and mentored four habilitation theses.

Werner Römisch's original mathematical background was in numerical mathematics, which he also taught at HUB. Beginning in the 1980s, his research increasingly focused on stochastic optimization, particularly on the convergence rates of approximation methods. Inspired by developments in nonlinear parametric optimization at HUB, he later devoted much of his attention to questions of solution stability in stochastic optimization. A whole series of joint publications with Rüdiger Schultz on solution stability in problems with recourse or probabilistic constraints received wide international recognition and strongly influenced the subsequent work of other colleagues and students, particularly Darinka Dentcheva and me, later Andreas Eichhorn, Holger Heitsch, Hernan Leövey, and many others.

It is especially noteworthy that Werner Römisch's mathematical work was not confined to theoretical development; he always maintained a strong focus on practical applications, primarily in the energy sector (electricity and gas). This is evidenced by long-standing industrial collaborations with the East German utility VEAG, Electricité de France, and E.ON Ruhrgas. Of particular practical relevance were his algorithms for scenario reduction and generation, based on the previously developed theory of solution stability and the use of problem-adapted probability metrics. His publication "Scenario Reduction Algorithms in Stochastic Programming" (with Holger Heitsch) has been cited over a thousand times, and the associated SCENRED algorithm is in widespread use. Another of his research focuses was the study of polyhedral risk measures in multistage stochastic optimization problems. Over the past ten years, Werner Römisch turned his attention to the study of Monte Carlo and quasi-Monte Carlo methods within stochastic optimization frameworks.

Werner Römisch was an active member of the Stochastic Programming Community. He was the organizer of the 9th ICSP, which took place in Berlin in 2001, and he was co-editor of the Stochastic Programming E-Print Series (1999-2018).

Werner Römisch was known by his many colleagues and friends around the world as a kind, calm, and sincere person with whom one could always have enriching conversations, not only in mathematics. He mentored his numerous students with exemplary dedication and remained interested in their professional careers even after their graduation.

On a personal note, I owe Werner more than could fit on a single page, especially for guiding me toward optimization problems under probabilistic constraints and the concepts of generalized differentiation. I have lost a teacher, mentor, co-author, and above all, a friend.

In Memoriam: Gautam Mitra

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We are deeply saddened to announce the passing of Professor Gautam Mitra, a distinguished academic and visionary thinker, who passed away on February 2024 at the age of 83.

Gautam's contributions to the fields of stochastic programming, computational optimization, and quantitative decision analytics were instrumental in bridging the gap between rigorous optimization theory and its real-world applications, particularly in supply chain, finance, and risk management.

His academic and professional journey began in 1968 when he pursued a Ph.D. in Computational Methods in Operational Research at the Institute of Computer Science, University of London. In the early 1970s, he started his academic career at Brunel University, where he was much more than a professor. He served for many years as Director of the Mathematics and Statistics Department and founded the CARISMA research *Centre for the Analysis of Risk and Optimisation Modelling Applications*.

Gautam's earliest and most influential contributions emerged in the mid-1970s when large-scale linear and integer programming was still evolving. He tackled a deceptively simple yet fundamentally important observation: real-world optimization problems often contain hidden structures that, if properly identified, can dramatically improve computational performance. This work epitomizes his research ethos—combining algorithmic insight with practical implementation to enhance the scalability and applicability of optimization tools.

Building on these foundations, Gautam became a leading voice in the stochastic programming community in the 1990s. His research on multi-stage stochastic optimization introduced new modeling paradigms to finance, supply chain management, and energy systems. He developed techniques for scenario generation and solution methods robust to real-world data noise. Notably, he applied these techniques to *Asset and Liability Management* (ALM), creating dynamic stochastic models that empowered pension funds and financial institutions to make informed, risk-aware decisions over long horizons.

In the 2000s, Gautam made remarkable advances in risk-sensitive optimization. He was among the first to integrate *second-order stochastic dominance* (SSD) into portfolio selection, developing models that respect risk-averse preferences beyond mean-variance analysis. This work bridged theory and regulatory finance by offering alternative portfolio optimization approaches accounting for investor utility and downside risk. Simultaneously, he contributed to robust optimization, helping develop solvers and modeling languages that manage data uncertainty with bounded adversarial assumptions—critical for logistics and supply chain risk.

In his later years, Gautam extended his vision to alternative data in finance, becoming an early adopter of textual sentiment analysis for investment strategies. His work integrated news sentiment and NLP-derived signals into portfolio construction models—what he termed *Sentiment-Enhanced Signals* (SES). This research anticipated the data-rich, AI-driven finance landscape of today's quantitative investment world.

Yet Gautam's impact extended far beyond academia. He was a visionary entrepreneur who founded Unicom Seminars and later *OptiRisk Systems*, translating his research in optimization, risk management, and stochastic programming into practical software solutions and professional training initiatives widely used by financial institutions and businesses worldwide. But perhaps more than any publication or project, it is his mentorship that defines Gautam's enduring legacy for those of us privileged to learn from him. He pursued excellence without blame, viewing mistakes as opportunities for growth. He firmly believed that generosity, knowledge sharing, transparency, and integrity were fundamental values. Despite his demanding roles as Head of Department and business leader, he was always generous with his time. He made time for every student—discussing research directions and revising papers (except on Saturday mornings, which he reserved for tennis!). His door was always open for thoughtful and stimulating discussions. He consistently shared in and celebrated the successes of his students and collaborators, honoring both their professional achievements and personal milestones. Even late into his career, Gautam remained a catalyst for knowledge sharing and community building.

To this day, many of his former students and collaborators remain closely connected, a testament to the strong, supportive community he so thoughtfully nurtured. He will be remembered as a pioneer, mentor, and builder of bridges—between disciplines, between theory and practice, and between people.

He is survived by his wife, son, daughter, and beloved young granddaughter. We extend our deepest condolences to his family, friends, and colleagues. Dear Gautam, you will be greatly missed.

Gautam Mitra

Invited Columns: Optimization under Decision-Dependent Uncertainty

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This section of the Newsletter hosts contributions from distinguished colleagues invited to share their recent contributions on decision-dependent uncertainty, an emerging research subfield within optimization under uncertainty.

Decision-Dependent Uncertainty (DDU) arises when the uncertainty in a model is affected by the decisions made within that model. Unlike classical stochastic or robust optimization—where uncertainty is modeled as exogenous and independent from the decision variables—in DDU, decisions can influence the distribution, support, or realization of uncertain parameters. DDU arises in many realistic situations. For example, a sensor placement may change the distribution of identifying a disaster, or the pricing decision may affect the demand uncertainty. In those cases, the traditional exogenous uncertainty does not capture this quantitative relationship, which may lead to suboptimal or misleading decisions. To model uncertainty's decision-dependency, we can deploy the following model formulations for different types of optimization models:

$$
\begin{aligned}
(SP) \quad & \min_{x \in \mathcal{X}} \ \mathbb{E}_{\mathbb{P}(x)}[f(x,\xi)], \\
(RO) \quad & \min_{x \in \mathcal{X}} \ \max_{\xi \in \Xi(x)} f(x,\xi), \\
(DRO) \quad & \min_{x \in \mathcal{X}} \ \max_{\mathbb{P} \in \mathcal{P}(x)} \mathbb{E}_{\mathbb{P}}[f(x,\xi)],
\end{aligned}
$$

where the decision can directly affect the distribution $\mathbb{P}$, the uncertainty set Ξ, or the ambiguity set $\mathcal{P}$.

In the first invited article, Miguel Lejeune from the George Washington University provides a comprehensive overview of the types of uncertainty dependent on the decision: Type 1, where decisions can directly affect the probability distributions and such change can be further categorized by four different classes, and Type 2, where decisions affect the uncertainty realization mechanism. Miguel focuses on the first type and illustrates the properties and methods for chance-constrained programs under decision-dependent uncertainty with three specific examples.

In the second article, Xian Yu and Güzin Bayraksan from the Ohio State University discuss a specific, yet very important type of optimization model under decision-dependent uncertainty — Contextual Stochastic Optimization under Decision Dependent Uncertainty (DD-CSP). Their article offers some important insights about why such a model is computationally challenging and how to approximate it in a tractable fashion. The article also serves as a continuation of the data-driven optimization in the previous newsletter, which is an important trend in this big-data era of operations research.

As Miguel points out in his article, modeling the decision-dependent uncertainty has been gaining momentum in the stochastic programming field, not only reflected by the increasing number of works in different model formulations and solution methodologies, but also underscored by the upcoming *Mathematical Programming* special issue titled "Stochastic Programming and DRO under Decision-Dependent Uncertainty", Eds: Lejeune, Krokhmal and Romeijnders. We hope these two papers can inspire our readers with more ideas to tackle this challenging class of problems and derive new theoretical and applied results.

Enjoy your read!

Stochastic Optimization under Decision-Dependent Uncertainty: Overview and New Chance-Constrained Models

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Executive Summary: *Most stochastic programming and distributionally robust optimization models focus on problems involving exogenous uncertainty. Relatively few have addressed decision-dependent (or endogenous) uncertainty, where the probability distribution of the random variables is altered by the decisions taken within the optimization problem. This work provides an overview of the various forms of decision-dependent uncertainty and demonstrates that such models extend beyond traditional risk-neutral and recourse-based formulations. In particular, we focus on chance-constrained problems under decision-dependent uncertainty and present a succinct summary of three novel models that incorporate different types of decision-dependent uncertainty.*

Stochastic Programming (SP) is a well-established framework for modeling and solving optimization problems under uncertainty, in which uncertainty generally manifests into two main categories: exogenous and endogenous, also referred to as decision-dependent, uncertainty [3]. Exogenous uncertainty is independent of the decision variables, and the probability distribution of the random variables is not affected by the decisions made. In contrast, decision-dependent uncertainty arises when decisions directly impact the probability space, indicating that current choices can shape the uncertainty faced in the future. While most of the SP literature has traditionally focused on exogenous uncertainty, interest in decision-dependent uncertainty has grown significantly in recent years and the area has been gaining momentum. The upcoming Mathematical Programming special issue titled "Stochastic Programming and Distributionally Robust Optimization Under Decision-Dependent Uncertainty" underscores this emerging research trend.

The relatively limited body of work on decision-dependent uncertainty in SP can largely be attributed to the inherent and significant modeling and computational challenges. These challenges stem from the intricate interplay between decision and random variables. Accurately capturing the dependency of random variables on decision variables requires advanced formulations. A *coupling function* [1] is typically employed to characterize how decisions influence the underlying stochastic processes and probability spaces. Incorporating such dependencies typically introduces nonlinear and nonconvex terms into the optimization model, significantly increasing its computational complexity. As a result, the numerical solution of such models is challenging and often necessitates the development of specialized algorithmic methods.

In SP models with decision-dependent uncertainty, decisions can influence the probability space of random variables in distinct ways. We present a concise taxonomy that captures the different mechanisms through which decisions can affect the probability space of decision-dependent random variables. Two main *types* of SP models with decision-dependent uncertainty have been identified in the literature [2]. In *Type 1* SP problems with decision-dependent uncertainty, decisions directly alter the probability distribution of the random variables. In contrast, in *Type 2* SP problems with decision-dependent uncertainty, also known as *problems with decision-dependent information structure*, decisions affect the time at which information is revealed and uncertainty is resolved. These models typically arise in multi-stage SP problems with recourse, where decisions determine which non-anticipativity conditions should be enforced. In such cases, binary decision variables are often embedded within disjunctive constraints to activate or ignore specific non-anticipativity conditions, thereby shaping the information structure of the problem.

The Type 1 category can be further subdivided into four main subclasses, based on the specific characteristic of the probability distribution that is influenced by the decisions:

- *Class A - Decision-dependent probabilities.* In this subclass, decisions modify the *probabilities* of each possible outcome or scenario. A baseline, decision-independent set of probabilities is estimated in advance. The coupling function or *decision-dependent distortion function* [8] specifies the functional form (e.g., linear, exponential, multiplicative) under which the decisions distort the decision-independent set of probabilities. In some cases, the coupling function defines a linear or convex combination of several decision-independent set of probabilities, resulting in a mixture distribution.
- *Class B - Decision-dependent support.* The decisions influence the *support* of the random variables. Similar to Class A, the coupling function defines how the baseline (decision-independent) support of the distribution is modified based on the decisions made.
- *Class C – Decision-dependent parameters.* Decisions determine the *parameterization* (e.g., mean, variance) of the probability distribution governing the random variables. The coupling function specifies how decisions map to the values of these parameters (e.g., arrival rate of a

Poisson process). This subclass is well-suited for continuous distributions.

- *Class D – Decision-dependent distribution function.* In this subclass, integer decision variables select a particular probability distribution from a predefined set of candidate distributions. The coupling function is a logic and combinatorial function that maps the decisions made to one of the candidate probability distributions.

In addition to Type 1 and Type 2, a third form of decision-dependent uncertainty — *Type 3* — arises in the context of distributionally robust optimization (DRO). In Type 3 DRO problems, decisions directly influence the size of the ambiguity set (e.g., radius of ambiguity ball) [5, 6], and, by corollary, the degree of conservativeness of the DRO problem.

Several key observations emerge from the existing literature on SP under decision-dependent uncertainty:

- *Prevalence of Type 2 problems.* A large part of the extant literature addresses Type 2 problems, which involve decision-dependent information structures.
- *Predominance of risk-neutral models.* Most SP models with decision-dependent uncertainty have a risk-neutral perspective and rely on expectation-based risk measures. Risk-averse formulations incorporating for example chance constraints, stochastic dominance, or conditional value-at-risk (CVaR) remain underexplored.
- *Emphasis on recourse and multistage models.* SP models with decision-dependent uncertainty are predominantly formulated as SP problems with recourse. In the case of Type 2 uncertainty, they are typically multi-stage SP problems, reflecting the sequential nature of information revelation.
- *Network problem application focus.* Although decision-dependent uncertainty is pervasive and relevant to a wide range of real-world applications in business and industry, much of the current research is concentrated on network-based problems, such as network interdiction, fortification, and infrastructure protection.

In the remainder of this article, we show that SP models with decision-dependent uncertainty can be formulated, solved, and applied to a broader range of problems than those traditionally studied in the literature. We highlight the widespread presence of decision-dependent uncertainty across diverse application domains, the various mechanisms by which decisions influence probability distributions, and the potential for integration into risk-averse SP models. To illustrate these points, we present three recent studies [4, 7, 8] that propose novel chance-constrained optimization models involving Type 1 decision-dependent uncertainty. The three studies are based on different Type 1 decision-dependent uncertainty subclasses – decision-dependent probabilities in [8], decision-dependent support in [7], and decision-dependent parameters in [4] – and are developed for three markedly different application areas – medical evacuation of injured soldiers [4], impact of wildfires on power systems [8], and yield management [7].

Lejeune et al. [4] propose an integer nonlinear joint chance-constrained problem that incorporates both exogenous and parameter-dependent uncertainty (Type 1, Subclass C). The study is motivated by the medical evacuation (MEDEVAC) of severely wounded soldiers. The objective is to design a reliable evacuation network to quickly extricate the soldiers from the battlefield and to maximize their chance of survival and functional recovery. The model determines the location of medical treatment facilities (MTF), the deployment of air ambulances, and their assignment to casualty collection points (CCP). The objective function maximizes the number of critically injured soldiers who can be evacuated without delay (i.e., defined as the probability that an assigned air ambulance is immediately available upon a MEDEVAC request, avoiding queuing) with a prescribed reliability level.

Two sources of exogenous uncertainty are considered, namely (i) the availability of medical personnel and supplies at each MTF and (ii) the number of evacuation requests originating from each CCP. A key feature of the model is the decision-dependent uncertainty in air ambulance availability, modeled as parameter-dependent uncertainty. The availability of each air ambulance is modelled as a Bernoulli random variable, whose success probability (i.e., probability of being available) is endogenously determined as a function of assignment and workload decisions. This relationship is captured via a linear coupling function that links the probability of availability to the workload of the air ambulance. To handle the joint chance constraint, the authors develop a Boolean reformulation that yields a compact and equivalent representation of the feasible region. They devise a mixed-integer nonlinear programming (MINLP) solution framework that features a multiterm convexification method, a second-order cone relaxation and bounding scheme, and a novel branching rule coined the smallest domain branching rule. The authors also propose the *value of endogenous uncertainty framework* to assess the benefits of accounting for decision-dependent uncertainty.

Zhang et al. [8] propose a mixed-integer joint chance-constrained optimization model with decision-dependent probabilities (Type 1, Subclass A). The study is motivated by the operation of power distribution systems under wildfire risk – an increasingly critical challenge, as wildfires can severely compromise network reliability and trigger power line failures within the network. The model simultaneously reconfigures the network topology and determines optimal operational decisions in the face of wildfire ignition risks. The objective is to minimize the total system costs, including those associated with power generation, switching actions, and power imbalance penalties, while ensuring operational reliability.

The relationship between wildfire risk and power line availability is multifaceted and complex. The failure status of power lines is modeled as a multivariate random variable whose finitely supported distribution reflects both exogenous uncertainty (wildfire occurrence and propagation) and endogenous uncertainty (decisions affecting power flow levels). Wildfires may be initiated by arc-induced ignition following a line fault, and once ignited, can propagate rapidly due to environmental factors such as wind, vegetation, and fuel moisture—potentially causing cascading line failures across the network. Importantly, line failure probabilities are also driven by operational decisions, specifically, the power flow levels. To model this, the authors introduce a *decision-dependent distortion function*, which, in this problem, is a piecewise linear function that maps line loading percentages (i.e., ratio of power flow to capacity) to power line failure probabilities. The baseline (decision-independent) scenario probabilities are modified in a two-step process. First, the distortion function adjusts the marginal failure probabilities for individual lines based on power flow decisions. Second, an Archimedean copula function is used to model the joint dependence structure among line failures and furnishes a distorted multivariate distribution (i.e., distorted scenario probabilities) of network-wide power line availability that reflects both exogenous wildfire risk and decision-induced effects.

Nguyen and Lejeune [7] study a distributionally robust chance-constrained problem with support-dependent uncertainty (Type 1, Subclass B), where the support of the underlying distribution is shifted by decision variables. The study is motivated by a yield management problem aiming to determine a production strategy that maximizes the worst-case probability that the total profit exceeds a specified threshold. The model determines the optimal production quantities while satisfying operational constraints related to cost, yield capacity, and demand fulfillment, and explicitly captures how increased production may degrade product quality.

The random yield is modeled as a decision-dependent variable whose support shifts based on the yield rate, which is defined as the proportion of units that are non-defective and saleable, and which depends on production quantity. The authors use affine and exponential coupling functions to model the monotone decreasing relationship connecting yield rate and production quantities, since, as production volume increases, the yield rate tends to decline, reflecting quality deterioration. Exogenous uncertainty in yield stems from external factors, such as variations in raw material quality, supplier reliability, environmental conditions, and unplanned production disruptions. The authors construct a decision-independent distribution using a finite set of scenarios generated ex-ante to reflect the impact of external factors on yield. The scenarios are then endogenously modified by the decision-dependent yield rate.

The authors consider both moment-based (three variants) and Wasserstein ambiguity sets to represent the partial knowledge of the yield distribution. The generic formulation is a semi-infinite distributionally robust chance-constrained problem with adaptive chance constraints in which the probability level itself is a decision variable. For each ambiguity set and coupling function, the problem is reformulated in a finite-dimensional space as a nonconvex: (i) continuous optimization problem for the moment-based ambiguity sets and (ii) MINLP problem for the Wasserstein ambiguity set. In both cases, nonconvexity arises from bilinear terms involving products of bounded continuous variables. For the affine coupling, the feasible region is defined by linear constraints and a rotated second-order cone constraint. For the exponential coupling, an additional exponential cone constraint is introduced. The solution method relies on (i) the derivation of the envelope of the bilinear terms which are defined on specific (different from a box) domains with non-trivial bounds, and (ii) the embedding of the envelope-defining inequalities in a specialized cutting plane algorithm that progressively tightens the relaxation of the problem and guarantees finite convergence.

Acknowledgements

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Contextual Stochastic Optimization under Decision-Dependent Uncertainty

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Executive Summary: *Modeling uncertainty is a major challenge in real-world decision-making problems. Traditional stochastic optimization literature does not explicitly consider (i) contextual information that may influence uncertainty, and (ii) decision-dependent uncertainty, where the decisions being optimized can also significantly impact the uncertainty. A few recent papers have investigated the combination of these features by studying contextual stochastic optimization under decision-dependent uncertainty. In this article, we introduce the challenges faced by this class of problems, summarize some existing approaches to model and approximate such problems with desirable theoretical guarantees, and end with future research directions in this exciting and important area of research.*

Decision making under uncertainty is prevalent in many business, engineering, and scientific domains. In many important real-world applications, (i) uncertainty is often influenced by contextual information (also known as covariates, features, or side information), and (ii) the decisions being optimized can, in turn, also significantly affect that uncertainty, leading to the so-called *decision-dependent uncertainty.*

In this article, we briefly discuss contextual decision-making problems under decision-dependent uncertainty, provide some existing approaches to model and approximate such problems, and end with future research directions. Let us begin with several real-world examples of this type of problems.

Example 1 [Facility Location]. The decision maker needs to determine where to open new facilities in order to maximize total revenue under demand uncertainty. Demand could be affected by contextual information (e.g., seasonality, advertisements, promotions) as well as the facility location decisions themselves. For instance, opening a facility in an area could increase the demand in that area. One example of this class of problems is the Electric Vehicle (EV) charging station location problem, where opening a new charging station could increase the EV demand in that area [9].

Example 2 [Portfolio Management]. Incorporating contextual information such as economic indicators and company performance is critical to better predict uncertain stock returns and thus make better investment decisions. At the same time, decisions regarding when and how often to buy or sell stocks can influence returns, particularly in the case of high-volume trades or actions by major market participants.

Example 3 [Power System Expansion]. Electricity demand and renewable electricity production are affected by contextual factors such as seasonality, temperature, solar irradiation, wind speed, and so forth. Moreover, long-term investment decisions regarding electricity generation, expansion, and distribution can significantly influence the future electricity demand.

As the above examples demonstrate, accounting for both the contextual information and the impact of decisions on the underlying uncertainty is essential in many real-world applications. Let us now discuss a general stochastic optimization formulation to address such problems and the challenging aspects of this class of problems.

1. Decision-Dependent Contextual Stochastic Programs

Let us begin by introducing contextual stochastic programs *without* decision-dependent uncertainty. This class of problems can be modeled as

$$\min_{z\in\mathcal{Z}} \mathbb{E}[c(z,Y)|X=x], \tag{CSP}$$

where z denotes the decision vector, $\mathcal{Z} \subseteq \mathbb{R}^{d_z}$ represents the feasibility set, $X \in \mathcal{X} \subseteq \mathbb{R}^{d_x}$ denotes the random vector of covariates with x being its realization, and the random vector $Y \in \mathcal{Y} \subseteq \mathbb{R}^{d_y}$ denotes the model uncertainty. The expectation is taken with respect to the conditional distribution of Y given $X = x$. In the above setup, the decision maker typically has access to joint observations of (X, Y), and a new covariate x is observed *before* the optimization model is solved. Note that the above contextual model is different than the traditional stochastic programs due to the conditioning on the covariates $X = x$. In recent years, there has been a stream of works that focus on solving the above (CSP). We refer interested readers to the recent survey [7] for an extensive review on this topic.

The *decision-dependent* variant of the above contextual stochastic program is then given by

$$v^*(x) := \min_{z\in\mathcal{Z}} \mathbb{E}[c(z,Y)|X=x, Z=z]. \tag{DD-CSP}$$

Note that, among the decisions z, some may influence the random parameters Y, while others may have no effect. The above general form is used for notational convenience.

1.1 Challenges

Decision-dependent contextual stochastic programs pose several nontrivial challenges.

Challenge 1 [Need for Approximations]. In (DD-CSP), the conditional distribution of Y given the covariates x and decisions z is typically unknown—albeit assumed to exist—and the resulting conditional expectation, while assumed to be well defined and finite, typically cannot be calculated even for a fixed decision z. Consequently, (DD-CSP) cannot be solved exactly. Therefore, one must resort to data-driven approximations.

Challenge 2 [Learning Decision Dependency]. Because the decisions also affect the distribution of Y, learning this latent dependency can be challenging. For instance, implementing the decisions can be very costly (e.g., opening a facility); therefore, there may be scant data to learn the impact of decisions on the uncertain parameters. In many real-world applications, data is only available after a decision is made (factual), but its counterfactual (when an alternative decision was made) is not available, further complicating the estimation/learning.

Challenge 3 [Computationally Challenging Optimization]. Even if (DD-CSP) can be approximated and the impact of decisions on the random parameters can be estimated, the resulting models often lead to computationally challenging nonconvex problems. Incorporating nonparametric regression models or modern machine learning methods into a contextual optimization problem is not straightforward in the decision-dependent setting, as many such models lack a simple functional form.

Even for those whose structural properties allow for integration into optimization, the resulting models are often large-scale mixed-integer nonlinear formulations that remain computationally intractable.

Despite the above challenges, a small but a growing body of work investigate (DD-CSP) [2, 6, 10, 3]. In the next section, we will briefly go over these works, focusing on data-driven approximations of (DD-CSP) and then discuss several desired theoretical properties of such approximations.

1.2 Approximations of (DD-CSP)

Let $\mathcal{D}_n := \{(x^k, z^k, y^k)\}_{k=1}^n$ denote the joint observations of (X, Z, Y). Utilizing this dataset, we first summarize some existing approximations to (DD-CSP) based on the Sample Average Approximation (SAA) approach.

Reweighted SAA. [2] proposed assigning a weight to each data point based on the historical dataset $\mathcal{D}_n$. In a decision-dependent setting, the reweighted SAA can be written as

$$\min_{z\in\mathcal{Z}} \sum_{k=1}^{n} w_{n,k}(x,z)c(z,y^k),$$

where $w_{n,k}(x,z)$ is the data-driven weight assigned to data point k that depends on the covariate x and decision z. [2] provided several options for choosing the weights based on nonparametric regression models, including k nearest neighbors, kernel methods, and classification and regression trees.

Empirical Residuals Based SAA. [1, 8] proposed using residuals from the prediction model to construct an empirical residuals-based distribution in the optimization model. [5] formalized and investigated the theoretical properties of the so-called empirical residuals-based SAA (ER-SAA) approach. This approach, adapted to the decision-dependent setting, assumes the random parameter Y has the form $Y = f^*(X,Z) + \epsilon$, where $f^*(x,z) := \mathbb{E}[Y|X=x, Z=z]$ represents the true regression function, which does not need to be linear, and ϵ denotes the regression error with zero mean. Here, the additive error ϵ is assumed to be independent of both X and Z, but generalizations are possible. If one learns the true regression function $f^*(x,z)$ on data $\mathcal{D}_n$, thereby obtaining an estimated regression function $\hat{f}_n(x,z)$, the empirical residuals can be calculated from each observation k through $\hat{\epsilon}_n^k := y^k - \hat{f}_n(x^k, z^k)$. Then, given a new covariate realization $x \in \mathcal{X}$, the empirical residuals-based decision-dependent SAA (ER-DD-SAA) can be formed by

$$\min_{z\in\mathcal{Z}} \frac{1}{n}\sum_{k=1}^{n} c\big(z, \hat{f}_n(x,z) + \hat{\epsilon}_n^k\big).$$

Above, it is possible to project each point $\hat{f}_n(x,z)+\hat{\epsilon}_n^k$ used in ER-DD-SAA onto the support set $\mathcal{Y}$ or a known superset of $\mathcal{Y}$ (e.g., nonnegative orthant). This changes each point to $\mathrm{proj}_{\mathcal{Y}}(\hat{f}_n(x,z) + \hat{\epsilon}_n^k)$ for $k = 1, \ldots, n$, where $\mathrm{proj}_{\mathcal{S}}(y)$ denotes orthogonal projection of y onto set $\mathcal{S}$. Note that this method can accommodate a variety of learning methods.

Distributionally Robust Empirical Residuals Based SAA. To account for the estimation error in the empirical distribution, [4] proposed an empirical residuals-based distributionally robust optimization (ER-DRO) by constructing ambiguity sets around the empirical distribution. In a decision-dependent setting, the empirical distribution can be constructed as $\hat{P}_n^{ER}(x,z) := \frac{1}{n}\sum_{k=1}^n \delta_{\hat{f}_n(x,z)+\hat{\epsilon}_n^k}$, where δ denotes the Dirac measure. Again, it is possible to use projected values instead. In this setting, the estimation error in approximating the conditional distribution of Y given x and z through $\hat{P}_n^{ER}(x,z)$ can be substantial, particularly in light of Challenge 2 discussed above. To mitigate this issue, [10] proposed the following empirical residuals-based decision-dependent DRO (ER-D^{3}RO)

$$\min_{z\in\mathcal{Z}} \sup_{Q\in\hat{\mathcal{P}}_n(x,z)} \mathbb{E}_{Y\sim Q}[c(z, Y(x,z))]$$

aimed at finding optimal decisions against the worst-case expectation taken with respect to a distribution Q from the ambiguity set $\hat{\mathcal{P}}_n(x,z)$. The ambiguity set $\hat{\mathcal{P}}_n(x,z)$ can be constructed via (i) the *Wasserstein distance*, i.e., by selecting all distributions that are sufficiently close to the empirical distribution $\hat{P}_n^{ER}(x,z)$ according to p-Wasserstein distance for some $p \in [1,\infty]$, (ii) a *sample robust* approach that can perturb the atoms $\hat{f}_n(x,z) + \hat{\epsilon}_n^k$ of the empirical distribution $\hat{P}_n^{ER}(x,z)$ while keeping their probabilities the same $(1/n)$, or (iii) with *same-support* approaches such as ϕ-*divergences* that keep the atoms of $\hat{P}_n^{ER}(x,z)$ the same while potentially changing their probabilities.

In addition to the above approximations, [6] developed a local linear regression model to learn the decision-dependent uncertainty; however, their model did not incorporate any non-decision covariates X. [3] analyzed the statistical properties of two approaches for solving (DD-CSP): (i) predict-then-optimize, which first learns the dependence between decisions, covariates, and the uncertainty and then feeds the prediction model into the downstream optimization step (like the SAA approaches outlined above); and (ii) estimate-then-optimize, which directly estimates the conditional expectation $\mathbb{E}[c(z,Y)|X=x,Z=z]$ in the objective of (DD-CSP).

2. Desirable Theoretical Guarantees

Before we outline desired theoretical properties of data-driven approximations of (DD-CSP), let us introduce some notation. We denote the optimal solution set and optimal objective value to the original problem (DD-CSP) as $S^*(x)$ and $v^*(x)$, respectively. The objective function of (DD-CSP) is denoted by $g(z,x) := \mathbb{E}[c(z,Y)|X=x,Z=z]$. Similarly, the optimal objective value of the above approximations using data $\mathcal{D}_n$ is denoted as $\hat{v}_n(x)$, and an optimal solution to these approximations is represented by $\hat{z}_n(x)$. Distance between a point a and set $\mathcal{S}$ is given by $\text{dist}(a,\mathcal{S}) := \inf_{b\in\mathcal{S}} \|a-b\|$ using Euclidean norm $\|\cdot\|$. For sequences of random variables X_n and real values a_n, $X_n = O_p(a_n)$ denotes X_n/a_n is bounded in probability, and $\xrightarrow{P}$ denotes convergence in probability. In the following, we present several statistical guarantees that one could seek for these approximation problems. Note that it is possible to pursue other asymptotic and finite-sample properties.

1. **Consistency and asymptotic optimality:** The optimal value $\hat{v}_n(x)$ and solution $\hat{z}_n(x)$ of the approximation problem converge to the true ones in probability, i.e.,
$$\hat{v}_n(x) \xrightarrow{P} v^*(x), \quad \text{dist}(\hat{z}_n(x), S^*(x)) \xrightarrow{P} 0, \quad \text{and } g(\hat{z}_n(x),x)) \xrightarrow{P} v^*(x).$$
2. **Rate of convergence:** For some constant $r \in (0,1]$, the optimal value $\hat{v}_n(x)$ and solution $\hat{z}_n(x)$ of the approximation problem converge to the true ones at a certain rate, i.e.,
$$|\hat{v}_n(x) - v^*(x)| = O_p(n^{-r/2}) \text{ and } |g(\hat{z}_n(x),x) - v^*(x)| = O_p(n^{-r/2}).$$
3. **Finite sample solution guarantee:** The solution $\hat{z}_n(x)$ of the approximation problem satisfies for a.e. $x \in \mathcal{X}$, given $\eta > 0$, there exists constants $\Gamma(\eta,x) > 0$, $\gamma(\eta,x) > 0$ such that
$$\mathbb{P}\Big\{\text{dist}(\hat{z}_n(x), S^*(x)) \geq \eta\Big\} \leq \Gamma(\eta,x)e^{-n\gamma(\eta,x)}.$$
4. **Finite sample certificate guarantee:** For a given risk level $\alpha \in (0,1)$, the optimal value $\hat{v}_n(x)$ provides a high-confidence upper bound on the out-of-sample cost of $\hat{z}_n(x)$, i.e.,
$$\mathbb{P}\Big\{g(\hat{z}_n(x),x) \leq \hat{v}_n(x)\Big\} \geq 1-\alpha.$$

Note that each of the three approximation problems discussed in Section 1.2 has been shown to satisfy a part of these theoretical guarantees, with consistency and asymptotic optimality being the most commonly studied one. The finite sample certificate guarantee is typically shown for distributionally robust variants. For example, [2] showed the consistency and asymptotic optimality of the reweighted SAA problem; [9] presented the consistency and asymptotic optimality of the ER-DD-SAA problem under a two-stage facility location problem; and [10] provided conditions under which all the above properties are satisfied for the ER-D^{3}RO problem.

3. Concluding Remarks and Future Work on (DD-CSP)

In this article, we briefly discussed recent advances in contextual stochastic optimization under decision-dependent uncertainty. We summarized three approximation frameworks to handle decision-dependent uncertainty and presented several desirable theoretical properties, including consistency and asymptotic optimality, rates of convergence, and finite sample guarantees.

Decision-dependent contextual stochastic optimization is a growing field, rich in statistical, computational, modeling, and optimization challenges. Furthermore, given the many real-world applications that fit into this framework, advances in this area have the potential to make a real-world impact.

As noted in Section 1.1, there are many avenues for future work, which include but are not limited to the following. First, appropriate fusion of causal inference and optimization brings forth modeling and theoretical analysis challenges that merit future work. Moreover, as detailed in Challenge 3, decision dependency introduces additional computational optimization challenges, which opens several avenues for further exploration. For example, devising efficient formulations and algorithms to incorporate highly complex parametric and nonparametric regression/machine learning models into a decision-dependent contextual setting would be valuable. Furthermore, many real-world applications naturally involve a sequential cycle of learning and decision-making, motivating the development of novel multistage frameworks that capture the contextual and decision-dependent dynamics. This necessitates new modeling approaches, theoretical analyses, and computational optimization tools.

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Stochastic Programming Events in 2025-2026

Please find below the selected events over the next 12 months that we believe are of interest to our community. Mark your calendars!

- ICCOPT 2025, *International Conference on Continuous Optimization*
  Where/when: Los Angeles University of Southern California (USA), July 19-24, 2025
  More at https://sites.google.com/view/iccopt2025/home
- LOD 2025, *11th International Conference on Machine Learning, Optimization, and Data Science*
  Where/when: Riva del Sole Resort & SPA (IT), September 21–24, 2025
  More at https://lod2025.icas.events/venue/
- ICSP 2025, *International Conference of Stochastic Programming*
  Where/when: Paris (France), July 28 - August 1, 2025
  More at https://icsp2025.org/
- AI-OPT 2025, *2025 Workshop on AI-based Optimisation*
  Where/when: Carlton, Australia, August 7-8, 2025
  More at https://optima.org.au/2025-workshop-on-ai-based-optimisation-ai-opt-2025/
- ODS2025, *International Conference on Optimization and Decision Science 2025*
  Where/when: Milan (IT), September 1-4, 2025
  More at https://www.airoconference.it/ods2025/
- PhD Course, *Nordic PhD course in stochastic programming*
  Where/when: Bergen (NO), September 22-26, 2025
  More at https://www.ntnu.edu/nordab/nordic-phd-course-in-stochastic-programming
- CPAIOR 2025, *The 22nd International Conference on the Integration of Constraint Programming, Artificial Intelligence and Operations Research*
  Where/when: Melbourne, Australia, November

10-13, 2025
More at https://sites.google.com/view/cpaior2025

- JuMP2025, *JuMP-dev 2025*
  Where/when: Auckland (NZ), November 17–20, 2025
  More at https://jump.dev/meetings/jumpdev2025/
- *2025 Winter Simulation Conference*
  Where/when: Seattle, USA, December 7-10, 2025
  More at https://meetings.informs.org/wordpress/wsc2025/
- OP26, *SIAM Conference on Optimization*
  Where/when: Edinburgh (UK), June 2-5, 2026
  More at https://www.siam.org/conferences-events/siam-conferences/op26/
- OL2A, *International Conference on Optimization, Learning Algorithms and Applications*
  Where/when: Malaga (SP), June 10-12, 2026
  More at https://ol2a.ipb.pt/ui/#/home
- INFORMS 2026, *Advances in Decision Analysis Conference*
  Where/when: Duke University, North Carolina (USA), June 15-17, 2026
  More at https://www.informs.org/Meetings-Conferences/INFORMS-Conference-Calendar/2026-INFORMS-Advances-in-Decision-Analysis-Conference
- IFORS2026, *The 24th Conference of the International Federation of Operational Research Societies: Decision Support for a Sustainable World*
  Where/when: Vienna (AT), July 12-17, 2026
  More at https://www.ifors2026.at/home/
- *Optimization 2026*
  Where/when: Lisbon (Portugal), July 20-22, 2026
  More at https://optimization2026.iseg.ulisboa.pt/
- *INFORMS Annual Meeting 2026*
  Where/when: Detroit (USA), October 24-26, 2026.
  More at https://www.informs.org/Meetings-Conferences/INFORMS-Conference-Calendar/2026-INFORMS-Annual-Meeting

ICSP XVII

July 28 - August 1, 2025 Paris, France

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Mark your calendars! We are going to hold the seventeenth International Conference on Stochastic Programming (ICSP), during the last week of July 2025: July 28 – August 1, 2025, at École des Ponts, Noisy-le-Grand, France.

You can find the information on the website: https://icsp2025.org/. We have a great line-up of plenary speakers (Francis Bach, Erick Delage, Niao He, Jim Luedtke, Francesca Maggioni, Huifu Xu). The mini-symposium and invited session information has already been released on the website. We have planned a nice visit for the social program in Château de Fontainebleau.

Excursion at Château de Fontainebleau

New Website for the Stochastic Programming Society

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At the COSP Business Meeting during ISMP 2024, we discussed the urgent need to modernize the Stochastic Programming Society's online presence. The previous website—running on outdated software—had become both difficult to maintain and a potential security risk. As a result, it was taken offline.

We used this opportunity to rebuild the site from the ground up. Following internal iterations within the COSP throughout late 2023 and early 2024, a working group refined the structure and engaged professional support for the relaunch. The result is now live at www.stoprog.org.

SPS new website

The new site is clean, mobile-friendly, and easier to update. It retains essential historical content—such as past ICSP conferences and prize winners—while providing a more flexible platform going forward. Most importantly, the site is intended to evolve with the needs of the community. Feedback is welcome and will be incorporated where feasible.

Please contact the COSP webmaster, Wolfram Wiesemann, at ww@imperial.ac.uk with suggestions or contributions.

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