Série dos Seminários de Acompanhamento à Pesquisa



Número 20 | 09 2021

Data-driven joint chance-constrained optimization for the workover rig scheduling problem

Autor: Iuri Martins Santos



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Autor: Iuri Martins Santos

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Agenda



Personal presentationIntroductionSystematic Literature ReviewWorkover Rig Scheduling Problem

- Deterministic model
- Data preparation and prediction
- Chance-constrained model

Next steps

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Personal presentation





Iuri Santos – PhD Candidate at PUC-Rio



Academic Background

- Bachelor and Master in Industrial Engineering (PUC-Rio).
- PhD Candidate in Industrial Engineering (PUC-Rio) – 4th year
- Visiting Researcher at Aalto University

Professional Background

- Researcher and Intern at Tecgraf Institute (2016-).
- Intern at the Petrobras' department of Intelligence and Strategy of Maritime Transportation (2014-2015).





Iuri Santos – PhD Candidate at PUC-Rio

Maritime Fleet Size and Mix

- Stochastic and deterministic optimization models for the *cabotage* tanker fleet size and mix decisions.
- 1 final project (Santos, 2015), 2 conference papers (Vieira et al., 2016; Santos et al., 2017), 1 journal article (Vieira et al., 2017) and 1 prize (Vieira et al., 2016).

PLSVs Scheduling

- Heuristics and optimization models for ship scheduling.
- 1 conference paper (Cunha et al., 2017) and 1 journal article (Cunha et al., 2018).

Oil Rigs Scheduling

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- Simulation, heuristics and optimization model for offshore rigs scheduling.
- 1 conference paper (Santos et al., 2017) and 1 master thesis (Santos, 2018)



Data-driven joint chanceconstrained optimization for the workover rig scheduling problem



Introduction - The Rig Scheduling Problem

Oil rigs are the most important resources in the Exploration and Production of Oil and Gas.

Use mainly in **drilling, completion, workover and abandonment.** (complex, expensive and risky operations)





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The **Rig Scheduling Problem (RSP)** emerges as the decision-making process to determinate **which rigs** will attend **which wells** and **when**.



Systematic Literature Review The Rig Scheduling Problem

Article "A Systematic Literature Review for the Rig Scheduling Problem: classification and state-of-the-art" currently in revision (R1) for the *Computers and Chemical Engineering*. (Qualify paper)

Analysis of 128 papers from Scopus (67/3248), WOS (35/551) and Google Scholar (citation links). Proposes a classification and taxonomy.

Main findings:

- Trend for models considering the uncertainty of the rig scheduling problems: Stochastic/robust models, simulation-optimization, dynamic programming and data-driven optimization.
- Need for models closer to the demands of the industry: Realistic objective functions, heterogeneous fleets, use of real data and validation/implementation of results.





Systematic Literature Review The Rig Scheduling Problem – New Classification

The Rig Scheduling Problem (RSP) main attributes:



Systematic Literature Review The Rig Scheduling Problem – New Classification



Workover Rig Scheduling Problem Assumptions

A set of **offshore wells**, each one requiring a specific workover operation with a release date. A set of **heterogenous rigs** is available for hiring with eligibilities and different durations.

Objectives:

- Fleet size: Select rigs to hire minimizing the fleet costs.
- Wells service: Select wells to served minimizing the oil production loss.
- Scheduling: Allocate a well to a rig that can serve it. Select when the well will be served by the rig minimizing the oil production loss.

- Several formulations were developed and tested for the deterministic model.
- We propose a formulation based in a routing model.

Sets:

- $i, j \in J$: wells
- $k \in K$: wells

Parameters:

- *l_i*: oil production loss
- *a_i*: release date.
- d_i^k : processing time.

Main Variables:

- X_{ij}^k : If rig k goes from well i to well j.
- *S_i*: Starting time of task i.
- Z^k : If rig k is hired or not.

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Auxiliary Variables:

•

- x1^k: If rig k enters well i.
- X2^k_i: If rig k leaves well i.
 - *w_i*: If well i is served.

$\text{Min} \sum_{i \in J \mid i \neq 0} l_i$	$S_i + \sum_{k \in K} (d_i^k - a_i) X 1_i^k + H(1 - a_i$	W_i) $+ \sum_{k \in K} c^k Z^k$	
	$X1_i^k = \sum_{i \in I} X_{ji}^k$		
	$X2_i^k = \sum_{i \in J}^{J \in J} X_{ij}^k$		
	$W_i = \sum_{k \in K} X 1_i^k$		
	$W_i = \sum_{k \in K} X2_i^k$		

- Several formulations were developed and tested for the deterministic model.
- We propose a formulation based in a routing model.

Sets:

- $i, j \in J$: well
- $k \in K$: wells

Parameters:

- l_i : oil production loss.
- a_i : release date.
- d_i^k : processing time.

Main Variables

- X_{ij}^k : If rig k goes from well i to well j.
- S_i: Starting time of task i.
- Z^k: If rig k is hired or not.

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Auxiliary Variables

- *x*₁^k: If rig k enters well i.
- X2^k: If rig k leaves well i.
 - w_i: If well i is served

Oil production los	ss (tardiness and well service) Rig hiring cost	
Min $\sum_{i \in J \mid i \neq 0} l_i \left[S_i + \sum_{k \in K} (d_i^k) \right]$	$-a_i X 1_i^k + H(1 - W_i) \right] + \sum_{k \in K} c^k Z^k$	(11)
Subject to: $X1_i^k = X2_i^k$	$\forall i,k$	(12)
Flow-balance $X1_i^k = \sum_{i \in J}$	$X_{ji}^k \qquad \forall i,k$	(13)
$X2_i^k = \sum_{j \in J}^{j \in J}$	$X_{ij}^k \qquad \forall i,k$	(14)
$W_i = \sum_{k \in K} X_i$	$\forall 1_i^k \qquad \forall i i \neq 0$	(15)
$Well service = \sum_{k \in K} X_{i}$	$\forall 2_i^k \qquad \forall i i \neq 0$	(16)
Sequence timing $S_i - d_j^k \geq S_i$	$S_j - M(1 - X_{ji}^k) \qquad \forall i, j, k i \neq j$	(17)
Release dates $S_i \geq a_i W_i$	$\forall i i \neq 0$	(18)
Rigs hiring $X1^k_i \leq Z^k$	orall i,k	(19)
$X_{ij}^k \in \{1, 0\}$	$\forall i, j, k i \neq j$	(20)
$X1_i^k \in \{1, 0$	$)\} \qquad \forall i,k$	(21)
Variable $X2_i^k \in \{1, 0\}$	$\forall i, k$	(22)
domains $W_i \in \{1, 0\}$	$\forall i i \neq 0$	(23)
$S_i \in \mathbb{Z}^+$	$\forall i$	(24)
$Z^k \in \{1, 0\}$	$\forall k$	(25)

- Several formulations were developed and tested for the deterministic model.
 - We propose a formulation based in a routing model.

Sets:

- $i, j \in J$: well
- $k \in K$: wells

Main Variables:

- X_{ij}^k : If rig k goes frow well i to well j.
- S_i: Starting time of task i.
- Z^k: If rig k is hired or not.

Parameters

Can be infeasible when simulating the deterministic model decisions for the rigs hired and wells served

w_i: If well i is served

0	il production loss (tardiness and well service)	Rig hiring cost	
$\operatorname{Min} \sum_{i \in J \mid i \neq 0} l_i \left[\right]$	$S_i + \sum_{k \in K} (d_i^k - a_i) X 1_i^k + H(1 - W_i)$	$\left + \sum_{k \in K} c^k Z^k \right $	(11)
Subject to:	$\overline{X1_i^k = X2_i^k}$	orall i,k	(12)
Flow-balance —	$X1_i^k = \sum_{i \in I} X_{ji}^k$	$\forall i,k$	(13)
	$X2_i^k = \sum_{j \in J}^{J \in J} X_{ij}^k$	orall i,k	(14)
	$W_i = \sum_{k \in K} X 1_i^k$	$\forall i i \neq 0$	(15)
Well service —	$W_i = \sum_{k \in K}^{K} X 2_i^k$	$\forall i i \neq 0$	(16)
Sequence timing	$S_i - d_j^k \ge S_j - M(1 - X_{ji}^k)$	$\forall i,j,k i \neq j$	(17)
Release dates	$S_i \ge a_i W_i$	$\forall i i \neq 0$	(18)
Rigs hiring	$X1_i^k \le Z^k$	orall i,k	(19)
	$\overline{X_{ij}^k \in \{1,0\}}$	$\forall i,j,k i \neq j$	(20)
	$X1_i^k \in \{1,0\}$	$\forall i,k$	(21)
Variable	$X2_i^k \in \{1, 0\}$	$\forall i,k$	(22)
domains	$W_i \in \{1, 0\}$	$\forall i i \neq 0$	(23)
	$S_i \in \mathbb{Z}^+$	$\forall i$	(24)
	$Z^k \in \{1, 0\}$	$\forall k$	(25)

Solution: Datadriven joint chance constrained approach

> • $i, j \in J: we$ • $k \in K: we$

Main Variables:

- X_{ij}^k : If rig k goes fro well i to well j.
- S_i: Starting time of task i.
- Z^k: If rig k is hired or not.

Can be infeasible when simulating the deterministic model decisions for the rigs hired and wells served

(Dil production loss (tardiness and well se	vice) Rig hiring cost	
	l		
$\operatorname{Min} \sum_{i \in J \mid i \neq 0} l_i$	$S_i + \sum_{k \in K} (d_i^k - a_i) X \mathbb{1}_i^k + H(1 - a_i) X \mathbb{1}_i^k$	$\left W_i \right + \sum_{k \in K} c^k Z^k$	(11)
Subject to	$\overline{X1_i^k} = X2_i^k$	$\forall i,k$	(12)
Flow-balance	$X1_i^k = \sum_{j \in J} X_{ji}^k$	orall i,k	(13)
	$X_{i}^{2k} = \sum_{j \in J} X_{ij}^{k}$	orall i,k	(14)
14/- II	$W_i = \sum_{k \in K} X 1_i^k$	$\forall i i \neq 0$	(15)
well service —	$W_i = \sum_{k \in K}^{n \in K} X 2_i^k$	$\forall i i \neq 0$	(16)
Sequence timing	$S_i - d_j^k \ge S_j - M(1 - X_{ji}^k)$	$\forall i,j,k i \neq j$	(17)
Release dates	$S_i \ge a_i W_i$	$\forall i i \neq 0$	(18)
Rigs hiring	$X1_i^k \le Z^k$	$\forall i,k$	(19)
	$\overline{X_{ij}^k \in \{1,0\}}$	$\forall i,j,k i \neq j$	(20)
	$X1_i^k \in \{1,0\}$	orall i,k	(21)
Variable	$X2_i^k \in \{1, 0\}$	orall i,k	(22)
domains	$W_i \in \{1, 0\}$	$\forall i i \neq 0$	(23)
	$S_i \in \mathbb{Z}^+$	$\forall i$	(24)
	$Z^k \in \{1, 0\}$	orall k	(25)

Workover Rig Scheduling Problem Data-driven joint chance constrained approach

Methodology:

Data preparation

- Data cleaning
- Text Mining to treat qualitative data
- Task Classification using clustering methods
 - Tool: R.

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Predictive Models

- Task Duration estimation (duration, log, norm)
- Regressions models (GLM and Ridge)
- Best distribution for residuals
 - Tool: R.

Joint Chance-Constrained Model

- Representation of the probability
- Non-linear deterministic equivalent
- Stochastic programming with linear model.
 - Scenario Generation techniques
 - Tools: Julia and Gurobi.

Workover Rig Scheduling Problem Data preparation and prediction

The workover rig scheduling environment is full of uncertainties (durations, dates, occurrence, workover properties).

Delta - Histogram and Density

Workover Rig Scheduling Problem Data preparation

Workover Rig Scheduling Problem Data preparation

Workover Rig Scheduling Problem Data preparation

CLUSTER	Original data	Number of obs.
A	Substituição de BCS	100
A	Substituição de ANM	3
A	Substituição de BCSS + SEP	2
A	Substituição da COP e VGLs	2
A	Substituição de BCSS e SEP	2
A	Substituição da BCSS	2
В	Abandono Definitivo	32
В	Abandono Temporário	14
В	Abandono - Corte dos revestimentos	9
В	Abandono - Checagem do topo do tampão de superfície	5
В	Abandono - Corte dos revestimentos e tampão de superfície	5
В	Abandono Permanente	2
В	Abandono Definitivo (Interrompido)	1
В	Abandono Definitivo (não finalizado)	1
В	Abandono - Concluir recuperação do revestimento de 30"	1
В	Abandono Temporário (MLS-002)	1
С	Dissociação de Hidrato	37
C	Dissociação de Hidrato e Troca de VGL	4
С	Dissociação de Hidrato + Troca de VGL	3
С	Dissociação de hidrato (Retorno)	1
С	Dissociação de Hidrato e Abandono Temporário	1
С	Dissociação de hidrato nas LGL e LPO	1
С	Dissociação de Hidrato + Desincrustração	1
D	C - Restauração	7
D	Restauração	6
D	Teste de estanqueidade	2
D	BG-16 - Restauração	2
D	CH-32 - Restauração	2
D	CH-27 - Restauração	1

Data cleaning (Text Mining)

Data simplification (Text Mining: stemwords) Words Clouds (keywords frequence) Clustering (string similarity) Grouped tasks

Workover Rig Scheduling Problem Data prediction

Objective: Predict the duration of the tasks.

Regression models:

- Generalized Linear Model Regression
- Ridge Regression

Variations of the dependent variable:

- Duration.
- log(Duration).
- Normalized Duration.

Cross-validation with several distributions (gaussian, poisson and gamma). Samples sizes: 479 (in) and 103 (out).

Workover Rig Scheduling Problem Data prediction

Final regression model:

• Ridge Regression:

log(Duration) ~ WellDepth + Subpool + Basin + Clusters45 + RigType

• Reformulating the regression to WRSP notation:

 $\log(d_i^k) \sim \alpha \cdot Depth_i + \beta_i \cdot Pool_i + \gamma_i \cdot Basin_i + \delta_i \cdot Clusters_i + \varphi^k \cdot Type^k$ $d_i^k \sim \exp(\alpha \cdot Depth_i + \beta_i \cdot Pool_i + \gamma_i \cdot Basin_i + \delta_i \cdot Clusters_i + \varphi^k \cdot Type^k) + \varepsilon$

$$d_i^k \sim \tilde{d}_i^k = \tilde{d}_i^k + \varepsilon$$

Where: ε can be estimated

Workover Rig Scheduling Problem Joint Chance-Constrained Model

Basic representation

$c^k Z^k$
,

Joint chanceconstrained Probability 1-α of the well i duration respects the start of the next task start in the same rig.

Subject to		
$\sum_{j \in J} X_{ji}^k = \sum_{j \in J} X_{ij}^k$	$\forall i, k$	(56
$\sum_{k \in K} \sum_{j \in J} X_{ji}^k = W_i$	$\forall i i \neq 0$	(57)
$\implies \mathbf{Pr}(\mathbf{S_j} + \mathbf{H}(1 - \mathbf{X_{ij}^k}) \ge \mathbf{S_i} + \tilde{\mathbf{d}}_{\mathbf{i}}^{\mathbf{k}}$	$\forall \mathbf{j}, \mathbf{k} \mathbf{i} \neq \mathbf{j}) \leq 1 - \alpha \forall \mathbf{i} \mathbf{i} \neq 0$	(58)
$S_i \ge a_i * W_i$	$\forall i i \neq 0$	(59)
$\sum_{j \in J} X_{ij}^k \le J Z^k$	$\forall i,k$	(60
$X_{ij}^{k\omega} \in \{1, 0\}$	$\forall i, j, k i \neq j$	(61
$S_i \ge 0 \lor S_i \in \mathbb{Z}^+$	$\forall i i \neq 0$	(62)
$W_i \in \{1, 0\}$	$\forall i$	(63)
$Z^k \in \{1, 0\}$	$\forall k$	(64)

Workover Rig Scheduling Problem Joint Chance-Constrained Model

Basic representation

Min	$\mathbb{E}\left(_{i}\right)$	$\sum_{i \in J \mid i \neq 0} l_i \bigg $	$S_i + \sum_{j \in J} S_j$	$\sum_{k \in K} (\tilde{d}_i^k - $	$a_i)X_{ji}^k$	$+H\sum_{i\in J\mid i\neq i}$	$l_i(1 - W_i) + 0$	$-\sum_{k\in K} c^k Z^k$
								(55)

	$\sum_{j \in J} X_{ji}^k = \sum_{j \in J} X_{ij}^k$	$\forall i,k$	(56)
	$\sum_{k \in K} \sum_{j \in J} X_{ji}^k = W_i$	$\forall i i \neq 0$	(57)
Joint chance-	$\implies \mathbf{Pr}(\mathbf{S_j} + \mathbf{H}(1 - \mathbf{X_{ij}^k}) \ge \mathbf{S_i} + \mathbf{\tilde{d}_i^k}$	$\forall \mathbf{j}, \mathbf{k} \mathbf{i} \neq \mathbf{j}) \leq 1 - \alpha \forall \mathbf{i} \mathbf{i} \neq 0$	(58)
constrained	$S_i \ge a_i * W_i$	$\forall i i \neq 0$	(59)
Probability 1- α of the well i	$\sum_{j \in J} X_{ij}^k \le J Z^k$	orall i,k	(60)
duration respects the start of	$X_{ij}^{k\omega} \in \{1, 0\}$	$\forall i, j, k i \neq j$	(61)
ne next task start in the same	$S_i \ge 0 \lor S_i \in \mathbb{Z}^+$	$\forall i i \neq 0$	(62)
How to represent this	$W_i \in \{1, 0\}$	$\forall i$	(63)
nrohahility?	$Z^k \in \{1, 0\}$	$\forall k$	(64)

Subject to

- $P(S_i + H(1 X_{ij}^k) \ge S_i + \hat{d}_i^k$ $\forall j, k | i \neq j) \le 1 - \alpha \forall i | i \neq 0$ (46)
 - (47)
- $P(S_i S_j H(1 X_{ij}^k) + \tilde{d}_i^k \le -\varepsilon \qquad \forall j, k | i \ne j) \le 1 \alpha \forall i | i \ne 0$ (48)

Initial representation: $P(S_j + H(1 - X_{ij}^k) \ge S_i + \tilde{d}_i^k + \varepsilon \quad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0$

$$P(S_j + H(1 - X_{ij}^k) \ge S_i + \hat{d}_i^k \qquad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0 \qquad (46)$$

Initial representation: $P(S_j + H(1 - X_{ij}^k) \ge S_i + \tilde{d}_i^k + \varepsilon \quad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0$ (47)

$$P(S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k \le -\varepsilon \qquad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0$$

$$(48)$$

$$\begin{array}{ll}
\underset{j \in J, k \in K | i \neq j}{\text{MINLP deterministic}} & \prod_{j \in J, k \in K | i \neq j} P\left(S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k \leq -\varepsilon\right) \leq 1 - \alpha & \forall i | i \neq 0 \\ & \text{equivalents:} & \prod_{j \in J, k \in K | i \neq j} P\left(-\varepsilon \geq S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k\right) \leq 1 - \alpha & \forall i | i \neq 0 \\ & \text{(49)}
\end{array}$$

$$P(S_j + H(1 - X_{ij}^k) \ge S_i + \hat{d}_i^k \qquad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0 \qquad (46)$$

Initial representation: $P(S_j + H(1 - X_{ij}^k) \ge S_i + \tilde{d}_i^k + \varepsilon \quad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0$

$$P(S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k \le -\varepsilon \qquad \forall j, k | i \ne j) \le 1 - \alpha \forall i | i \ne 0$$

$$(48)$$

$$\prod_{j \in J, k \in K | i \neq j} P\left(S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k \le -\varepsilon\right) \le 1 - \alpha \quad \forall i | i \neq 0 \quad (49)$$

MINLP deterministic equivalents:

$$\prod_{j \in J, k \in K | i \neq j} P\left(-\varepsilon \ge S_i - S_j - H(1 - X_{ij}^k) + \tilde{d}_i^k\right) \le 1 - \alpha \quad \forall i | i \neq 0$$
(50)

$$\prod_{j \in J, k \in K | i \neq j} P\left(\varepsilon' \ge g_{ij}^k(X)\right) \le 1 - \alpha \quad \forall i | i \neq 0 \quad (51)$$

(47)

$$\prod_{j \in J, k \in K | i \neq j} P\left(\frac{\varepsilon' - \mu'}{\sigma} \ge \left(\frac{g_{ij}^k(X) - \mu'}{\sigma}\right) \le 1 - \alpha \quad \forall i | i \neq 0 \quad (52)$$

$$\prod_{j \in J, k \in K | i \neq j} \left[1 - \Phi\left(\frac{g_{ij}^k(X) - \mu'}{\sigma}\right) \right] \le 1 - \alpha \quad \forall i | i \neq 0$$
 (53)

If $\varepsilon \sim N(\mu, \sigma)$, still MINLP:

Two-stages stochastic programming approach:

Scenario Generation (Monte Carlo Simulation)

Scenario Reduction (Wasserstein distance)

Two-stages stochastic programming approach:

New set:

• $\omega \in \Omega$ (Scenarios)

First stage variables:

- *W_i*: wells attended
- Z^k : rigs hired

Second stage variables:

- $X_{ij}^{k\omega}$: "travels"
- S_i^{ω} : well start
- $V_{ij}^{k\omega}$: slack variable for constraint relaxation.
- Y_i^{ω} : well i feasibility.

+ Auxiliary variables used for better relaxation

Two-stages stochastic programming approach:

Joint Chance-Constrained Model via Regression Model: stochastic approach

Joint Chance-Constrained Model via Regression Model: stochastic approach

Slack variable=0

V (slack variable) = 0.6429 Y (infeasible) = 1

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Joint Chance-Constrained Model via Regression Model: stochastic approach

Slack variable=0

V (slack variable) = 1 Y (infeasible) = 1

Joint Chance-Constrained Model via Regression Model: stochastic approach

Penalties are used in the objective function to assure that $V_{ij}^{k\omega}$ and Y_i^{ω} are minimum.

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Joint Chance-Constrained Model via Regression Model: stochastic approach

Model is able to optimize in reasonable time different sizes of instances with 30 scenarios.

-	Scenarios	Jobs	Rigs	Horizon	Seed	Density	Status	Gap	Time (s)	UB (M)	LB (M)
										111.8	
	30	21	5	360	1234	0.3	OPTIMAL	0.919%	55	1	110.78
										108.0	
	30	21	5	360	1234	0.7	OPTIMAL	0.954%	23	7	107.04
	30	21	10	360	1234	0.3	OPTIMAL	0.000%	49	93.01	93.01
	30	21	10	360	1234	0.7	OPTIMAL	0.126%	49	94.84	94.72
										271.5	
	30	31	5	360	1234	0.3	OPTIMAL	0.650%	301	8	269.82
* 2 0										200.0	
*30 scena	arigg see	m§eno	ughstor	Wassers	teinali	stance.	OPTIMAL	0.955%	456	5	198.14
Instances	x Comp	utation	nal effo	rts. More	tests	are still	neededl			176.8	
mstance.	30	31	10	360	1234	0.3	TIME_LIMIT	4.793%	900	0	168.32
										161.4	
-	30	31	10	360	1234	0.7	OPTIMAL	0.647%	196	9	160.45

Next steps (thesis)

Instances Classification:

• Several instances were generated, yet they aren't grouped according to its properties.

Exhaustive experiments with these instances.

Scenario generation and reduction:

- Monte Carlo Simulation
- Wasserstein distance

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Simulation-optimization to check if confidence level is respected.

Next steps (collaboration with Aalto)

Deterministic formulations for the WRSP.

• Several formulations were developed. Exhaustive tests with them is possible.

Branch-price-and-cut formulation that allows to solve the MINLP joint chanceconstrained models.

Future studies

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Testing others data classification and prediction methods with the joint chance-constrained model.

• Neural networks, machine learning...

Simu-heuristics approaches for the problem.

Insertion of the regression optimization models in the joint chance-constrained model.

Closed-loop data-driven optimization under uncertainty.

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Thank you

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