

Quantified Programming applied to Runway Scheduling TOR Workshop 2018

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Outline



- Quantified Programming
 - Motivation: IP vs QIP
 - QIP Formulation
- Runway Scheduling
 - Basic Idea
 - Adding Uncertainty
 - Restricting Uncertainty
 - Solving Quantified Programs
- Conclusion and Outlook



Section 1

Quantified Programming



- Robust optimization is crucial
 - uncertain input data
 - optimal deterministic plan is only best-case scenario



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 - optimal strategy is required



- Robust optimization is crucial
 - uncertain input data
 - optimal deterministic plan is only best-case scenario
 - replanning is expensive
 - optimal *strategy* is required
- Interested in strategy with optimal worst case outcome
 - ightarrow for each possible data situation we want a "good" solution

IP vs QIP: Example



$$\min_{x_1, x_2} -2x_1 - x_2
s.t. 2x_1 - x_2 \le 1
- x_1 + 2x_2 \le 1
x_1, x_2 \in \{0, 1\}$$

IP vs QIP: Example



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IP vs QIP: Example



$$\min_{x_1} \left\{ -2x_1 + \max_{y} \min_{x_2} -x_2 \right\}
s.t. \quad \exists x_1 \in \{0, 1\} \quad \forall y \in \{0, 1\} \quad \exists x_2 \in \{0, 1\} :
2x_1 - x_2 \le 1 - y
- x_1 + 2x_2 \le 1 + y$$

IP vs QIP



	IP	QIP
variables	basically one type of variables	
variable	no (relevant) variable	
order	order	
objective	min or max function	
function		
solution	variable assignment +	
format	objective value	
game	single-player game	
type		

IP vs QIP



	IP	QIP		
variables	basically one type of	two types of variables: exis-		
	variables	tential (\exists) and universal (\forall)		
variable	no (relevant) variable	explicit order of the variable		
order	order	blocks		
objective	min or max function	min-max objective		
function				
solution	variable assignment +	assignment strategy $+$ objec-		
format	objective value	tive value of optimal play		
game	single-player game	two-person zero-sum game		
type				

QIPs - Formulation



Parameters:

- variable domain $\mathcal{D} = \{x \in \mathbb{Z}^n \mid I \leq x \leq u\}$
- quantification vector $Q \in \{\exists, \, \forall\}^n$
- matrix A, right-hand side vector b, objective vector c

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Problem statement:

$$\min_{x^{(1)}} \left(c^{(1)} x^{(1)} + \max_{x^{(2)}} \left(c^{(2)} x^{(2)} + \min_{x^{(3)}} \left(\dots + \min_{x^{(\beta)}} c^{(\beta)} x^{(\beta)} \right) \right) \right)$$

s.t.
$$Q \circ x \in \mathcal{D}$$
: $Ax \leq b$

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$$\exists x_1 \in [l_1, u_1]_{\mathbb{Z}} \ \forall x_2 \in [l_2, u_2]_{\mathbb{Z}} \ \exists x_3 \in [l_3, u_3]_{\mathbb{Z}} \ \forall x_4 \dots : Ax \leq b$$



Robust Runway Scheduling



Motivated by cooperative research with FAU Erlangen (Frauke Liers).

A. Heidt, H. Helmke, F. Liers, and A. Martin. Robust runway scheduling using a time-indexed model. In D. Schäfer, editor, Proceedings of the SESAR Innovation Days (2014) EUROCONTROL, 2014. ISBN 978-2-87497-077-1.



- Set of time slots $W = \{1, \dots, T\}$
- Set of airplanes $A = \{1, \dots, n\}$



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B-Matching

- Each airplane must be assigned to exactly one time slot
- At most b airplanes can be assigned to each time slot



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- At most b airplanes can be assigned to each time slot

Schedule each airplane to a time slot with minimal overall costs.

The Basic Model



$$\begin{aligned} & \min & & \sum_{i \in A} \sum_{j \in W} c_{i,j} x_{i,j} \\ & \text{s.t.} & & \sum_{i \in A} x_{i,j} \leq b \\ & & & \sum_{j \in W} x_{i,j} = 1 \\ & & & \forall i \in A \\ & & x_{i,j} \in \{0,1\} \end{aligned} \qquad \forall i \in A, j \in W$$



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• Earliest and latest landing time via objective function, additional constraints or specific time windows W_i for each airplane $i \in A$:

The Basic Model



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 Earliest and latest landing time via objective function, <u>additional</u> <u>constraints</u> or specific time windows W_i for each airplane i ∈ A:

$$\mathsf{earliest}_i \leq \sum_{j \in \mathcal{W}} j \cdot x_{i,j} \leq \mathsf{latest}_i \qquad \forall i \in \mathcal{A}$$



Actual time window of arrival is uncertain



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- ∃ a cheap initial plan
- ∀ possible time windows
- ∃ a cheap recovery plan



1	2	3	4	5	6
Airplane 1 1	0	1	5	7	9
Airplane 2 4	1	0	2	5	7
Airplane 3 4	1	0	3	4	7
Airplane 4 5	2	1	0	1	5



1	2	3	4	5	6
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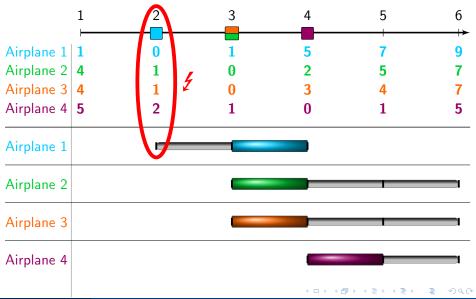


	1	2	3	4	5	6
Airplane 1 Airplane 2 Airplane 3 Airplane 4	4	0 1 1 2	1 0 0	5 2 3 0	7 5 4 1	9 7 7 5
Airplane 1		_				
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	1	2	3	4	5	6
Airplane 1 Airplane 2 Airplane 3	4	0 1 1	1 0 0	5 2 3	7 5 4	9 7 7
Airplane 4	5	2	1	0	1	5
Airplane 1		_				
Airplane 2						
Airplane 3			•			
Airplane 4				-		
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Adding Uncertainty: Costs of replanning



Possible costs for replanning:

a) replanning an airplane result in a fixed fee of ℓ

Adding Uncertainty: Costs of replanning



Possible costs for replanning:

- a) replanning an airplane result in a fixed fee of ℓ
- b) replanning/moving an airplane k time windows costs $k \cdot \ell$

Adding Uncertainty: Costs of replanning



Possible costs for replanning:

- a) replanning an airplane result in a fixed fee of ℓ
- b) replanning/moving an airplane k time windows costs $k \cdot \ell$
- c) replanning an airplane i costs $\tilde{c}_{i,j}$ of the selected time slot j
- d) ... practical knowledge needed

Adding Uncertainty: The Quantified Program



$$\min \sum_{i \in A} \sum_{j \in W} c_{i,j} x_{i,j} + \max \left\{ \min \left\{ \sum_{i \in A} \sum_{j \in W} \ell z_{i,j} \right\} \right\}$$

Adding Uncertainty: The Quantified Program UNIVERSITÄT



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s.t.
$$\exists X \in \{0,1\}^{|A| \times |W|}$$

 $\forall S \in \mathcal{S}, \quad L \in \mathcal{L}$
 $\exists Y \in \{0,1\}^{|A| \times |W|}, \quad Z \in \{0,1\}^{|A| \times |W|}$:

Adding Uncertainty: The Quantified Program Universität



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$$\sum_{j \in W} x_{i,j} = 1 \qquad \sum_{j \in W} y_{i,j} = 1 \quad \forall i \in A$$

$$\sum_{i \in A} x_{i,j} \le b \qquad \sum_{i \in A} y_{i,j} \le b \qquad \forall j \in W$$

$$z_{i,j} \ge y_{i,j} - x_{i,j} \qquad \forall i \in A, \quad j \in W$$

$$s_i \le \sum_{i \in W} j \cdot y_{i,j} \le s_i + l_i \qquad \forall i \in A$$

Adding Uncertainty: The Quantified Program Universität



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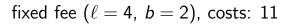
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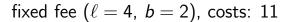
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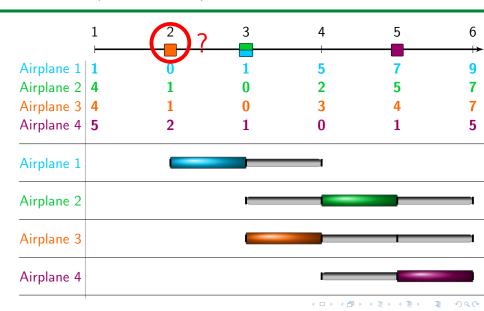


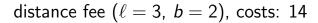


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Restricting Universal Power



We are able to implicitly add an (independent) universal constraint system $A^{\forall}x < b^{\forall}$.

- force the selected interval lengths to be larger than x on average
- forcing the intervals to be "close to" zero-cost time slot

Solving QIPs: The DEP



Interested in first stage solution (here: Initial plan X).

Solving QIPs: The DEP



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- build the deterministic equivalent program:
 - for each "scenario" (assignment of the universal variables) the constraint system is stated explicitly
 - An IP is formed with exponentially growing size regarding the number of universal variables

Solving QIPs: The DEP



Interested in first stage solution (here: Initial plan X).

- build the deterministic equivalent program:
 - for each "scenario" (assignment of the universal variables) the constraint system is stated explicitly
 - An IP is formed with exponentially growing size regarding the number of universal variables
- solve the resulting IP using standard software (CPLEX, Gurobi, etc.)

Problem: rapid growth \Rightarrow insufficient memory + IP is NP-complete



• having an opponent (universal variables) sounds like game playing



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- combine game playing techniques with linear programming techniques



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Advantages:

 no problem storing the instance itself (of course the search tree might grow rapidly)



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Advantages:

- no problem storing the instance itself (of course the search tree might grow rapidly)
- insignificant/easy scenarios (branches) can be cut off

	CPLEX (DEP)] [Yasol (CPLEX as LP Solver)		
Instance	Feas.	Value	Time		Feas.	Value	Time
FP_A7_W9_b2_T147_ol_S40_R73	-	-	3600		feasible	40	33
FP_A5_W7_b2_T190_l_S25_R96	-	-	3600		feasible	25	64
FP_A90_W120_b4_T_I_S_R75	-	-	3600		-	-	3600
FP_A60_W100_b2_T_ol	-	-	3600		-	-	3600
FP_A8_W11_b2_T21_I_S44_R88_EAEA	-	-	3600		feasible	44	9
FP_A5_W7_b2_T2_ol_S25_R96_EA	-	-	3600		feasible	25	1
FP_A60_W110_b2_T_I_S_R96	-	-	3600		infeas.	-	4
FP_A7_W12_b2_T16_ol_S36_R96_EAEA	feasible	36	15		feasible	36	3
FP_A9_W11_b3_T3013_S45_EA	-	-	3600		feasible	45	753
FP_A5_W12_b2_T2_ol_S18_R96_EAEA	feasible	18	1		feasible	18	1
FP_A7_W9_b2_T180_ol_S36_R96	-	-	3600		feasible	36	50
FP_A5_W12_b2_T2_ol_S18_R96_EA	feasible	18	0		feasible	18	1
FP_A5_W14_b2_T360_I_S26_R96_EA	-	-	3600		feasible	26	91
FP_A8_W11_b2_T35_I_S44_R88_EA	-	-	3600		feasible	44	7
FP_A70_W95_b3_T_I_S_R80	-	-	3600		infeas.	-	3
FP_A6_W9_b2_T6_ol_S26_R96_EAEA	feasible	26	5		feasible	26	4
FP_A85_W110_b3_T_I_S_R75	-	-	3600		1	-	3600
FP_A7_W12_b2_T21_ol_S36_R96_EA	feasible	36	15		feasible	36	4
FP_A5_W7_b2_T2_ol_S25_R96	-	-	3600		feasible	25	1
FP_A30_W50_b2_T_ol	-	-	3600		infeas.	-	2
FP_A7_W9_b2_T82_ol_S40_R92	-	-	3600		feasible	40	46
FP_A9_W11_b3_T2490_S45_EAEA	-	-	3600		feasible	45	1052
FP_A7_W9_b2_T122_ol_S41_R86	-	-	3600		feasible	41	42
FP_A5_W14_b2_T1068_I_S26_R96_EAEA	-	-	3600		feasible	26	28
FP_A7_W10_b2_T228_ol_S33_R80	-	-	3600		feasible	33	105
FP_A45_W60_b2_T_I_S_R78	-	-	3600		infeas.	-	2
FP_A5_W7_b2_T2_ol_S25_R96_EAEA	-	-	3600		feasible	25	1
FP_A150_W200_b4_T_I_S_R80	-	-	3600		-	-	3600
FP_A6_W9_b2_T6_ol_S26_R96_EA	feasible	26	5		feasible	26	3
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Investigated matching problem under uncertainty



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- Used quantified programs to model and solve them



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Enhancing and improving the model



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- Enhancing and improving the model
- how does a realistic/relevant instance look like?



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- Used quantified programs to model and solve them
- Our general QMIP solver beats the DEP approach (Cplex) on those instances

- Enhancing and improving the model
- how does a realistic/relevant instance look like?
- design problem specific heuristics to attack relevant instances

Thank you!

App: The Deterministic Equivalent Program



The original QIP

App: The Deterministic Equivalent Program



The original QIP

The corresponding DEP

App: The Deterministic Equivalent Program



The original QIP

The corresponding DEP

Solution of DEP:

$$k = 2$$
 $x_1 = 1$ $x_3^0 = 0$ $x_3^1 = 0$