

ARRIVAL Project



Robust & Online Railway Optimization The ARRIVAL Experience

Christos Zaroliagis (project coordinator) R.A. Computer Technology Institute, Greece

Algorithms for Robust and online Railway optimization: Improving the Validity and realiAbility of Large scale systems IST FET STREP FP6-021235-2

RailZurich2009 [12 February 2009]





- Advanced Algorithmic Research for planning optimization of large-scale and highly-complex systems
- ARRIVAL case study: railway systems
 - Most complex & largest in scale transportation setting
 - Railway Optimization Problems: Planning & scheduling over several time horizons



ARRIVAL Consortium



CTI (R.A. Computer Technology Institute, Greece) coordinator & site leader: *Christos Zaroliagis*

UniKarl (Universität Karlsruhe, Germany) – site leader: *Dorothea Wagner* **TUB** (Technische Universitaet Berlin, Germany) – site leader: *Rolf Möhring* **UniGoe** (Universität Goettingen, Germany) – site leader: *Anita Schöbel*

EUR (Erasmus University Rotterdam, Netherlands) – site leader: *Leo Kroon* **TUE** (Techn. Universiteit Eindhoven, Netherlands) – site leader: *Leen Stougie*

ETHZ (Eid. Tech. Hochschule Zürich, Switzerland) – site leader: *Peter Widmayer*

ULA (Universita degli Studi dell' Aquila, Italy) – site leader: Gabriele Di Stefano
UniBo (University of Bologna, Italy) – site leader: Paolo Toth
DEI (Dept. of Information Engineering, University of Padova, Italy) site leader: Matteo Fischetti

USE (University of Seville, Spain) – site leader: *Juan Mesa* UPVLC (Universidad Politecnica de Valencia, Spain) site leader: *Federico Barber*

SNCF (Société Nationale des Chemins de Fer, France) site leader: *Christian Weber*



Project Focus



• Focus: deal with *disruptions*



Robust planning (proactive approach)

- Online planning (reactive approach)



Project Focus



Robust plan

 maintains feasibility and as much as possible of the quality of an optimal solution

Online plan

 retains as much as possible of the quality of a solution that would have been achieved if the entire sequence of disruptions was known in advance





- Foundational algorithmic research for robust and online planning of complex & large-scale (railway) systems
- Measuring (the "prices" of)
 - *Robustness* of a plan (trade-off between optimal & robust plan)
 - *Recoverability* of a plan (trade-off between online & optimal plan)



Interaction: may have conflicting objectives

 Understand the interplay between strategic (off-line) planning, robustness issues, and online planning





 Hierarchical breakdown may waste optimization potential



• Can integration of planning stages gain optimization potential ?





- Generic foundational framework for robust and online large-scale optimization
- Measure robustness and recoverability of plans
- Understand interaction between online, offline, and robust planning
- Explore integration of planning stages
- Identify the technically mature methods and experimentally validate their theoretical performance





- New concepts of measuring robustness and recoverability of plans
- Integration of planning stages to gain further optimization potential
- Algorithmic game-theoretic approaches for robust network and line planning
- New multidisciplinary models & methods for
 - Robust & online timetabling
 - Resource rescheduling
 - Timetable information querying and updating
 - Delay management



A few Key Results



- Robust Optimization
 - Recoverable Robustness & Related Concepts
 - Train Platforming
 - Delay Management
 - Timetabling
 - Line Planning
- Online Optimization
 - Crew Re-scheduling
 - Timetable Information Querying & Updating
 - Freight Train Classification





General & powerful model

- Distinguish between
 - original optimization problem
 - imperfection of information, introduced by some scenario s
 - limited recovery possibilities
- Planning phase
 - compute a (feasible) solution x
 - Scenario s turns x to infeasible (by adding more constraints)
 - choose recovery algorithm A
- Recovery phase
 - algorithm A turns x into feasible solution under s (new set of constraints)



Price of Robustness of instance I

$$PoR(I) = \frac{\min_{(x,A) \in P \times \mathcal{A}} \{ f(x) \mid \forall s \in S : A(x,s) \in P_s \}}{\min\{f(x) \mid x \in P\}}$$

Price of Robustness = max{*PoR(I)*: for all I}

Price of Recoverability = min{*PoR(I)*: for all I}

	Flexible response	Compact model	Guaranteed Performance
2 Stage Stoch. Programming	~	*	*
Strict (classical) Robustness	×	\checkmark	\checkmark
Recoverable Robustness	~	~	~

Christos Zaroliagis



Recoverable-Robust Train Platforming



Train Platforming Problem (TPP)

- Study on real-world data
- Heuristic robustification of standard TPP model replaced by exact recovery-robust model
- Same nominal quality (throughput)
- Delay reduced by 25% on average
- Re-use of existing algorithm for TPP (off-theshelf implementation)

Recoverable-Robust Train Platforming





ARRIVAL-TR-0157, RailZurich 2009

"Recovery-Robust Platforming by Network Buffering" by Alberto Caprara, Laura Galli, Sebastian Stiller, Paolo Toth.







Multistage recoverable robustness

- Usually a sequence of delays appears
- A recovered timetable has to be robust against the next delay
- The recovered solution should again be robust to the next delay, and so on ...

We identified algorithms which are robust for multiple recoveries



Delay Management



Graph = Path



Christos Zaroliagis

RailZurich2009 [12 February 2009]



Robust Timetabling



Problem:

- optimized timetables might be too sensitive to disturbances
- need to adjust a given optimal timetable to be robust (allowing for some efficiency loss)

<u>Goal:</u>

• To find a fast (yet accurate) algorithm to improve the robustness of a timetable

Testing framework:







Common assumptions for "robustness training" methods:

- Allow for some percentage efficiency loss
- Limit the set of planning actions (good for small disturbances, leads to more tractable models)
 - => add buffer times (= stretch travel times)



Robustness training methods tested:

- Unif.: uniform allocation of buffer times (e.g. 7% nominal travel time)
- *Fat*: scenario-based stochastic programming formulation, aiming at minimizing expected delay
- Slim: heuristic version of *Fat* leading to a more tractable MIP formulation
- *LR*: Light Robustness (Fischetti and Monaci '08, ARRIVAL-TR-0119)



Robust Timetabling



<u>Results (10% efficiency loss w.r.t. the input timetable): (*)</u>



- Unif. is very fast but is the worst as to robustness
- Fat achieves the best robustness but is very slow
- LR is a good compromise between robustness and performances (~1000x faster than Fat)

^(*) average on 4 real congested corridors from Italian railway company



Incentive-Compatible Robust Line Planning



Line planning problem

- Line operator (LOP)
 - Competing entity: bids for getting
 - frequency
 - Private utility function
- Network operator: ensure fairness in ...
 - Max satisfaction of LOPs (social optimum)
 - Cost sharing of resources
- Provide solution that is robust against ...
 - Unknown preferences
 - Elastic frequency demands





Incentive-Compatible Robust Line Planning



Incentive-Compatible Robust Solution

- $R = \frac{p \quad q}{ut}$ $R = \frac{v \quad 1 \quad 0}{v \quad 1 \quad 1}$
- Robustness against imperfect knowledge (unknown utilities)
- *Recovery Scheme* to the unknown social optimum
 - Mechanism-design instance of a frequency game
 - Decentralized, dynamic, resource pricing and frequency allocation algorithm that converges to the social optimum

Online Crew Re-scheduling



7			Ut 3012	Asd	3012 Ar	mr 3012		Н	dr 30	033		A	mr :	3035 A	sd 303	85										
			16 4	6 49	19 21	56		33	3	9		42	2	14 1	74	7										
6	Amr	3019	Asd 301	9 Ut	3019		AI	h 3022	Ut	3022	As	d 3022	2													
	42	14	17 4	7 50	24		8	2	13 46		16 19	49	9													
5			Amr 30	08		Hdr 302	9 /	Amr 302	29 A	sd 30	29 Ut	3029	_		A	h 303	32	Ut 30	32 As	d 303	2					
			20	55		33	9 ~	12 4	44 47	,	17 20) :	54		3	8	13	16	46 49	19	9					
4	Hdr 302	1 A	mr 3021	Asd	3021 Ut	3021	Ah	Nm	Ar 3	024	Ut	3024	Asc	3024		An	nr 302	26								
	33	9 1	2 44	47	17 20	54	59	20	38	1	3 16	46	49	19		51		26								
3	Hdr 302	1		Am	r 3010		Hdr	3031	Am	r 303	1 Asc	3031	Ut	3031	Ah	Nm	Ah	3034	Ut	3034	Asd	3034 Ar	nr 30	34		
	33	9		50	25		3	39	9 42	1	4 17	47	50	24	4 29	50	8		43 46	16	19	49 51		26		
2					Hdr 302	27 Amr	3027	Asd 30	027			l	Ut 3	3026 /	Asd 30	26		Amr	3028							
					3	39 42	14	17	4			2	46	16 1	19	49		21	56							
1							Hdr	3031	_		Amr	3033	Asd	3033		Ut	3035	A	h Nn	n Ah	3038	3 Ut 3	3038	Asd	3038 An	nr 3038
							3	39)		12	44	47	17		50		24 29	9 50	8		43 46	16	5 19	49 51	26
		600			700		800)		90	0			1000			1100	C		1200)		130	0		1400

Disrupted crew duties

Online Crew Re-scheduling



7			Ut 3012	2 Asd	3012 An	nr 3012		Н	dr 3	8033	_		Am	r 3(035 A	sd 3	3035	Ut	3035	Ah	Nn	n Ah	3038	В				
			16	46 49	19 21	56		3	3	9			42		14 1	7	47	50	24	1 29	50	8		43				
6	Amr	3019	Asd 30	19 Ut	3019		A	h 3022							U	t 30	28	Asd	3028									
	42	14	17	47 50	24		8	2	43						1	6	46	49	19									
5			Amr 3	8008		Hdr 302	9 /	Amr 302	29						/	Asd	3026	Am	r 3026	Н	dr 304	5						
			20	55		33	9 ′	12 4	44							19	49	51	2	6 33	}	9						
4	Hdr 302	1 A	mr 302	1 Asd	3021 Ut	3021	Ah	Nm	Ał	3024		Ut 3	8029				Ah	303	2 U	3032	2 Asc	303	2 Amr	3032				
	33	9 1	2 4	4 47	17 20	54	59	20	38		13	20	54	1			38		13 16	6	46 49	19	9 21	56				
3	Hdr 302	1		Am	r 3010		Hdr	r 3031	A.m	nr 30	31	Asd	3022							Amr 3	3028							
	33	9		50	25		3	39	9 42		14	19	49							21	56							
2					Hdr 302	7 Amr 3	3027	Asd 30	027				ι	Jt 3	3031	А	h	Nm	Ah 3	3034	Ut 3	3034	Asd	3034 An	nr 3034	_		
					3	39 42	14	17	47				5	50	2	4 29	9	50	8	4	3 46	16	19	49 51	2	6		
1							Hdr	r 3031			A	mr 30	033 A	١sd	3024				Am	r 304	1 Asd	3041		Ut 3	038 A	sd 3	038 An	nr 3038
							3	39	9		12	2	44 4	9	19				12	4	4 47	17		46	16 1	9	49 51	2
		600			700		800)		9	00			1	1000				1100			1200)		1300			1400

Rescheduled crew duties

Christos Zaroliagis





- New method does not start from scratch
 - Implemented in practice
 - Reduces the re-scheduling throughput time significantly
- Adopted and used on a daily basis by NS

Timetable Information Querying & Updating



New techniques based on shortcutting & arc flags (SHARC)



Christos Zaroliagis

Online Train Classification



Freight Train Classification

- Developed powerful encoding for classification schedules
- Conducted algorithmic study yielding deeper understanding of optimal multistage sorting methods



- Derived useful integer programming formulation from encoding
- Modeled additional realworld constraints
 - Found improved classification schedule on classification yard Lausanne-Triage







- **EUR and DEI teams** won the *2008 Edelman Award* of INFORMS for the practical applicability of their methods to develop the 2007 timetable of NS
- Anita Schoebel (UniGoe site leader) received the 2007
 Klaproth-Preis for her railway-related research
- **Cor Hurkens** (TUE member) received the *First Prize of the* 2007 ROADEF Challenge for his algorithm to sequence maintenance and repair jobs
- **Christian Liebchen** (TUB member) received the *2007 HEUREKA Foerderpreis* of young scientists for his theoretical and practical work on Transport Optimization
- **Denis Huisman** (EUR member) finalist in the *2007 EURO Excellence in Practice award* for his crew rescheduling algorithm





- 40% common publications, 5 common PhDs
- SpringerLink
 Lecture Notes in
 Computer Scien
 - Algorithmic Methods for Railway Optimization, LNCS Volume 4359, 2007.
 - Robust and Online Large-Scale Optimization, forthcoming, 2009.
- Cooperation with railway companies (NS, SNCF, DB, SBB, FI, ...)



 TOPSU - Tool for Optimal planning & Steering under Uncertainty



 LinTim - Interaction between line planning, timetabling and delay management



 Time-dependent routing prototype (TomTom) mation Societ

CONCLUSIONS



ARRIVAL ...

- has not solved all problems in robust & online railway optimization
- .. but has done quite some progress
- Formed a critical mass of researchers, who
 - have understood real-world problems
 - advanced the theory to solve them
 - ready to bring this knowledge into practice

Thank you!