



Faculty of Transportation and Traffic Sciences "Friedrich List"

Institute for Traffic Telematics • Chair of Traffic Control and Process Automation



The Impact of Request Stops on Railway Operations

Christian Gassel, Dipl.-Ing.; Thomas Albrecht, Dr.-Ing.

Faculty of Transportation and Traffic Sciences "Friedrich List", TU Dresden





Agenda

- 1. Introduction
- 2. Present Request Stop Usage
- 3. Modeling Train Approaches at Request Stops
- 4. Optimizing Energy Consumption and Delays
- 5. Case Study
- 6. Conclusions



1. Introduction

2. Present Request Stop Usage

3. Modeling Train Approaches at Request Stops

.

1. Introduction

- Wide variety of measures to reduce energy costs
- Request stop train only stops on demand
 - → Influence on energy consumption unknown
 - → Significant difference for energy optimization



- Time slack with compulsory stops only:

$$t_r = \sum_{i=1}^n t_{F,i}$$

Scheduled time slack

- Time slack with request stops:

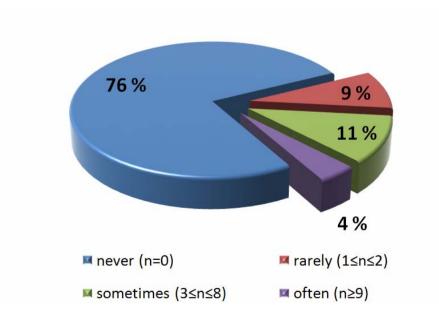
$$t_r = \sum_{i=1}^{n} t_{F,i} + \sum_{j=1}^{m} t_{g,j}$$

Additional time gain

3. Modeling Train Approaches 4. Optimizing energy consumption and delays ...

2. Present Request Stop Usage

Strongly varying usage of request stops on German railway lines

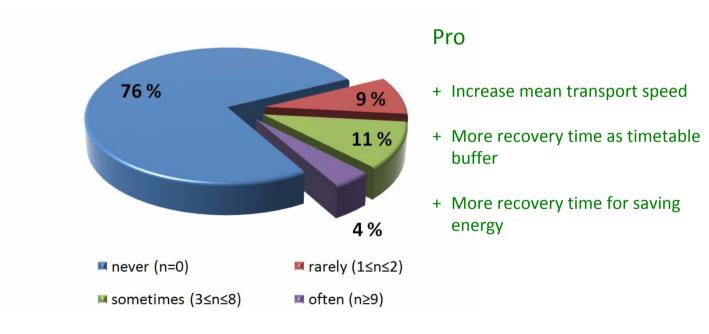


Appearance of request stops on local German railway lines (01/2008)

3. Modeling Train Approaches 4. Optimizing energy consumption and delays ...

2. Present Request Stop Usage

Strongly varying usage of request stops on German railway lines



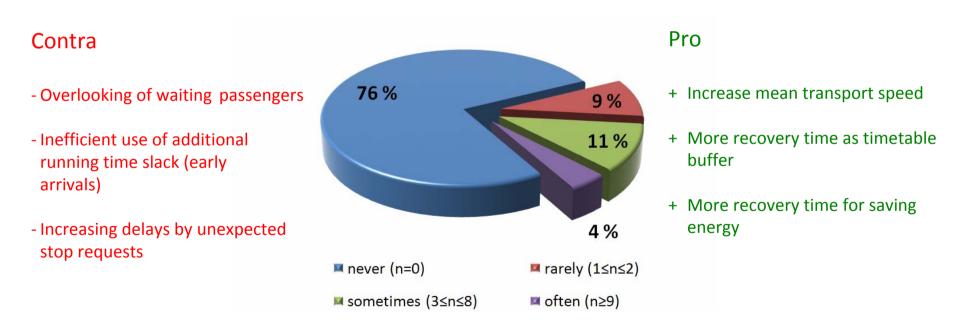
Appearance of request stops on local German railway lines (01/2008)



3. Modeling Train Approaches 4. Optimizing energy consumption and delays ...

2. Present Request Stop Usage

Strongly varying usage of request stops on German railway lines



Appearance of request stops on local German railway lines (01/2008)



3. Modeling Train Approaches 4. Optimizing energy consumption and delays ...

Task for Modeling and Optimization:

Find the optimal driving strategy considering the features of request stops!

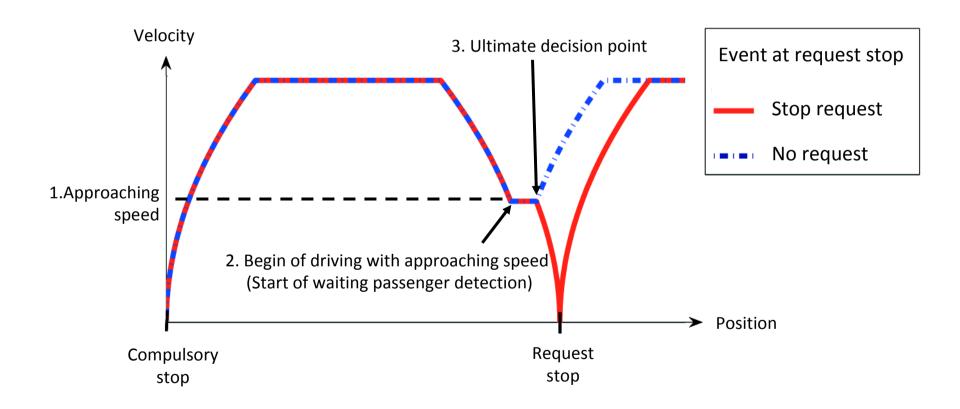
- **Energy-efficient** and **timetable consistent** distribution of time slack
- Appropriate model of train approaches at request stops



4. Optimizing Energy Consumption and Delays

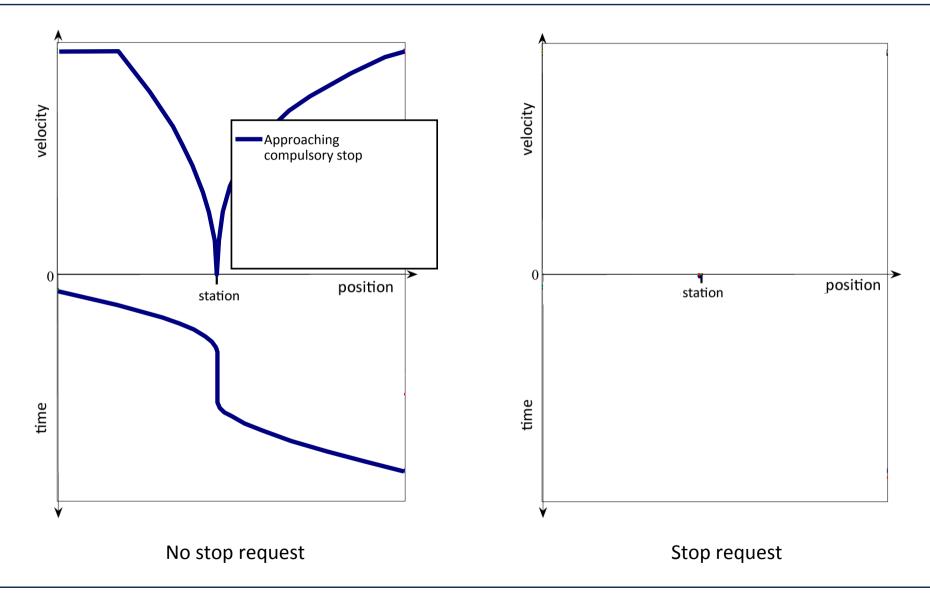
5. Case Study ...

3. Modeling Train Approaches at Request Stops



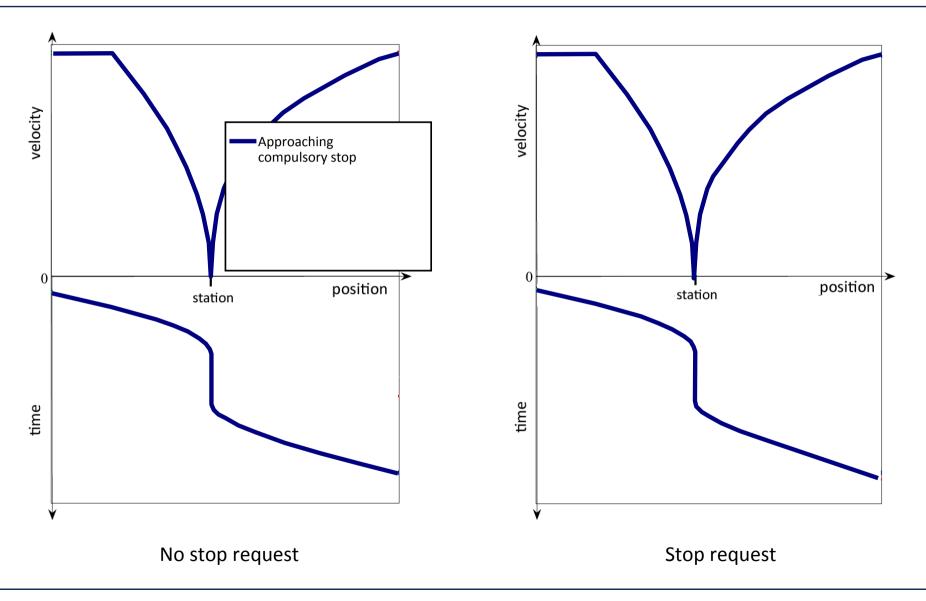


4. Optimizing Energy Consumption and Delays



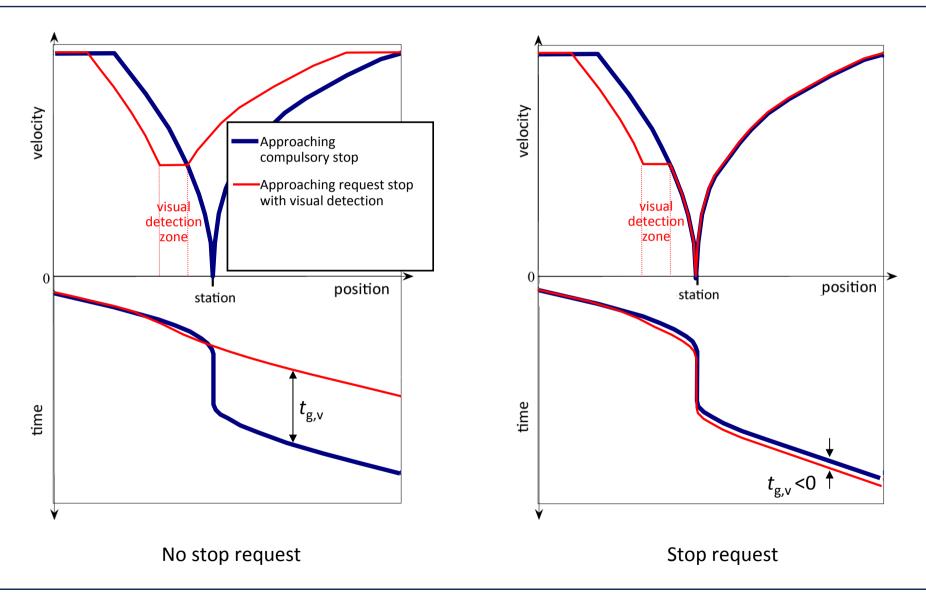


4. Optimizing Energy Consumption and Delays



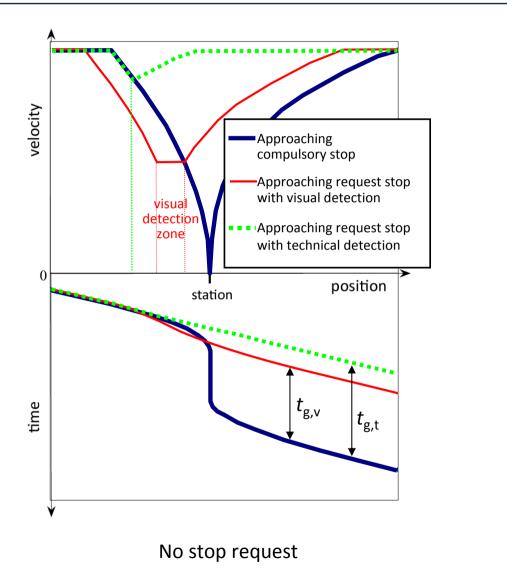


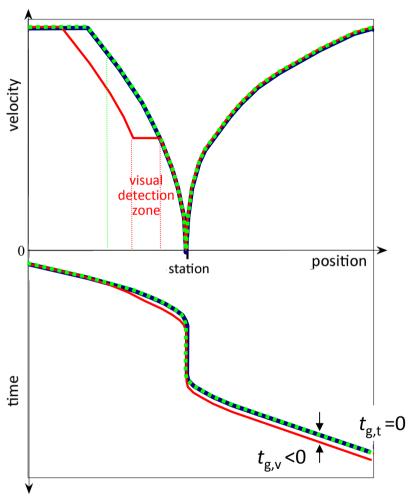
4. Optimizing Energy Consumption and Delays





4. Optimizing Energy Consumption and Delays





Stop request

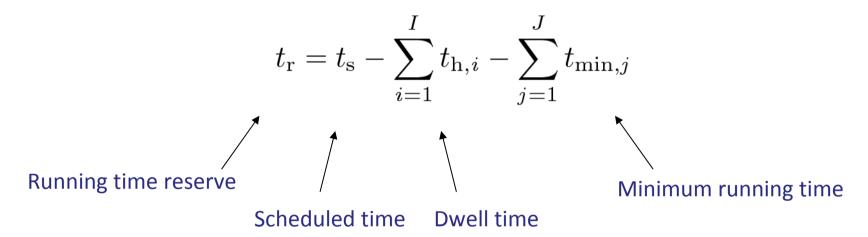


5. Case Study

6. Conclusions

4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves





5. Case Study

6. Conclusions

4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves

$$t_{\mathrm{r}} = t_{\mathrm{s}} - \sum_{i=1}^{I} t_{\mathrm{h},i} - \sum_{j=1}^{J} t_{\mathrm{min},j}$$

- Prediction of dwell times in categorical clusters
- Analysis of alighting and boarding passenger data



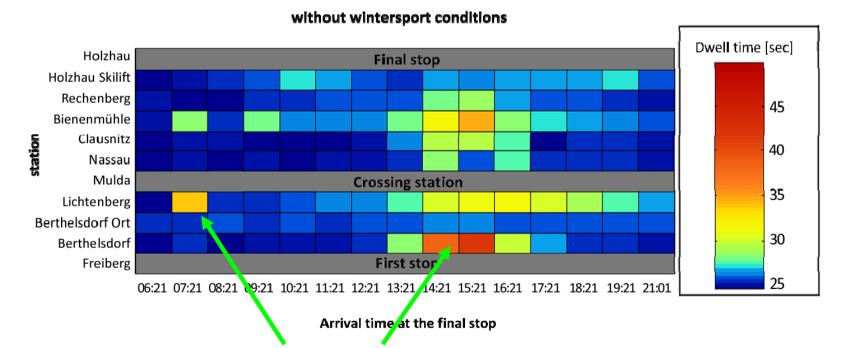
5. Case Study

6. Conclusions

4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves

Train rides from monday to friday



Identification of long dwell times \leftrightarrow small running time reserves

5. Case Study

6. Conclusions

4. Optimizing Energy Consumption and Delays

4.2 Time Slack Distribution Algorithm

- Distribution of time slack on each section by Dynamic Programming
- Strategies of distributing time gain:

(1) re-active distribution

- Assumption: Each request stop will be served
- No distribution of time gain t_g before this assumption is rejected (passing the request stop)
- No delays because of request stops

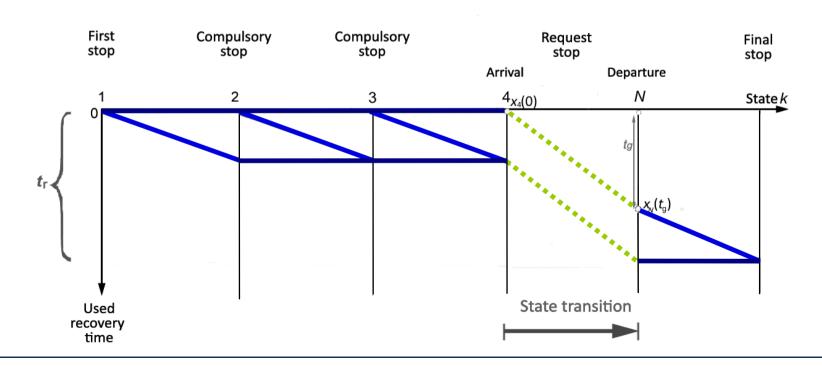


5. Case Study

6. Conclusions

Re-active distribution strategy

- Main assumption: train has to serve the request stop



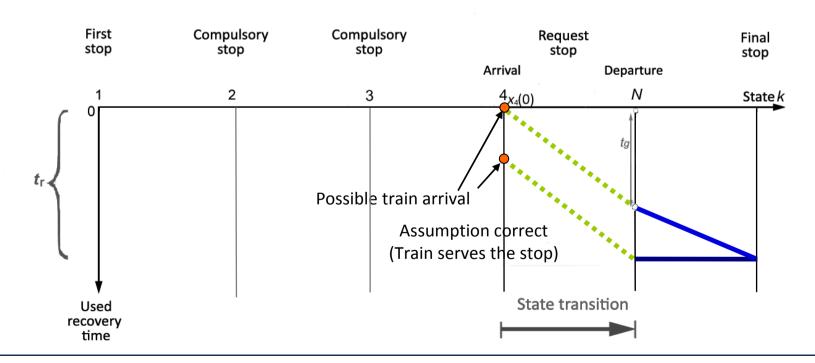


5. Case Study

6. Conclusions

Re-active distribution strategy

- Main assumption: train has to serve the request stop



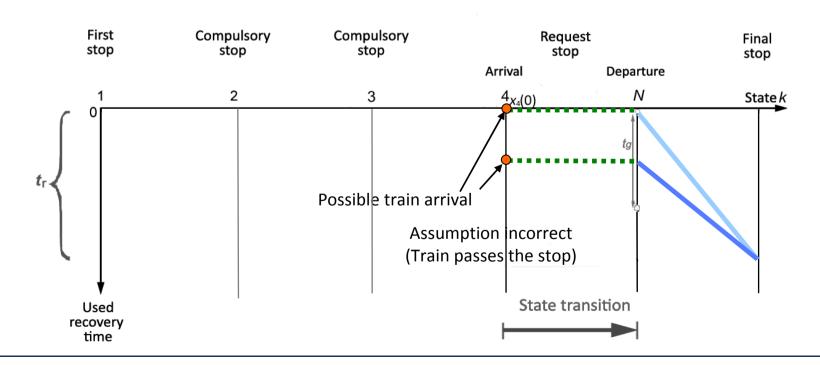


5. Case Study

6. Conclusions

Re-active distribution strategy

- Main assumption: train has to serve the request stop

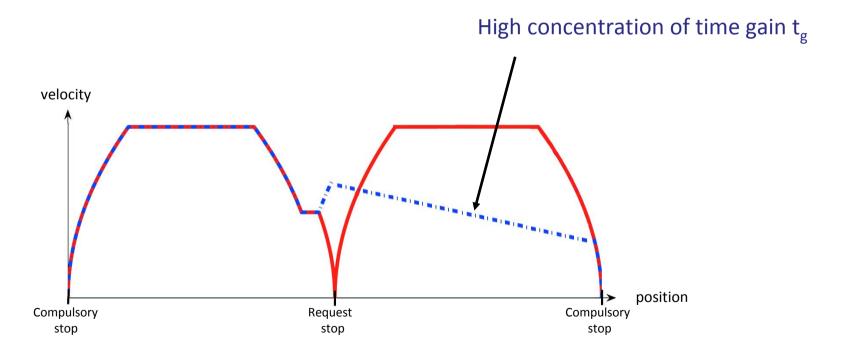




5. Case Study

6. Conclusions

Re-active distribution strategy





5. Case Study

6. Conclusions

4. Optimizing Energy Consumption and Delays

- 4.2 Time Slack Distribution Algorithm
- Distribution of time slack on each section by Dynamic Programming
- Strategies of distributing time gain:
- (1) re-active distribution (assumption: train will definitely stop)
- (2) pro-active distribution (assumption: train will pass with a certain probability)

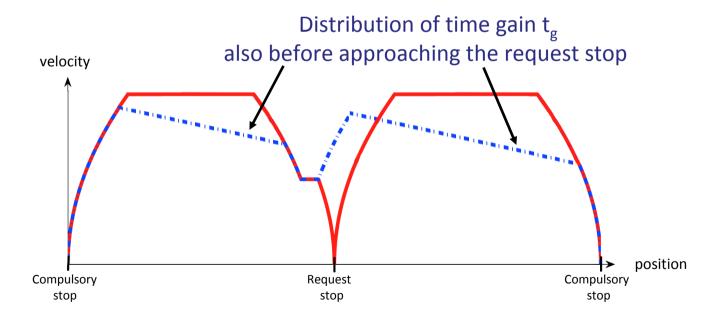


5. Case Study

6. Conclusions

Pro-active distribution strategy

- Distribution of time gain on all sections
- Delays are accepted for the benefit of less energy consumption





5. Case Study

6. Conclusions

Pro-active distribution strategy

- Approach: Probabilistic state transition at request stops
 - → involving stopping probability of each stop

Train rides from monday to friday

without wintersport conditions Stopping probability Holzhau Final stop Holzhau Skilift Rechenberg 8.0 Bienenmühle Clausnitz 0.6 Nassau **Crossing station** Mulda 0.4 Lichtenberg Berthelsdorf Ort 0.2 Berthelsdorf First stop Freiberg

Arrival time at the final stop

06:21 07:21 08:21 09:21 10:21 11:21 12:21 13:21 14:21 15:21 16:21 17:21 18:21 19:21 21:01

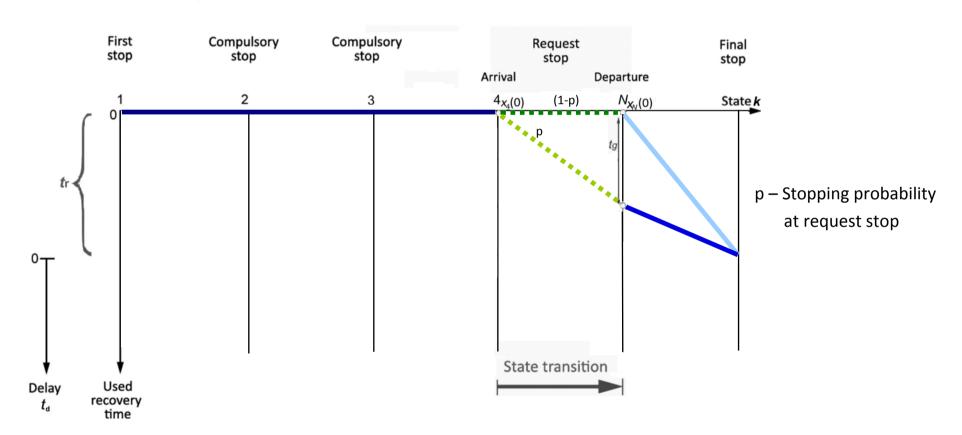
0



5. Case Study

6. Conclusions

Pro-active distribution strategy



$$Q_i(k, x_k) = p \cdot Q_i(k+1, x_{k+1}, z_{k+1} = t_g) + (1-p) \cdot Q_i(k+1, x_{k+1}, z_{k+1} = 0)$$

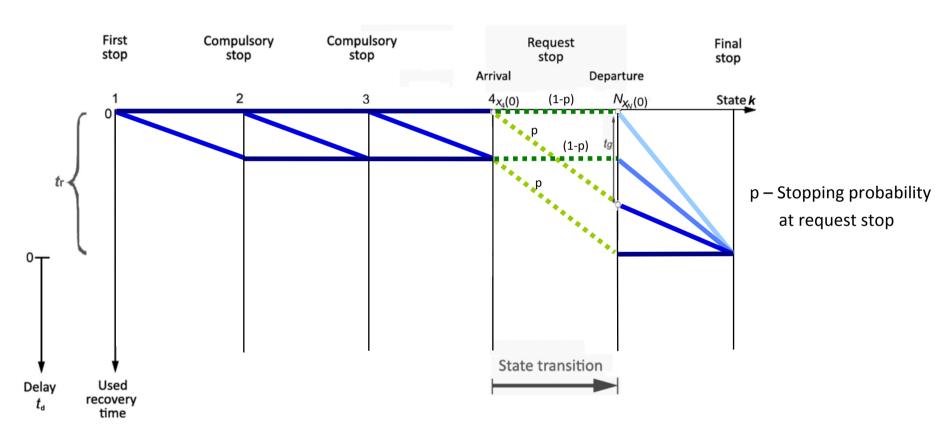
Cost functions Q_1 – energy consumption; Q_2 – delay



5. Case Study

6. Conclusions

Pro-active distribution strategy



$$Q_i(k, x_k) = p \cdot Q_i(k+1, x_{k+1}, z_{k+1} = t_g) + (1-p) \cdot Q_i(k+1, x_{k+1}, z_{k+1} = 0)$$

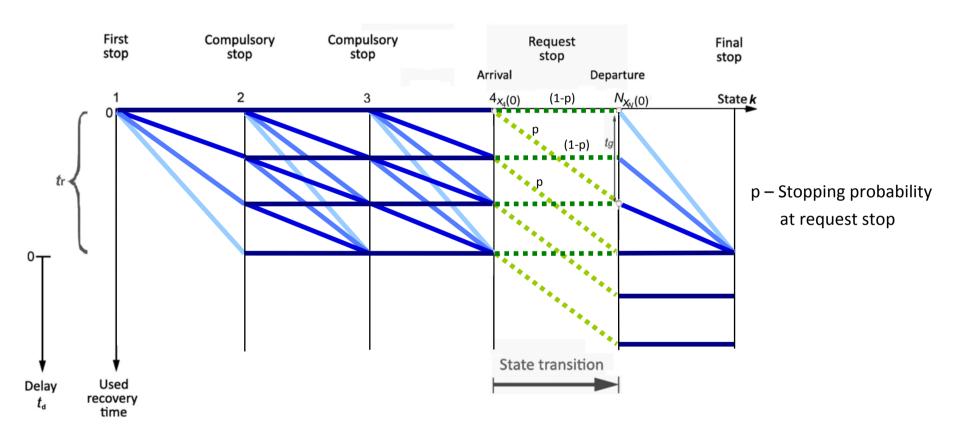
Cost functions Q_1 – energy consumption; Q_2 – delay



5. Case Study

6. Conclusions

Pro-active distribution strategy



$$Q_i(k, x_k) = p \cdot Q_i(k+1, x_{k+1}, z_{k+1} = t_g) + (1-p) \cdot Q_i(k+1, x_{k+1}, z_{k+1} = 0)$$

Cost functions Q_1 – energy consumption; Q_2 – delay



5. Case Study

6. Conclusions

4.3 Schedule-related Optimization Constraints

Classification	Parameter			
Hard constraint	 earliest arrival fulfilling connection service latest departure time fulfilling connection service earliest scheduled departure time 			
Soft constraint	- Latest scheduled arrival time			



5. Case Study

6. Conclusions

4.3 Schedule-related Optimization Constraints

Classification	Parameter
Hard constraint	 earliest arrival fulfilling connection service latest departure time fulfilling connection service earliest scheduled departure time
Soft constraint	- Latest scheduled arrival time

Hard constraint

- Deviations for the benefit of less energy consumption prohibited
- Restricted search space within Dynamic Programming



5. Case Study

6. Conclusions

4.3 Schedule-related Optimization Constraints

Classification	Parameter			
Hard constraint	 earliest arrival fulfilling connection service latest departure time fulfilling connection service earliest scheduled departure time 			
Soft constraint	- Latest scheduled arrival time			

Hard constraint

- Deviations for the benefit of less energy consumption prohibited
- Restricted search space within Dynamic Programming

Soft constraint

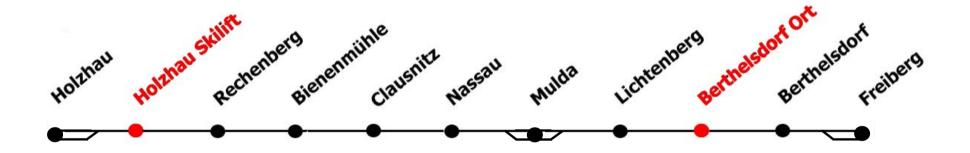
- Small delays at low frequented stops are tolerable
- Delay cost function is weighted stationwise by boarding/alighting passengers
- Trade-off cost function as a compromise between oppositional optimization goals



6. Conclusions

5. Case Study

• Single track line with two request stops



- Crossing station Mulda
 - Scheduled times treated as hard constraints → no interference with oncoming trains
- Train Model: DMU RegioShuttle 1 (StadlerRail)

6. Conclusions

• Simulation of 4 request stop scenarios with present time table (168 train rides)

[%] Present Minimum Moderate scenario Freiberg Berthelsdorf Drt Serthelsdorf Ort X X X X	Maximum scenario
Freiberg Berthelsdorf 21	scenario
Berthelsdorf 21	
Berthelsdorf Ort Lichtenberg Mulda Nassau Clausnitz Bienenmühle Rechenberg Holzhau Skilift Holzhau X X X X X X X X X X X X X	x x x x x x

^{*} Annual volume of boarding and alighting passengers in relation to Freiberg

Total number of stopping events [%]	100		
Avg. energy consumption [%]	100		



6. Conclusions

• Simulation of 4 request stop scenarios with present time table (168 train rides)

Course	Passenger Vol.*	Request stop scenario						
	[%]	Present	Minimum	Moderate	Maximum			
		state	scenario	scenario	scenario			
• Freiberg	100)							
Berthelsdorf	2 1				Х			
Berthelsdorf Ort	5	Х	Х	Х	Х			
Lichtenberg	29				Х			
Mulda	41							
Nassau	7		Х	Х	Х			
Clausnitz	9			Х	Х			
Bienenmühle	24				Х			
Rechenberg	14			Х	Х			
Holzhau Skilift	7	Х	Х	Х	Х			
Holzhau	26							
	* A servel velves of bounding and alighting account in solution to Facilities							

^{*} Annual volume of boarding and alighting passengers in relation to Freiberg

Total number of stopping events [%]	100	93	81	70
Avg. energy consumption [%]	100	95	88	81

6. Conclusions

Further results

- In spite of pro-active distribution acceptable delays
 - No delays at important stops (crossing station; major interchange stations)
 - $t_{d,90} < 30 \text{ sec}$
- Slight changes in timetable allows further increases in energy efficiency



6. Conclusions

Further results

- Comparison at the TU Dresden Driving Simulator: Experienced driver vs Algorithm
 - → Testing a line with 5 request stops (Medium scenario)

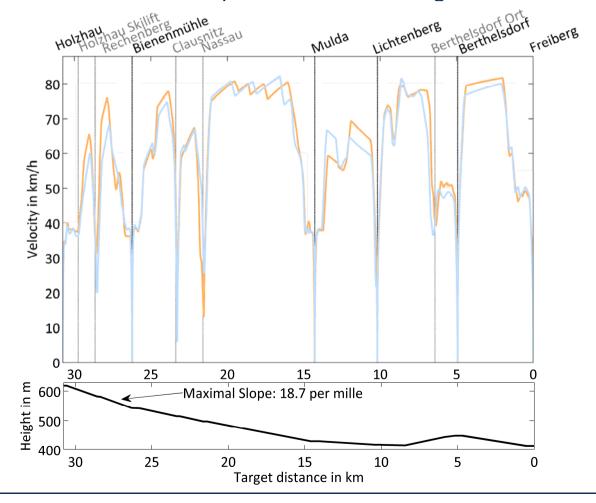




6. Conclusions

Further results

• Comparison at the TU Dresden Driver Simulator: Experienced driver vs Algorithm

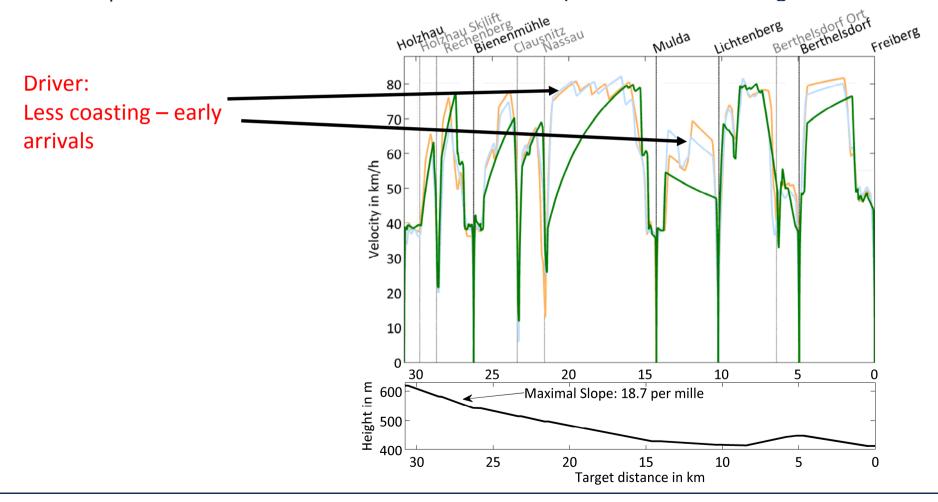




6. Conclusions

Further results

• Comparison at the TU Dresden Driver Simulator: Experienced driver vs Algorithm





6. Conclusions

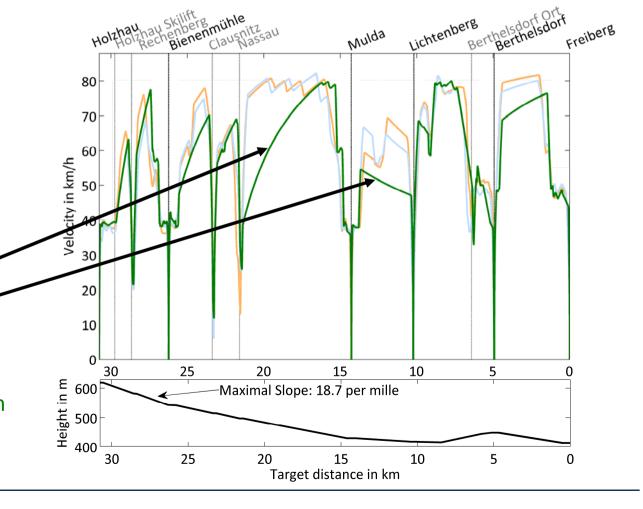
Further results

• Comparison at the TU Dresden Driver Simulator: Experienced driver vs Algorithm



Assistance:
Investing time gain in
longer ranges of coasting

→ 20% less energy consumption



6. Conclusions

6. Conclusions

- Request stops reveal a high potential of saving energy
- Taping these potentials requires an assistance system
 - probabilistic assumptions based on passenger statistics
 - pro-active distribution of time slack
- Delays can be confined effectively
 - by defining optimization constraints
 - by using a trade-off cost function (Multi-criterion Optimization)
- Energy optimization for tramway systems

