The Impact of Request Stops on Railway Operations

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Faculty of Transportation and Traffic Sciences „Friedrich List“, TU Dresden
The Impact of Request Stops on Railway Operations

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

- 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

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

- Time slack with compulsory stops only:

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

Scheduled time slack

Additional time gain
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)
2. Present Request Stop Usage

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Appearance of request stops on local German railway lines (01/2008)
2. Present Request Stop Usage

- Strongly varying usage of request stops on German railway lines

### Contra
- Overlooking of waiting passengers
- Inefficient use of additional running time slack (early arrivals)
- Increasing delays by unexpected stop requests

### Pro
- Increase mean transport speed
- More recovery time as timetable buffer
- More recovery time for saving energy

*Appearance of request stops on local German railway lines (01/2008)*
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
3. Modeling Train Approaches at Request Stops

- 1. Approaching speed
- 2. Begin of driving with approaching speed (Start of waiting passenger detection)
- 3. Ultimate decision point

Event at request stop:
- Stop request
- No request
3. Modeling Train Approaches

4. Optimizing Energy Consumption and Delays

5. Case Study ...

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3. Modeling Train Approaches

4. Optimizing Energy Consumption and Delays

5. Case Study...

**No stop request**

**Stop request**

- **Approaching compulsory stop**
- **Approaching request stop with visual detection**

$t_{g,v}$
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3. Modeling Train Approaches

4. Optimizing Energy Consumption and Delays

5. Case Study ...

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4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves

\[ t_r = t_s - \sum_{i=1}^{I} t_{h,i} - \sum_{j=1}^{J} t_{\text{min},j} \]

- Running time reserve
- Scheduled time
- Dwell time
- Minimum running time
4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves

$$t_r = t_s - \sum_{i=1}^{I} t_{h,i} - \sum_{j=1}^{J} t_{\text{min},j}$$

- Prediction of dwell times in categorical clusters
- Analysis of alighting and boarding passenger data
4. Optimizing Energy Consumption and Delays

4.1 Prediction of running time reserves

Identification of long dwell times ↔ small running time reserves
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
Re-active distribution strategy

- Main assumption: train has to serve the request stop
Re-active distribution strategy

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Re-active distribution strategy

High concentration of time gain $t_g$
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)
**Pro-active distribution strategy**

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

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

p – Stopping probability at request stop
Pro-active distribution strategy

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

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Cost functions $Q_1$ – energy consumption; $Q_2$ – delay
### 4.3 Schedule-related Optimization Constraints

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<tbody>
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**Hard constraint**
- Deviations for the benefit of less energy consumption prohibited
- Restricted search space within Dynamic Programming
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| 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
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)
### Simulation of 4 request stop scenarios with present time table (168 train rides)

<table>
<thead>
<tr>
<th>Course</th>
<th>Passenger Vol.* [%]</th>
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<td></td>
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<td>Present state</td>
</tr>
<tr>
<td>Freiberg</td>
<td>100</td>
<td>X</td>
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<tr>
<td>Berthelsdorf</td>
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<tr>
<td>Berthelsdorf Ort</td>
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* Annual volume of boarding and alighting passengers in relation to Freiberg

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<th>Total number of stopping events [%]</th>
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<td>Avg. energy consumption [%]</td>
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5. Case Study

6. Conclusions

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

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* 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 |
Further results

- In spite of pro-active distribution – acceptable delays
  - No delays at important stops (crossing station; major interchange stations)
  - $t_{d,90} < 30$ sec

- Slight changes in timetable allows further increases in energy efficiency
Further results

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

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

![Graph showing velocity and height changes with stops and target distance]
Further results

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

Driver:
Less coasting – early arrivals
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

• 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