Design and Optimization of Dynamic Routing Problems with Time Dependent Travel Times and Unknown Customers and the 800 CNG EcoFuel Tour

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Agenda

- Introduction and Background
- Less-than-truckload (LTL) Services
- LTL Routing
- Optimization Model and Analysis
- Time Dependent Travel Times
- Solution Approach
- Exemplary Application to Industrial Problems: The 800 CNG EcoFuel Tour
- Conclusion

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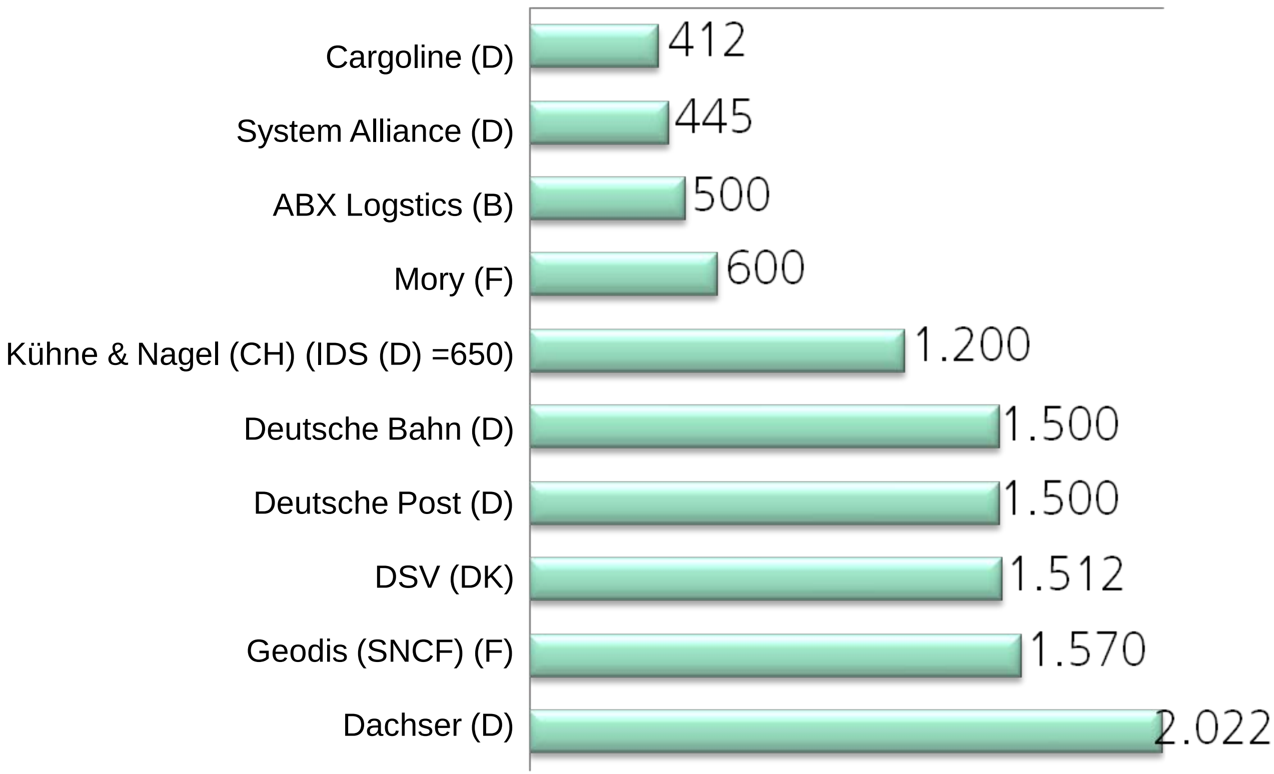
Less-than-Truckload (LTL) Services



European LTL freight - companies and turnover [m. €] (Klaus and Kille 2007)

- **Logistics market: 803 bn. €**
- **LTL Market: 32 bn. €**
- **Market share TOP 10: 35 percent**
- **Partner in co-operations like IDS, Cargoline, 24plus or System Alliance are often SME**

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LTL Freight

Exemplary LTL freight (GPAL, GDV, BAM 2008)

Definition

- **Packed or loose goods up to a weight of three tons**
- **Treated as handling-unit when being transported, transshipped or stored**
- **Palette as standard device**
- **Strongly heterogeneous**
- **Utilization of automatic transshipment devices is difficult**

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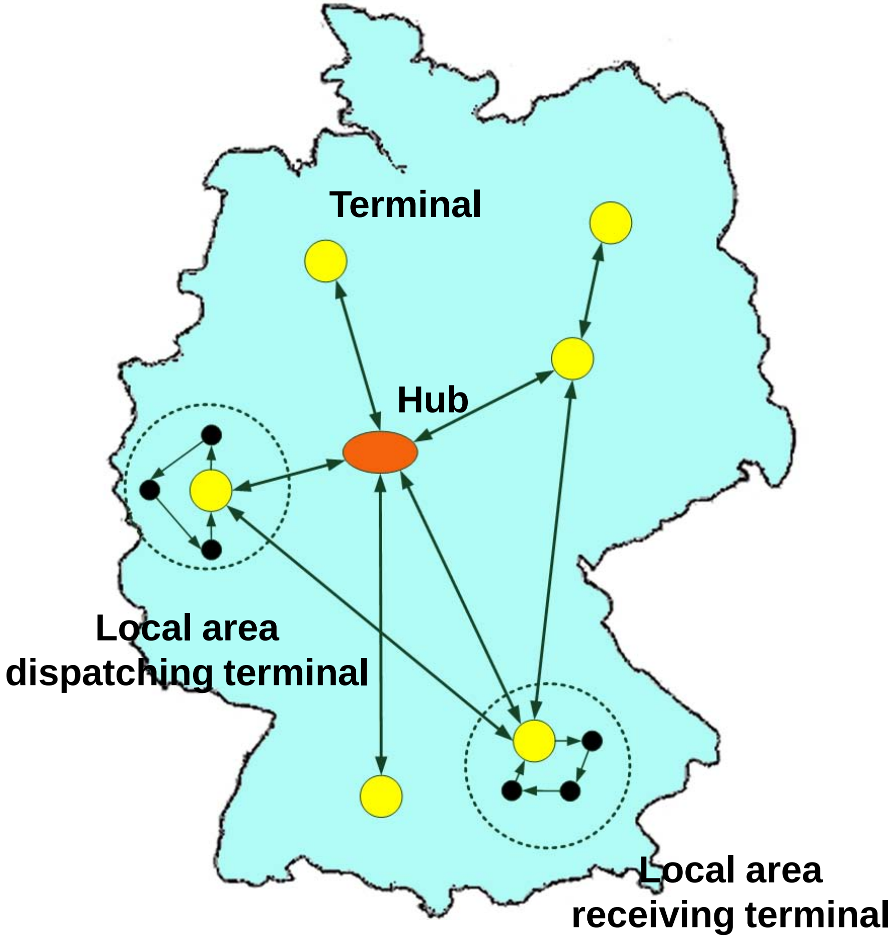
Operations of LTL Networks



- **Preliminary leg (inbound)**
  - Pickup of loads in origin regions (i.e., collection of shipments within short-distance traffic region)
  - Consolidation of commodities for transport
- **Main leg / line haul**
  - Transportation of shipments between transshipment points
- **Subsequent leg (outbound)**
  - Transshipment of commodities for transport
  - Delivery of consignments to customers in destination region (i.e., delivery of shipments within short-distance traffic region)

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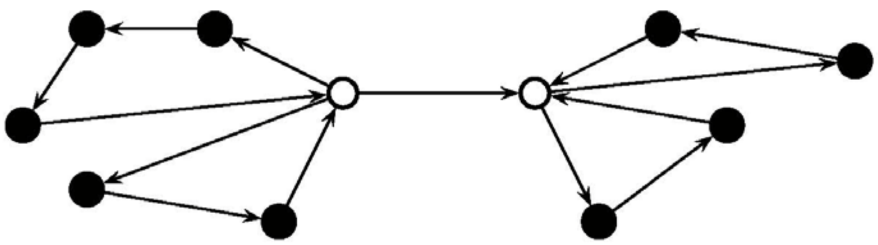
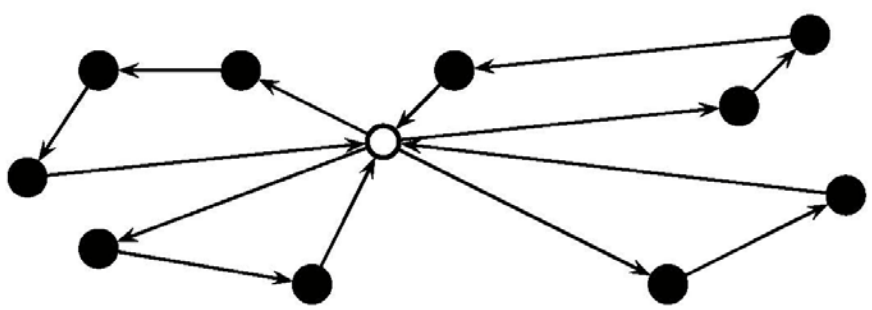
Operations of LTL Networks



Less-than-truckload freight network



Exemplary short distance service region

- **Preliminary leg (inbound)**
  - Pickup of loads in origin regions (i.e., collection of shipments within short-distance traffic region)
  - Consolidation of commodities for transport
- **Main leg / line haul**
  - Transportation of shipments between transshipment points
- **Subsequent leg (outbound)**
  - Transshipment of commodities for transport
  - Delivery of consignments to customers in destination region (i.e., delivery of shipments within short-distance traffic region)

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Motivation

Typical shipping companies have

- **Simultaneous deliveries and pickups**
- **Numerous orders, vehicles, and restrictions**
- **Business and end customers**
- **The requirement that pickup orders cannot be neglected**

Dynamics

- **Service requests shortly before pickup**
- **Varying travel times**
  - Predictable (e.g., rush hours)
  - Random (e.g., accidents)

Consequences: lateness, penalty fees, and bad vehicle utilization

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State of the Art

Solution techniques for PDPs

- **Exact optimization: e.g., MI(N)LP, branch-and-cut, column generation, . . . (e.g., Hiller et al. [1], Jaillet and Wagner [2], Kenyon and Morton [3], Savelsberg and Sol [4])**
- **(Meta) heuristics: sequencing policies, insertion, TABU search, genetic or evolutionary algorithms, . . . (e.g., Bent and Van Hentenryck [5], Branke et al. [6], Fleischmann et al. [7], Van Hemert and La Poutr´e [8])**

Primarily consideration of either

- **Varying travel times**
- **Unknown customer orders**
- **Time windows and capacities**

Neglect of specific requirements of forwarding agencies

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Objective and Approach

Objective

- **Overall, use of both anticipation of and reaction on unknown customer orders and varying travel times to improve vehicle routing**
- **Here, integration of varying travel times to reduce lateness and increase utilization**

Approach

- **Analysis of problem characteristics, modeling options, and definition and specifications**
- **Modeling of discrete mixed integer PDP optimization model**
- **Determination of travel time zones**
- **Development of solution approach and analysis in terms of**
  - Varying travel times
  - Real-time optimization within an intelligent planning system

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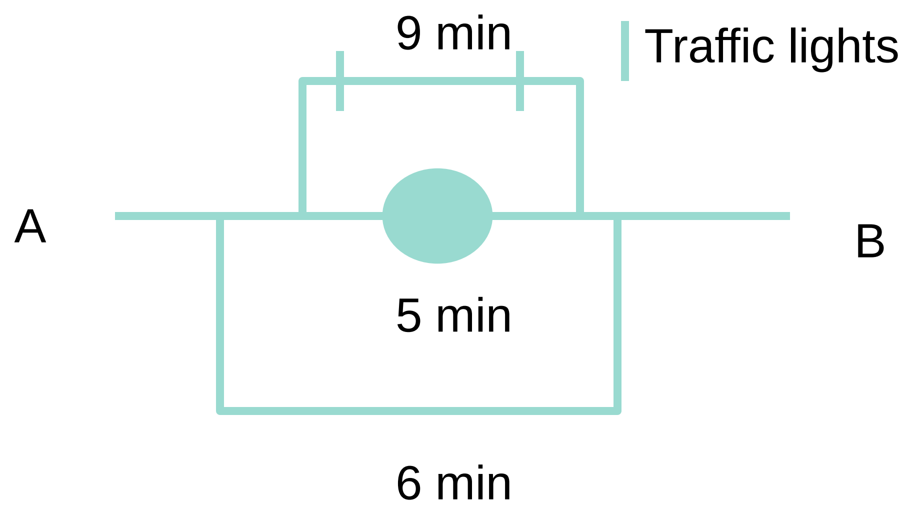
Time Dependent Travel Times

Non-busy period



Network with time dependent travel times

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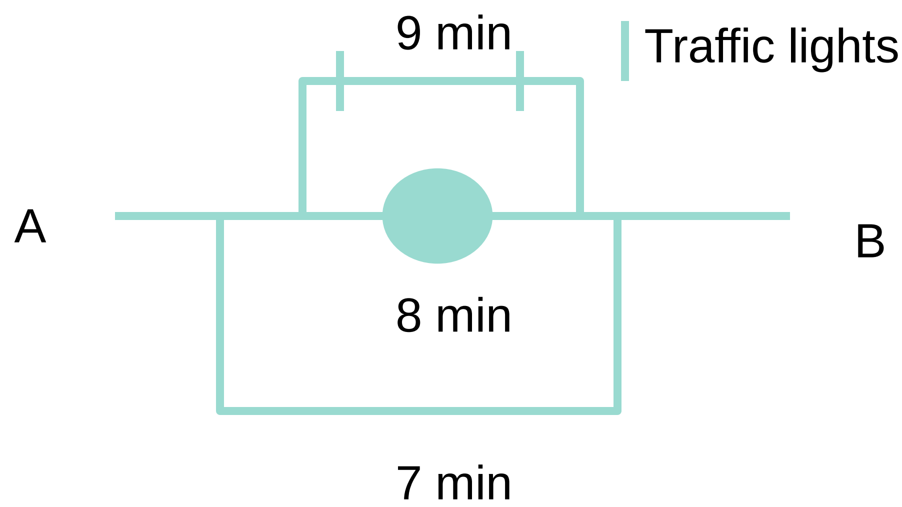
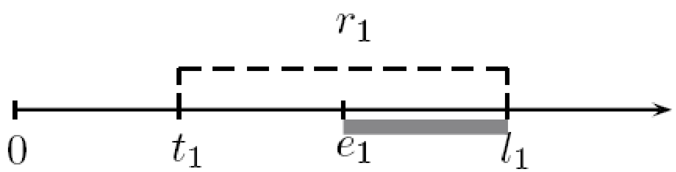
Time Dependent Travel Times

Rush hour



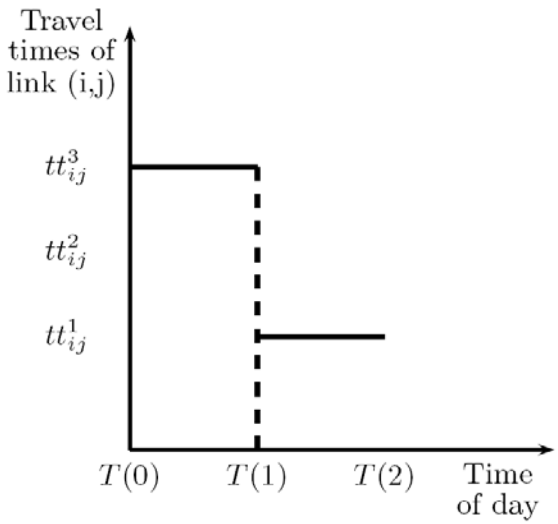
Network with time dependent travel times

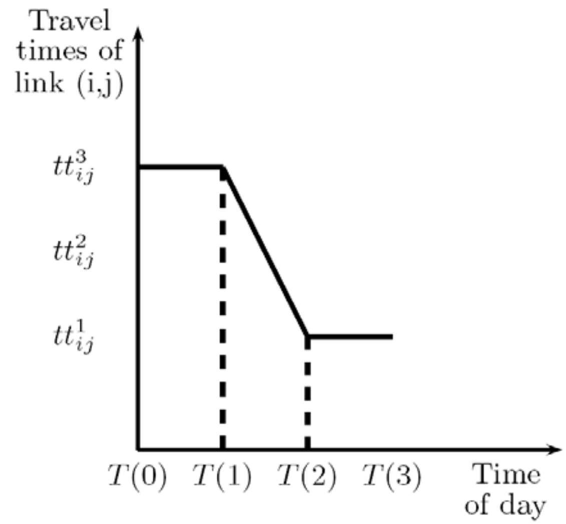
Degree of dynamism (Larsen [9])



$$edod_{tw} = \frac{1}{n_v + n_z} \sum_{i=1}^{n_v+n_z} \frac{T - (l_i - t_i)}{T}$$

Time dependent travel times





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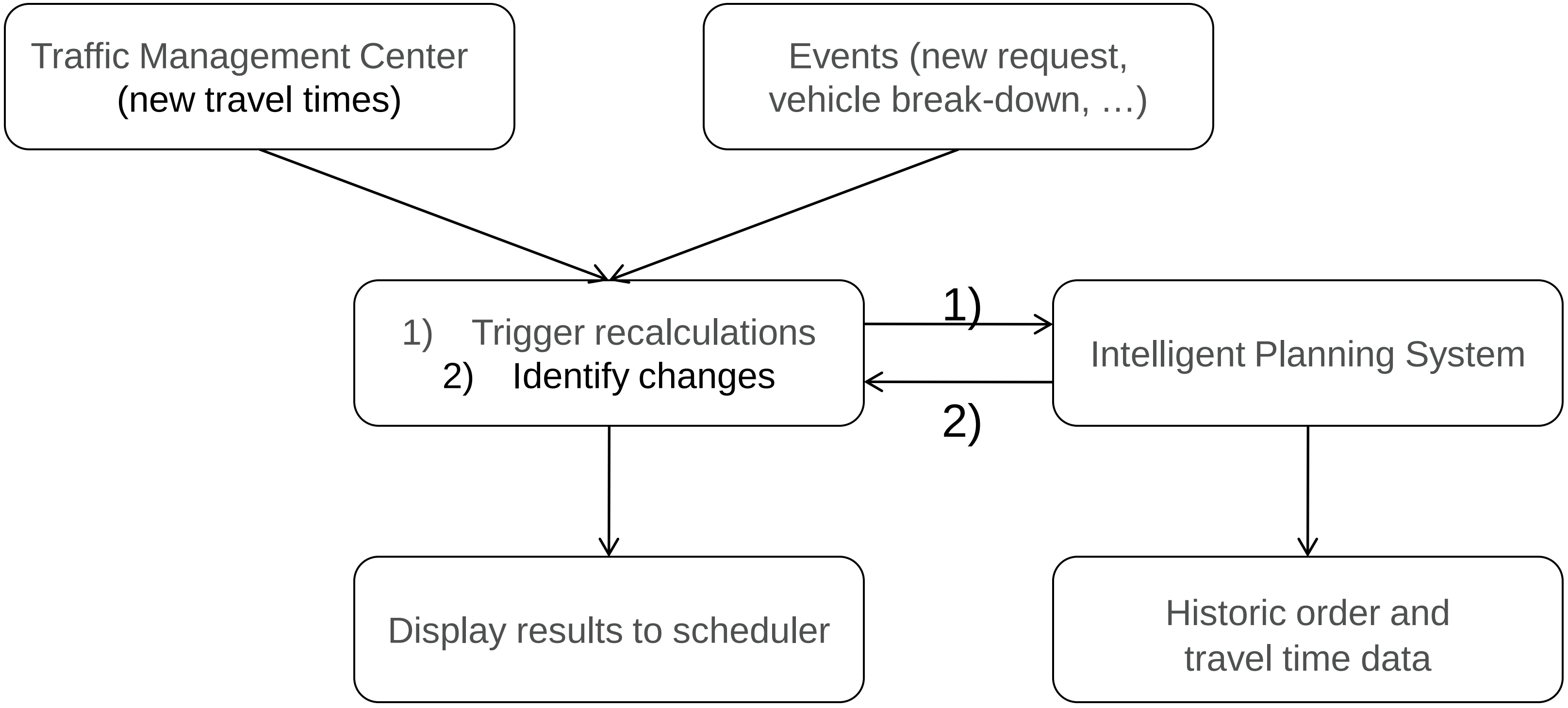
Intelligent Planning System



Intelligent Planning System

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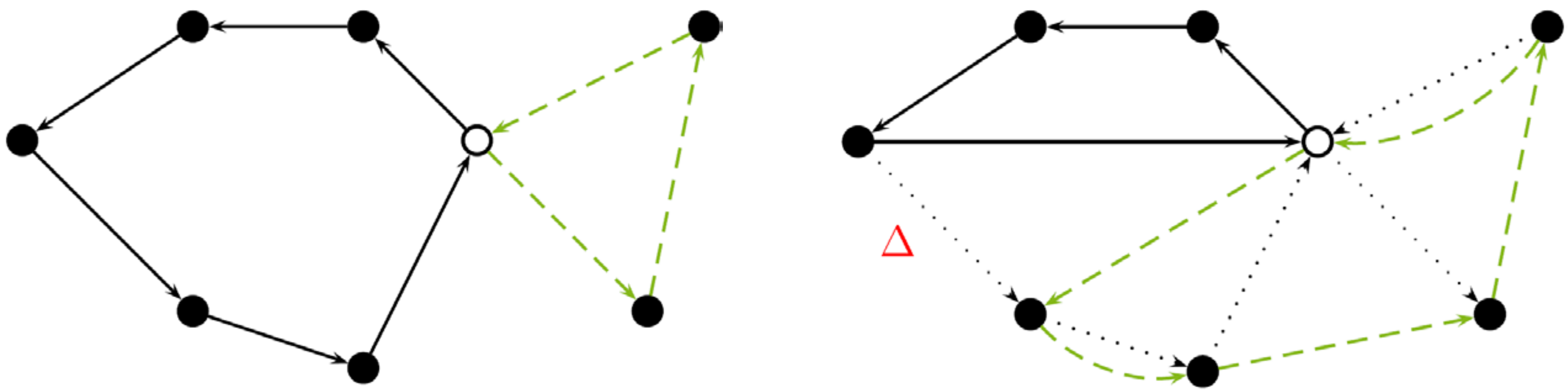
Real-time Optimization with Time Dependent Travel Times



Optimization with static travel times **Optimization with time dependent travel times**

Objectives and Modeling

The objective is to get robust and flexible tours

- **Robustness in a sense that, if travel times change or a new customers order arrive, if at all only minor changes in the schedule are necessary**
- **Flexibility allows to keep the general schedule, because the generated plan contains more options**

Assets and drawbacks of integration of stochastic data to reach desired tours

- **Stochastic scheduling performance worse with deterministic evaluation**
- **Hopefully, stochastic scheduling will reduce recourse costs**
- **Solving stochastic models vs. solving deterministic models with additional constraints**

→ Deterministic modeling seems favorable

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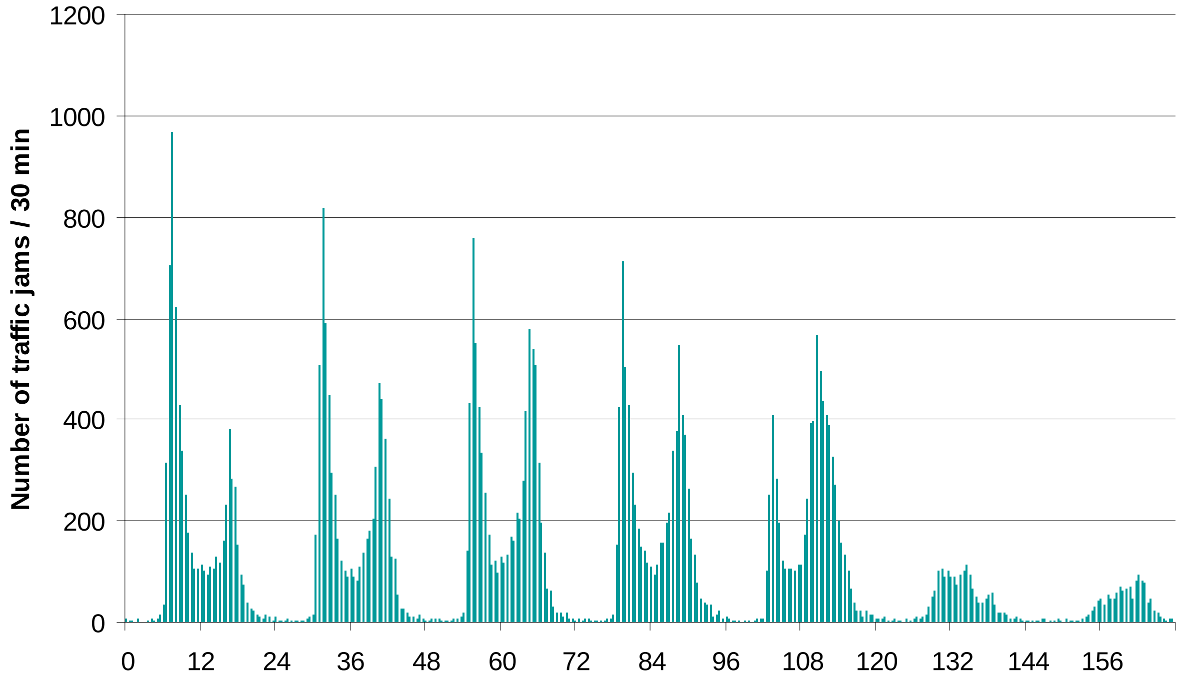
Number of Traffic Jams

- **Reported traffic jams on interstates in North Rhine-Westphalia in 2007**
- **Traffic jams of average weeks include**
  - **predictable**
  - **and random events**
- **Readily identifiable rush-hour times**



Number of traffic jams over 168 hours (Monday to Sunday)

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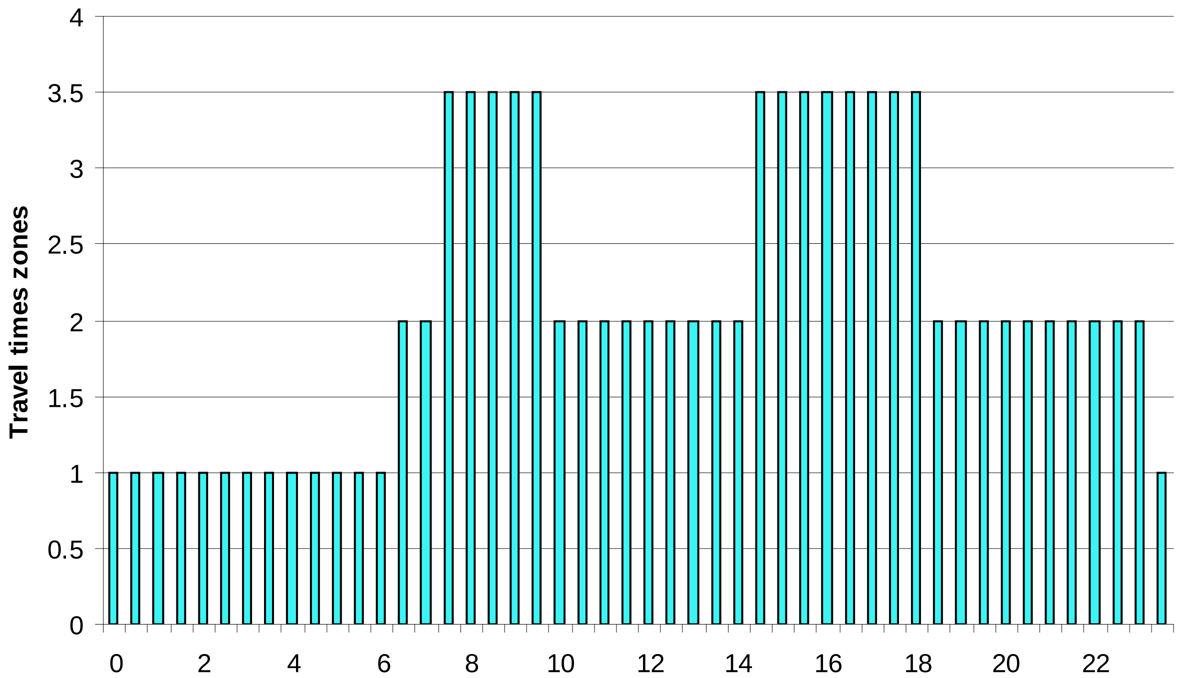
Deduced Travel Time Zones

- **Huge complexity of routing with individual travel times or time zones**
- **Identification of universally valid travel times**
- **Aggregation to appropriate time zones**



Travel time zones in North Rhine-Westphalia

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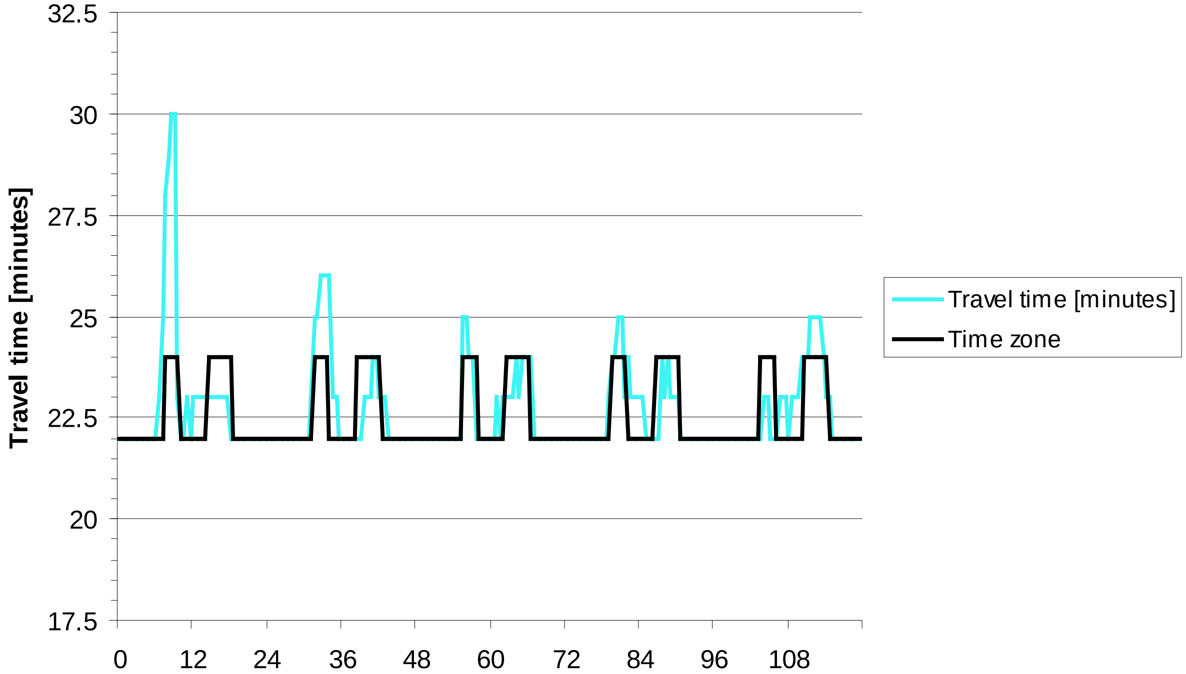
Time Zones vs. Real Travel Times

- **Rough estimates with general travel times**
- **The fit is reasonable well for first investigation of profitableness …**
- **Later fine-tuning is still possible, if routing with time zones is successful**



Travel time interval vs. travel time (Monday to Friday)

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Model Extract

Objective function

$$\min z = \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\sum_{z\in Z} tt_{ij}^{z} x_{ijk}^{z} + Z * \sum_{j\in C}\sum_{k\in K}\sum_{z\in Z} x_{1jk}^{z}$$

Customer and vehicle related constraints: e.g.,

$$\sum_{i\in V}\sum_{z\in Z} x_{ijk}^{z} - \sum_{i\in V}\sum_{z\in Z} x_{jik}^{z} = 0 \qquad \forall \quad j\in V;\ k\in K$$

Flow related constraints: e.g.,

$$f_{ijk} \le \sum_{z\in Z} x_{ijk}^{z} \sum_{h=2}^{|V|} (q_h + p_h) \qquad \forall \quad i,j\in V;\ k\in K$$

Time windows and travel times: e.g.,

$$a_{ik} + s_i + tt_{ij}^{z} - R * \left(1 - x_{ijk}^{z}\right) \le a_{jk} \qquad \forall \quad i,j\in C;\ k\in K;\ z\in Z$$

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Approach

Results of preliminary investigation

- Exact approaches (e.g., Column Generation, ...) require huge solving times
- Even small instances (i.e., a great deal smaller than practical problems) cannot be solved within given times
- Waiting strategies, especially with unknown customer orders, are only beneficial for a low number of unknown customers (see [6]).

Approach

- Enhancement of heuristics that have proven valuable
- For example, development of a tabu search (TS) with time-based delimitation and geographical distances
- Admission of reoptimization

→ Tabu search with reoptimization

Tabu Search

- … is a mathematical optimization method
- … belongs to the class of local search techniques
- … is a metaheuristic that guides a local search procedure to explore the solution space beyond local optimality
- … memory-based strategies are the hallmark of tabu search approaches
- … uses memory structures so that evaluated, but disregarded solutions are "tabu"
- Pros: Generally short solving times & generally quite good solutions for optimization problems
- Cons: Tabu list construction is problem specific (parameter settings) & no guarantee of global optimal solutions

Tabu Search
History to present

Tabu search is attributed to Fred Glover [12], because Glover

- **… describes a very simple memory mechanism to implement an oscillating assignment heuristic [13]**
- **… introduces tabu search as a "meta-heuristic" superimposed on another heuristic [14]**
- **… provides a full description of the method [12] [15]**

- **Current research suggest the suitability for a dynamic pickup und delivery problem, e.g.,**
  - Grendreau et al. [16] or
  - J.-F. Cordeau, G. Laporte, and A. Mercier [17]

Suitable, but neglect of requirements of forwarding agencies

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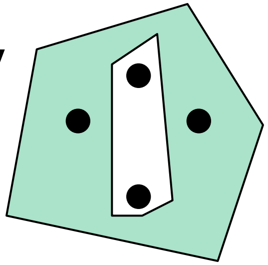
Tabu Search

- **TS explores only parts of the solution space by moving at each iteration to the most promising neighbor of the current solution**
- **Cycling is avoided by using a tabu list, where recently considered solutions are blocked out for a number of iterations**



- **Neighborhood are only solutions, complying with the time dependent travel times**
- **The objective function t^{η} associated with a particular solution η of an iteration is characterized by the vector $x^{\eta} = x_{ijk}^{z,\eta}$, denoting the used edges (i, j).**
- **An initial solution is required**

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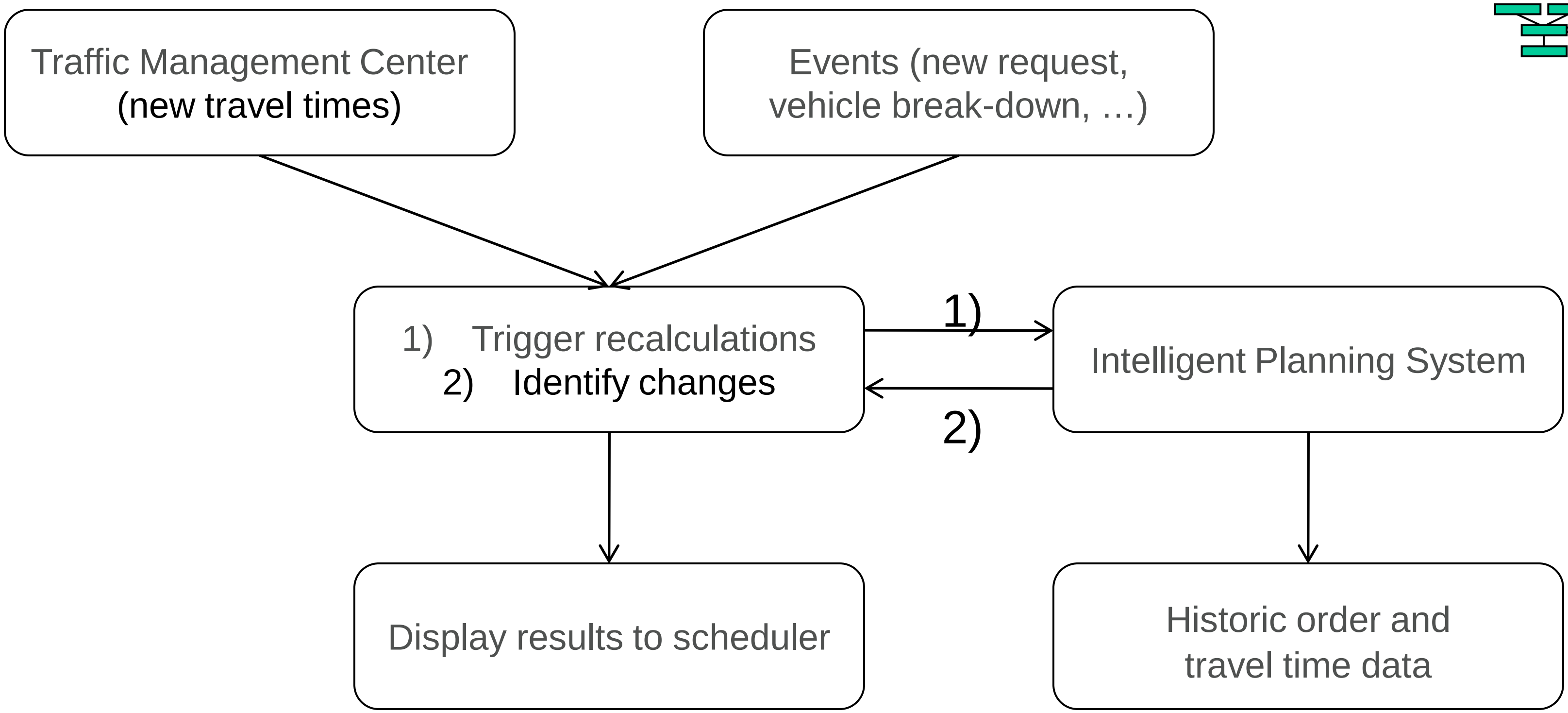
Preliminary Investigations



Intelligent Planning System

Anticipation of travel times is promising / of customer ord. is difficult

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Result Overview

Static vs. time dependent optimization		
Total travel time (%)	↗	5.35
Fleet size (%)	→	0.89
Reduction of late deliveries	↘	-68
Dynamic customers vs. dynamic customers with clusters		
Total travel time (%)	→	0.09
Fleet size (%)	→	- 0.91
Reduction of late deliveries	↘	-14
Time dependent and dynamic vs. combined optimization		
Total travel time (%)	→	-1.23
Fleet size (%)	→	1.82
Reduction of late deliveries	→	0

- About 2300 customers
- Between 0 and 30 percent unknown orders
- About 200 vehicles
- Up to 3 percent reduction of costly late arrivals

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Summary and Outlook

Conclusion

- **Evaluations show that dynamic routing with anticipation of travel times is promising**
- **Dynamic (real time) routing with anticipation might be beneficial for forwarding agencies in cases of**
  - High degrees of dynamism
  - Appropriate cluster strategies

- **Increasingly objectives in routing require the consideration of ecological and economical aspects**
- **A small example…**

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Germany 2009

The 800 CNG EcoFuel Tour:

800 gas stations in 80 days

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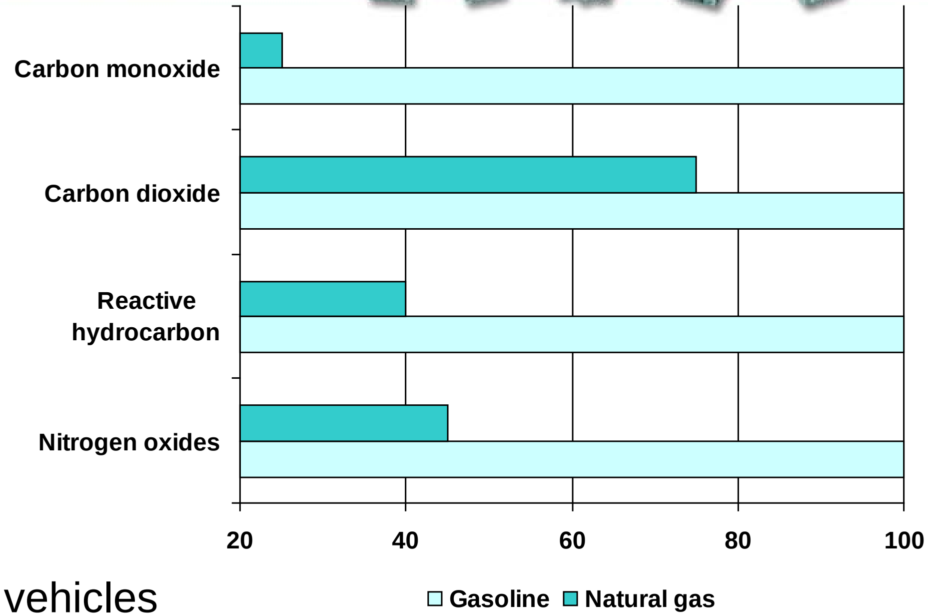
Natural Gas-Powered Vehicles

- **Pros:**
  - Low emissions
  - No petroleum taxes until 2018
  - Based on the energy-level natural gas costs 0,65-0,75 €/l compared to gasoline respectively diesel



Source: www.erdgasfahrzeuge.de

- **Cons:**
  - Ca. 1,500-3,000 € surcharges for new vehicles
  - Ca. 2,500-3,500 € surcharges for retrofitting
  - Small cruising range

- **Based on the average fuel costs natural gas is 50% cheaper compared to gasoline and 22 % cheaper compared to diesel**

Problem Definition & Setting

Ca. 800 natural gas stations

+

80 days

=

Optimal tour?

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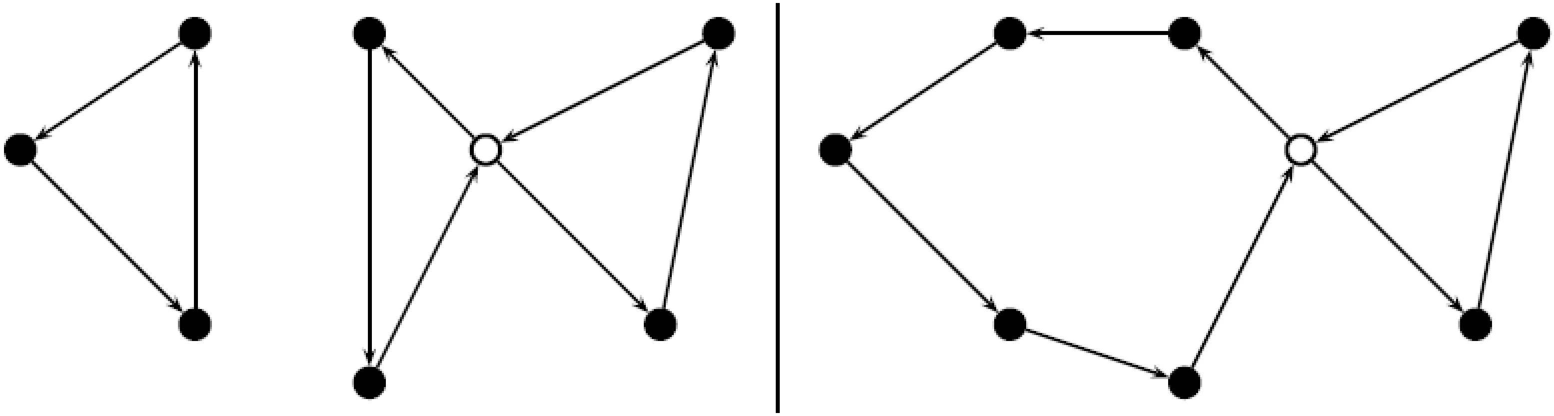
The Basic Travelling Salesman Problem

$$\text{Minimize } t = \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}$$

$$\text{subject to} \quad \sum_{i \in V} x_{ij} = 1 \qquad \forall \quad j \in V$$

$$\sum_{i \in V} x_{ji} = 1 \qquad \forall \quad j \in V$$

$$x_{ij} \in \{0, 1\} \qquad \forall \quad i, j \in V$$



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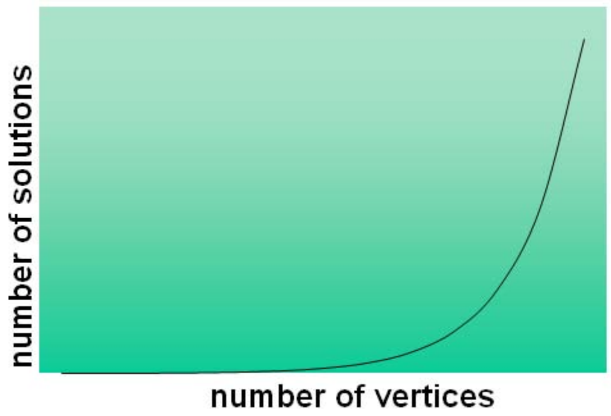
Problem Definition & Setting



- Optimal tour = Travelling Salesman Problem
- Visit *n* locations / vertices exactly once
- Number of solutions increases exponentially (n=20): 60.823.000.000.000.000
- No solution within polynomial time

Optimal tour?

Run-time

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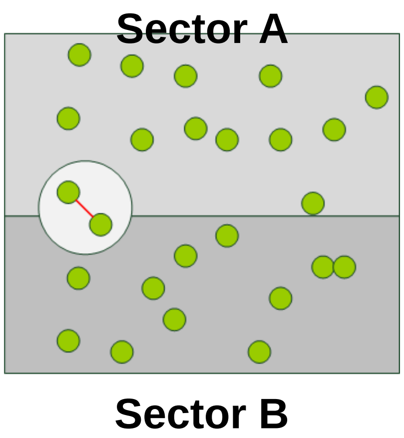
Solution Approach



Characteristics

- **Large problem space**
- **Strategic planning (solving time is not critical)**
- **Time constraints are less important**

→ Exact approach and partitioning of problem

1. **Criteria:**
   - Density of the natural gas stations
   - Geographic data
   - Max. number of gas stations in each sector: 170
2. **Calculation of shortest paths between six sectors**
3. **Calculation of the optimal solution for each sector**

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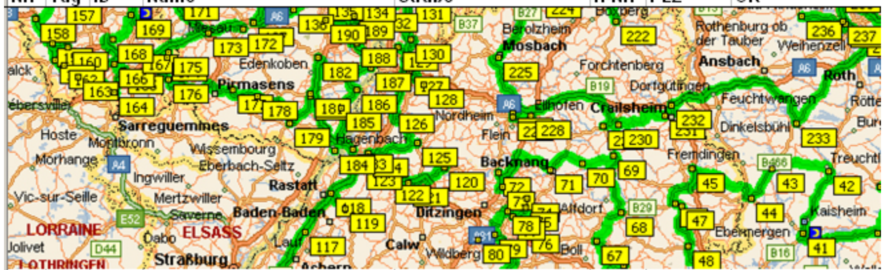
Solution Approach



Nr.	Tag	ID	Name	Straße	H-Nr.	PLZ	Ort
252	22	744	Avia Erdgastankstelle	Werner-von-Siemens-Straße	14	D-93413	Cham
253	22	745	Aral Erdgastankstelle	Schwandorfer Straße	10	D-93426	Roding
254	22	742	OMV Erdgastankstelle	Regensburger Straße	58	D-93133	Burglengenfeld
255	22	741	OMV Erdgastankstelle	Nordgaustraße	6	D-93059	Regensburg
256	22	740	Busbetriebshof-Erdgastankstelle	Bajuwarenstraße	3	D-93053	Regensburg
257	22	743	OMV Erdgastankstelle	Riedenburger Straße	37	D-93309	Kelheim
258	22	736	Freie Erdgastankstelle Rödl	Dreichlinger Straße	41	D-92318	Neumarkt in der Oberpfalz
259	22	729	Avia Erdgastankstelle	Nürnberger Straße	137	D-91217	Hersbruck
260	22	728	Esso Erdgastankstelle	Wichernstraße	2	D-91052	Erlangen
261	22	731	Globus Erdgastankstelle	Willy-Brandt-Allee	1	D-91301	Forchheim
262	22	732	Aral Erdgastankstelle	Breitenbacher Straße	18	D-91320	Ebermannstadt
263	22	759	Bavaria Petrol Erdgastankstelle	Von-Ketteler-Straße	4	D-96050	Bamberg
264	23	760	Busbetriebshof-Erdgastankstelle	Am Börstig		D-96052	Bamberg
265	23	761	Total Erdgastankstelle	Am Steinernen Kreuz		D-96110	Scheßlitz
266	23	773	Erdgastankstelle	Augsfelder Straße	6	D-97437	Haßfurt

- **Calculation of the optimal solution for each sector**
  - Using a developed MIP model
  - Solving the problems using commercial software
- **Max. deviation from the optimal solution for each sector: < 3 %**

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Results

Total distance:
18,000 km ≈ 11,184 miles

Total driving time:
265 hours

Total computing time:
≈ 29 hours

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Conclusion

- **Evaluations show that dynamic routing with anticipation of travel times is promising**
- **Dynamic (real time) routing with anticipation might be beneficial for forwarding agencies**

Future work

- **Development of an approach using anticipation within an intelligent and dynamic planning tool for operating LTL terminals combining**
  - Route planning, yard management or door assignment,
  - And transshipment processes
- **Objectives are the reduction of overall travel times and lateness, increasing vehicle utilization and transshipment productivity under consideration of ecological and economical aspects**

Thank you for your attention!

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Backup

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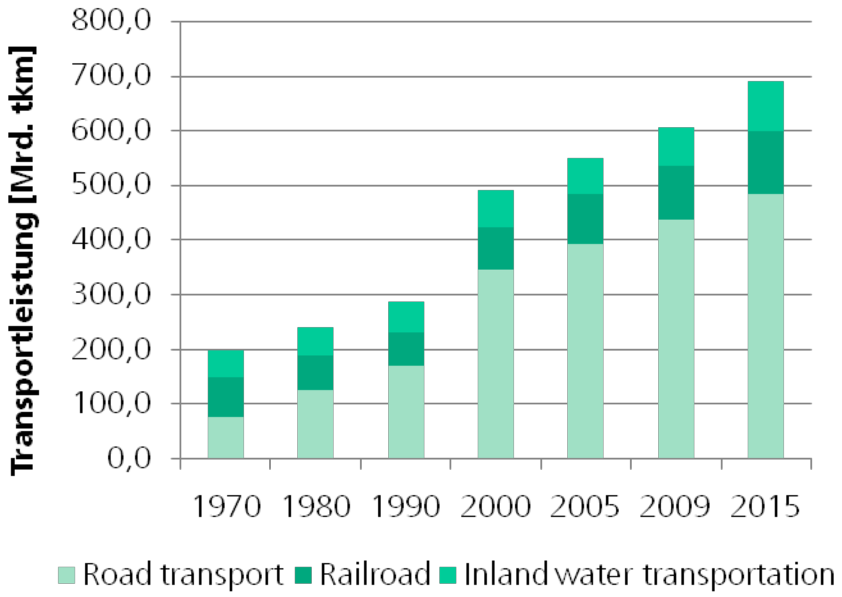
Driving forces



Driving forces of transport volume are Globalization

- **EU Enlargement**
- **Growing Economy**
- **Reduction of**
  - stocks
  - in-house production depth
- **Ship to order requirement**
- **…**

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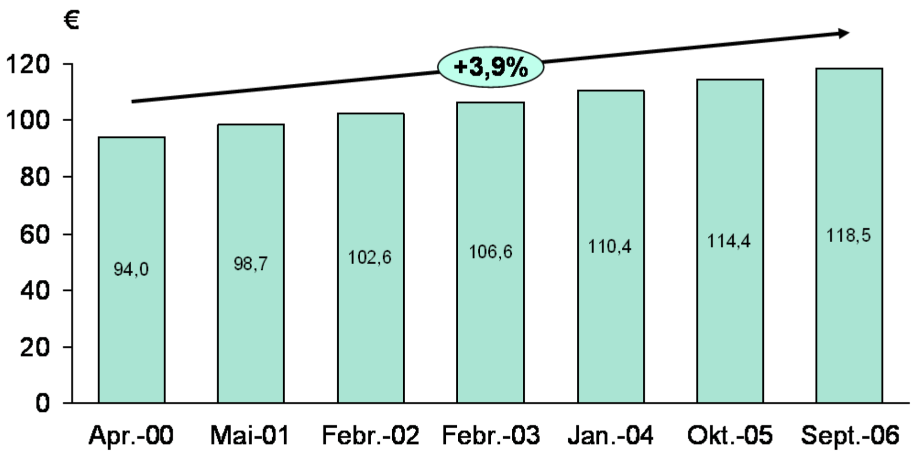
LTL - Price and Market Development



Deymann 2007

Price Development of an average shipment (230 kg, 500 km)

Dynamic Market Situation

- **Cost Drivers**
  - Introduction of Maut
  - Rising prices for new trucks and fuel
  - New labour rules
- **Acquisitions**
  - Large companies, e.g.
    - Kühne & Nagel in IDS
    - DSV in IDS
  - Cooperations, e.g.
    - Parts of ABX in Cargoline
    - Spedition 2000 in VTL

Telemetry

Telemetry (synonymous with telematics)

- **Telemetry is a technology that allows the remote measurement and reporting of information of interest to the system designer or operator.**
- **The word is derived from Greek roots**
  - tele = remote, and
  - metron = measure
- **Systems that need instructions and data sent to them in order to operate require the counterpart of telemetry, telecommand.**

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