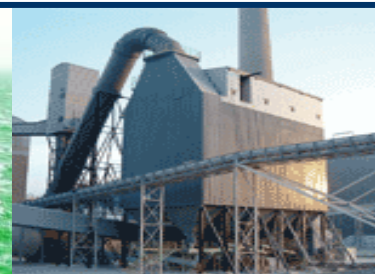




Optimization-based decision support within healthcare and transportation

eVITA Scientific Meeting
Geilo, Norway January 28, 2010
Geir Hasle, SINTEF ICT



Acknowledgment

- Henrik Andersson, NTNU
- Marielle Christiansen, NTNU
- Arild Hoff, Høgskolen i Molde
- Arne Løkketangen, Høgskolen i Molde
- Tomas Nordlander, SINTEF
- Atle Riise, SINTEF
- Martin Stølevik, SINTEF

Outline

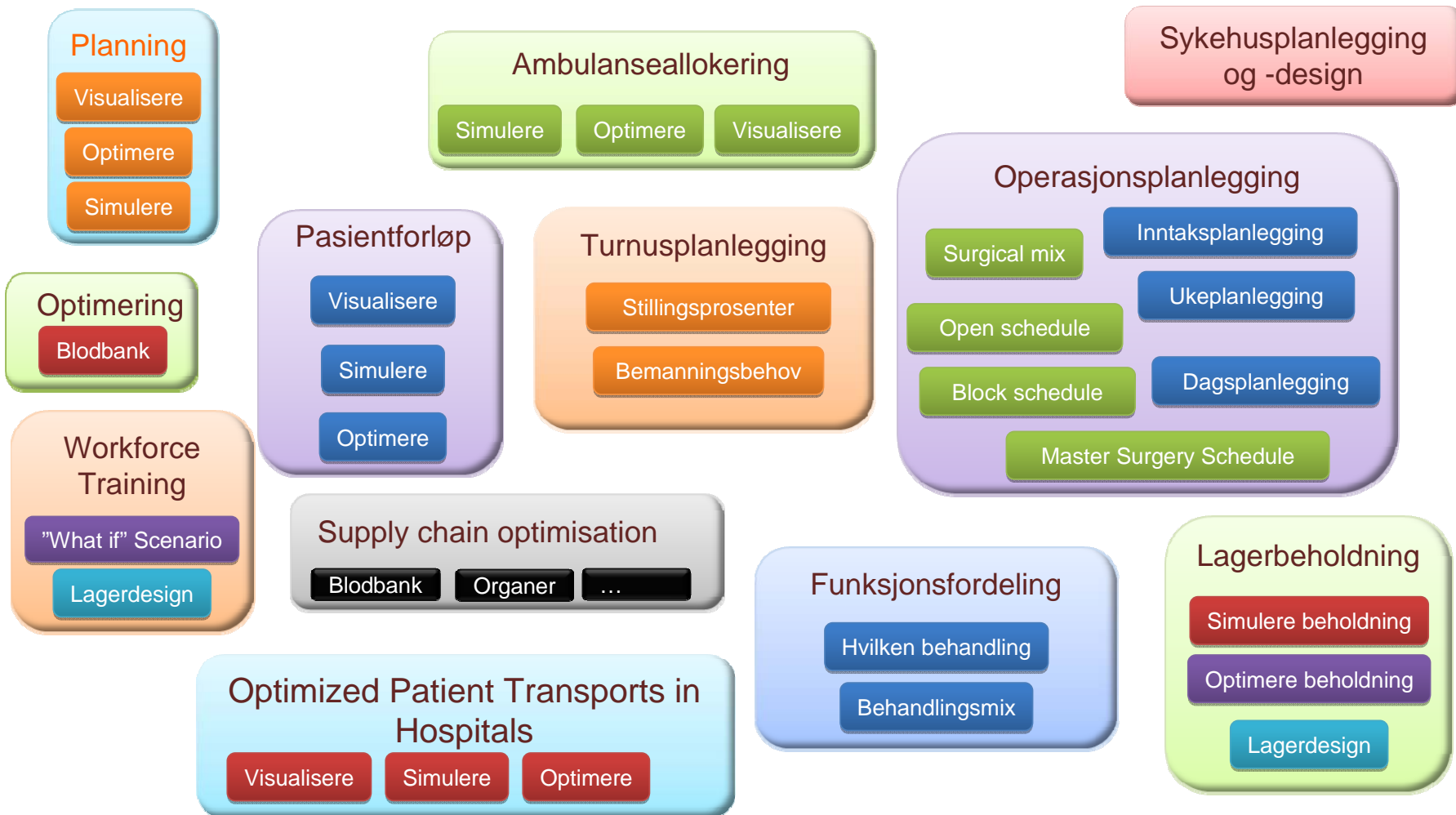
- Motivation – relevance to practice and eVita
- Discrete optimization
- Challenges
- Summary and conclusion

Messages

- Discrete optimization problems
 - central to better performance
 - hard
- Strong need for more powerful methods
- Several challenges and promising research avenues
- Short road from theoretical to practical improvements
- Important part of eScience

- Need for better coordination
 - Increasing demands
 - Patient focus: high quality treatment
 - Resource focus: Need to curb cost increase
- Design, planning
 - Crucial to performance
 - Too complex for manual decision-making
 - Time consuming and repetitive
- Need for decision support systems
 - Automated planning
 - Objectives and constraints
 - Computationally complex Discrete Optimization Problems
- Need for models and effective solution algorithms

Coordination challenges in healthcare



Vision: An optimized healthcare system

- Enterprise Models
- Information
- High quality data
- OR models
- Solution algorithms
- Computing power



Two cases in point

■ Nurse rostering

- Solved manually by experienced nurses
- Timetabling problem
- Computationally hard discrete optimization problem

■ Surgery scheduling

- Solved manually by experienced nurses
- Long-term, mid-term, short term
- Critical resources: operation theaters, surgeons
- Variants of the Job-Shop Scheduling Problem
- Computationally hard discrete optimization problem

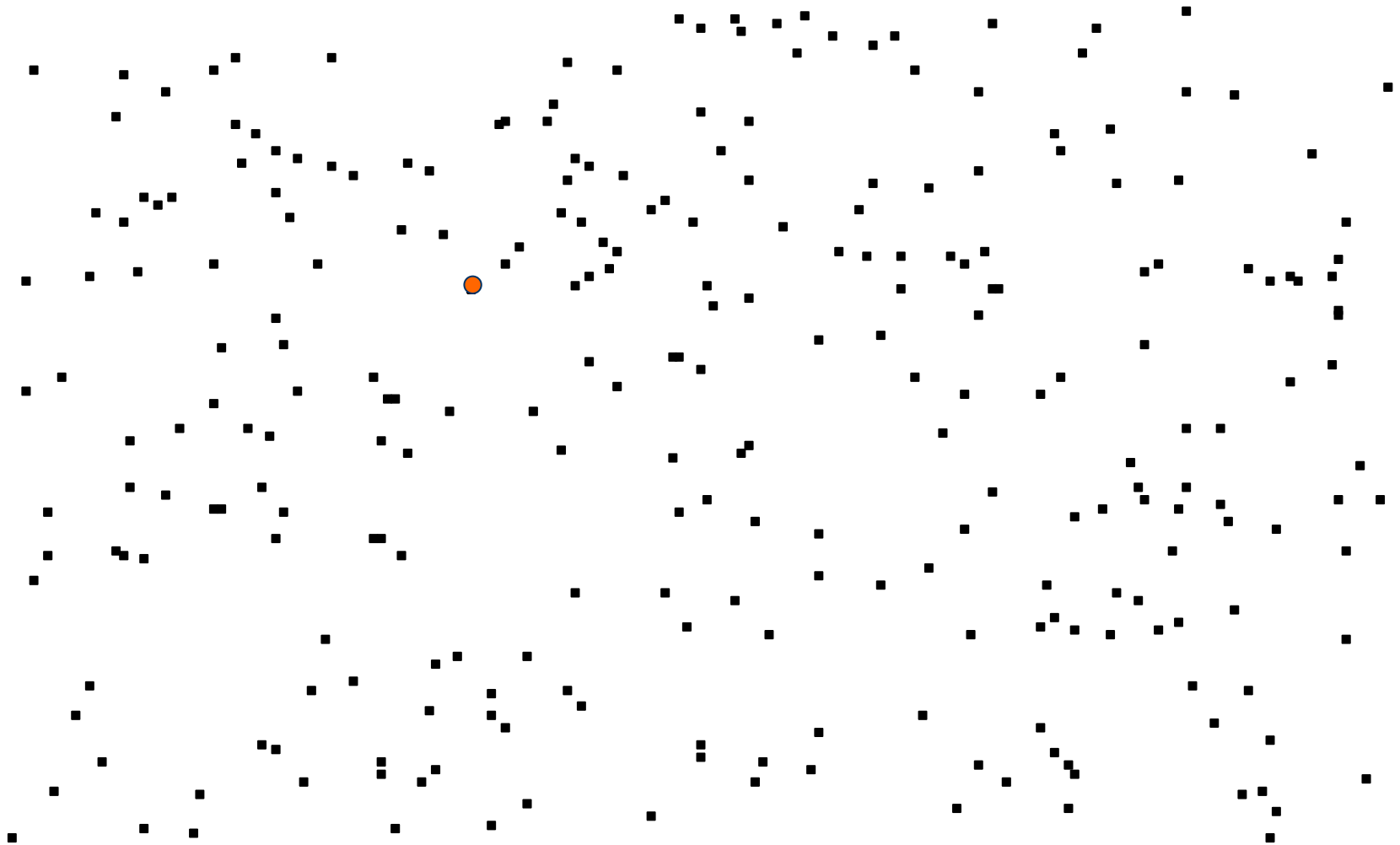
Discrete optimization (1)

- Central to real-life problems across many application areas
 - routing
 - scheduling
 - planning
 - design
- resources, time, activities
- economy, environmental effects
- Healthcare, transportation, manufacturing, oil & gas, finance, sports
- Computationally hard
- Physics, chemistry, biology, electronics, statistics, geometry, ...

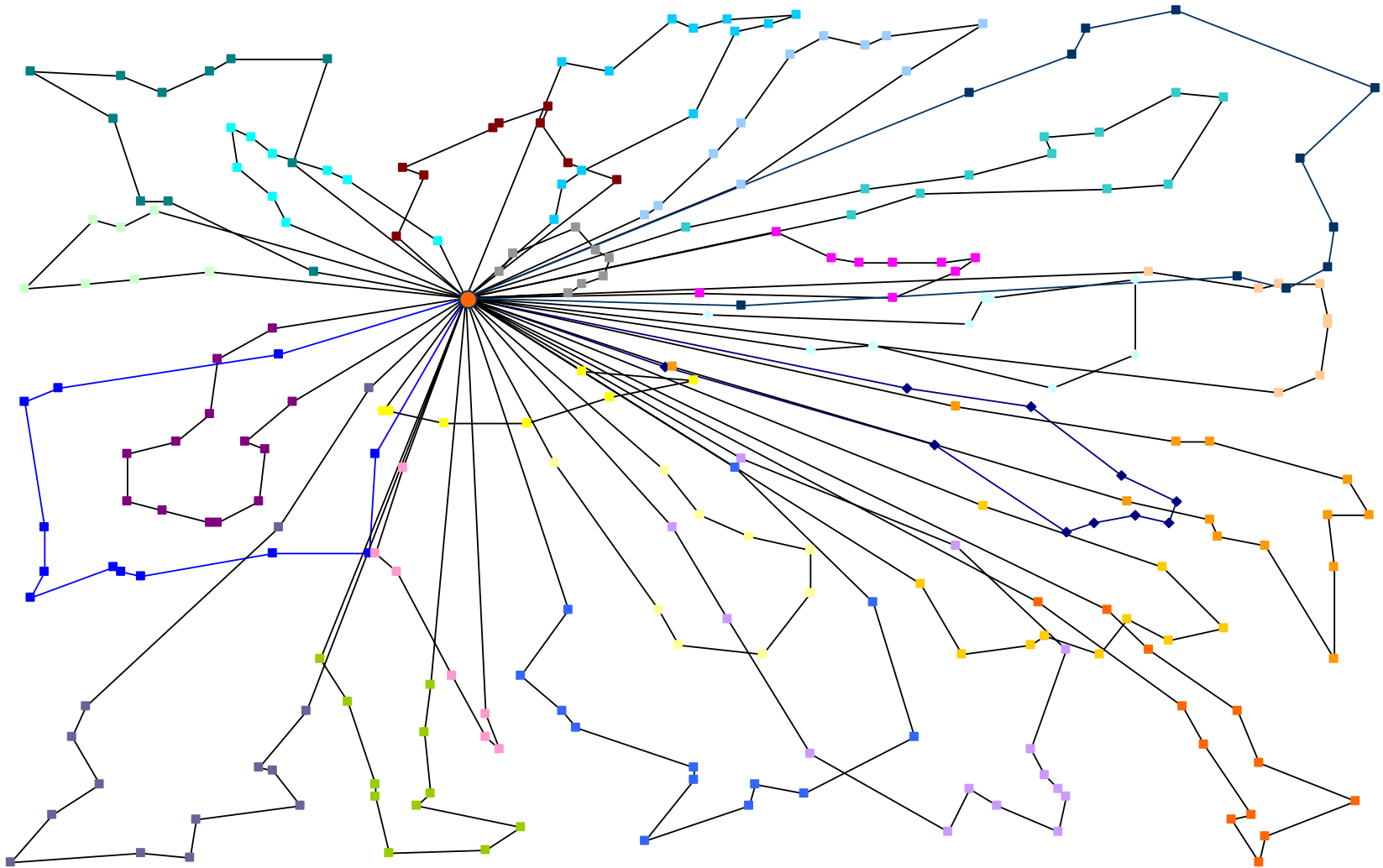
Discrete optimization (2)

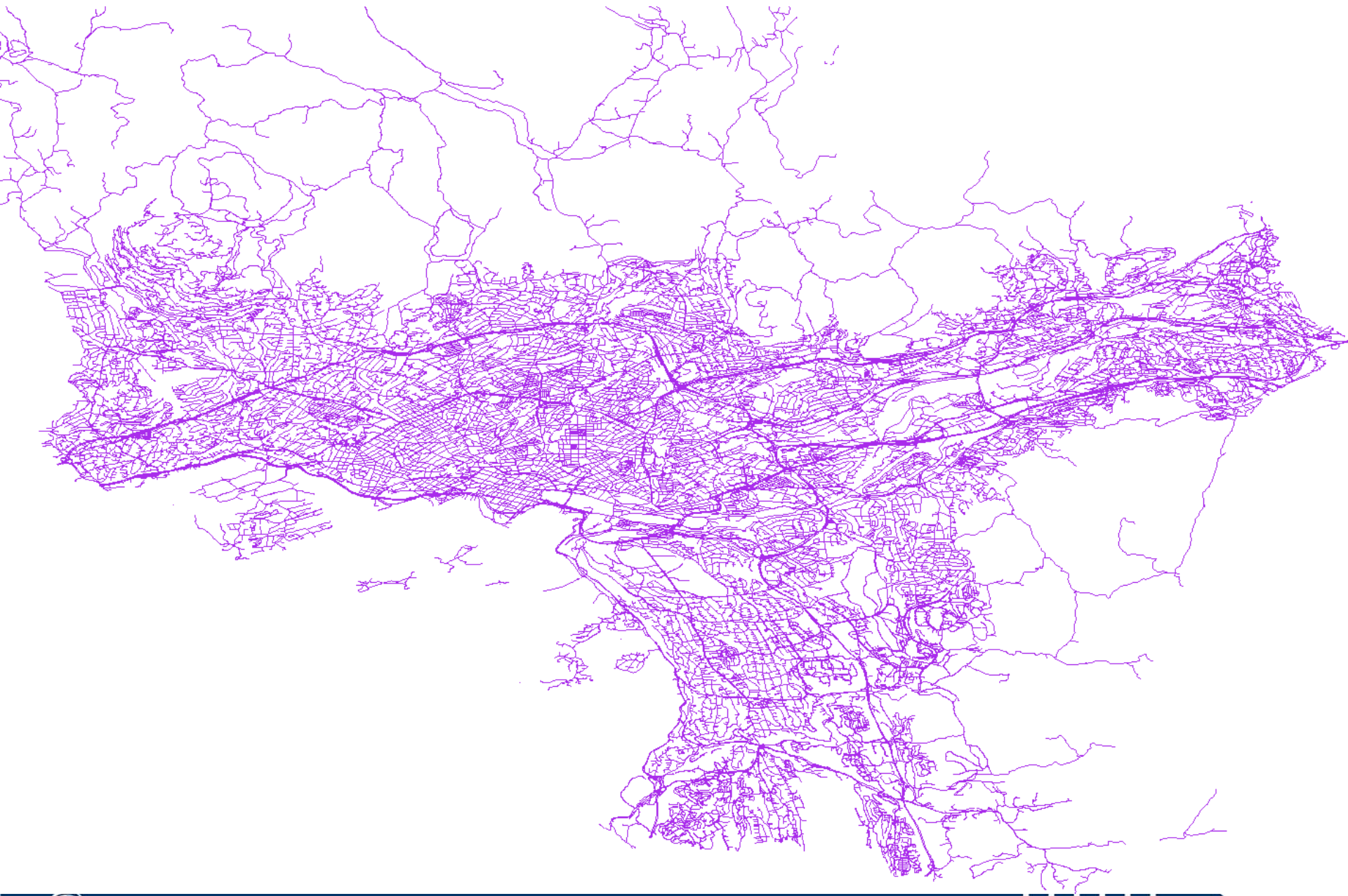
- Two basic types of method
- Exact, mathematical programming
 - guarantees to find the optimal solution
 - response time problematic
 - may be interrupted for feasible solution
 - low quality, but upper bound on error
- Approximative (typically heuristics)
 - greedy
 - local search
 - metaheuristics
 - good solutions in limited time
 - no useful error bound

Standard test instance G-n262-k25 (Gillett & Johnson 1976)

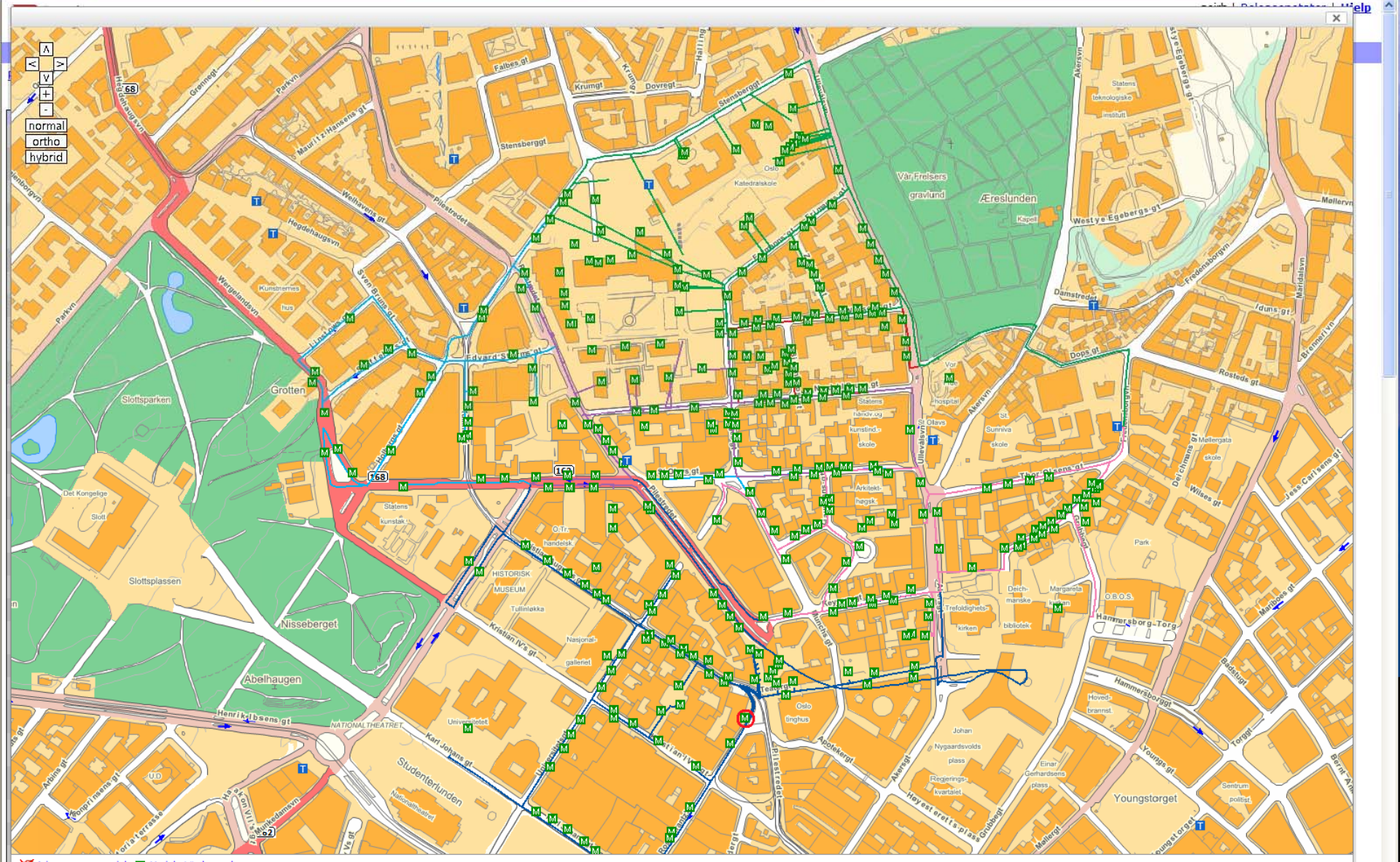


"The world record" for G-n262-k25: 5685 vs. 6119 (SINTEF 2003)









Moduler på rute - Windows Internet Explorer

http://app.d.no/app/Route/ModulesOnRoute.do?action=list&routeId=18924&pendingId=3968

File Edit View Favorites Tools Help

Forside - SINTEF TRANSPORT OPTIMIZATION ... Moduler på rute

normal
ortho
hybrid

Nordahl Bruns

St. Olavs gt

Adresser uten modul Modul Via kin valst rute

Discrete optimization – main challenges

- More powerful methods – exact and approximative
 - better solutions in shorter time
 - new applications
- Combining the strengths of exact methods and heuristics
- Decomposition and aggregation
- Multi-level solvers, different levels of abstraction
- Stochastic models
- Parallelization
 - fine grained, e.g. to exploit the architecture of modern commodity computers
 - multi-core and heterogeneous computing
 - coarse grained, e.g. cooperative hybrid solvers, multi-level solvers
- Self-adaptive methods

- Better benchmarks



DOMinant

Discrete Optimization Methods In Maritime and Road-based Transportation

Norwegian University of Science and Technology (NTNU),
Molde University College (HiM)
and SINTEF ICT

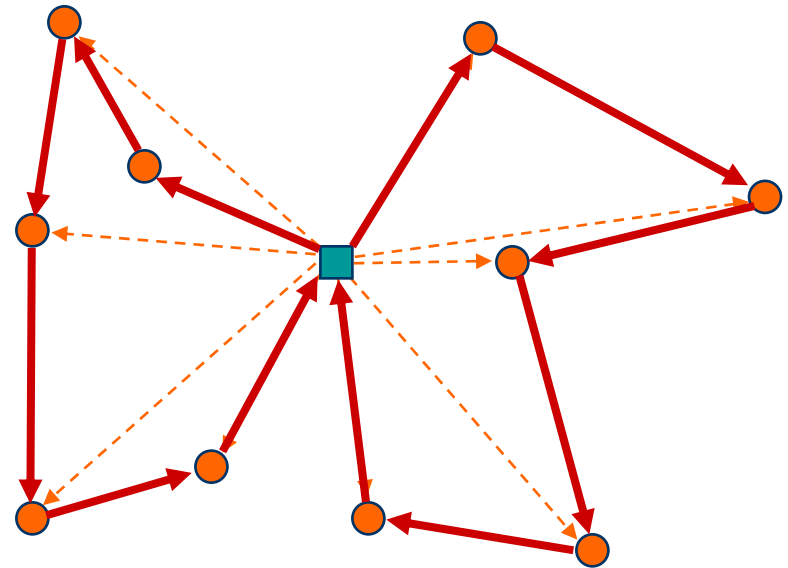


Main objective

- More efficient methods for rich, industrial variants of computationally hard discrete optimization problems in maritime and road-based transportation
- Two types of problems
 - Inventory routing
 - Fleet composition

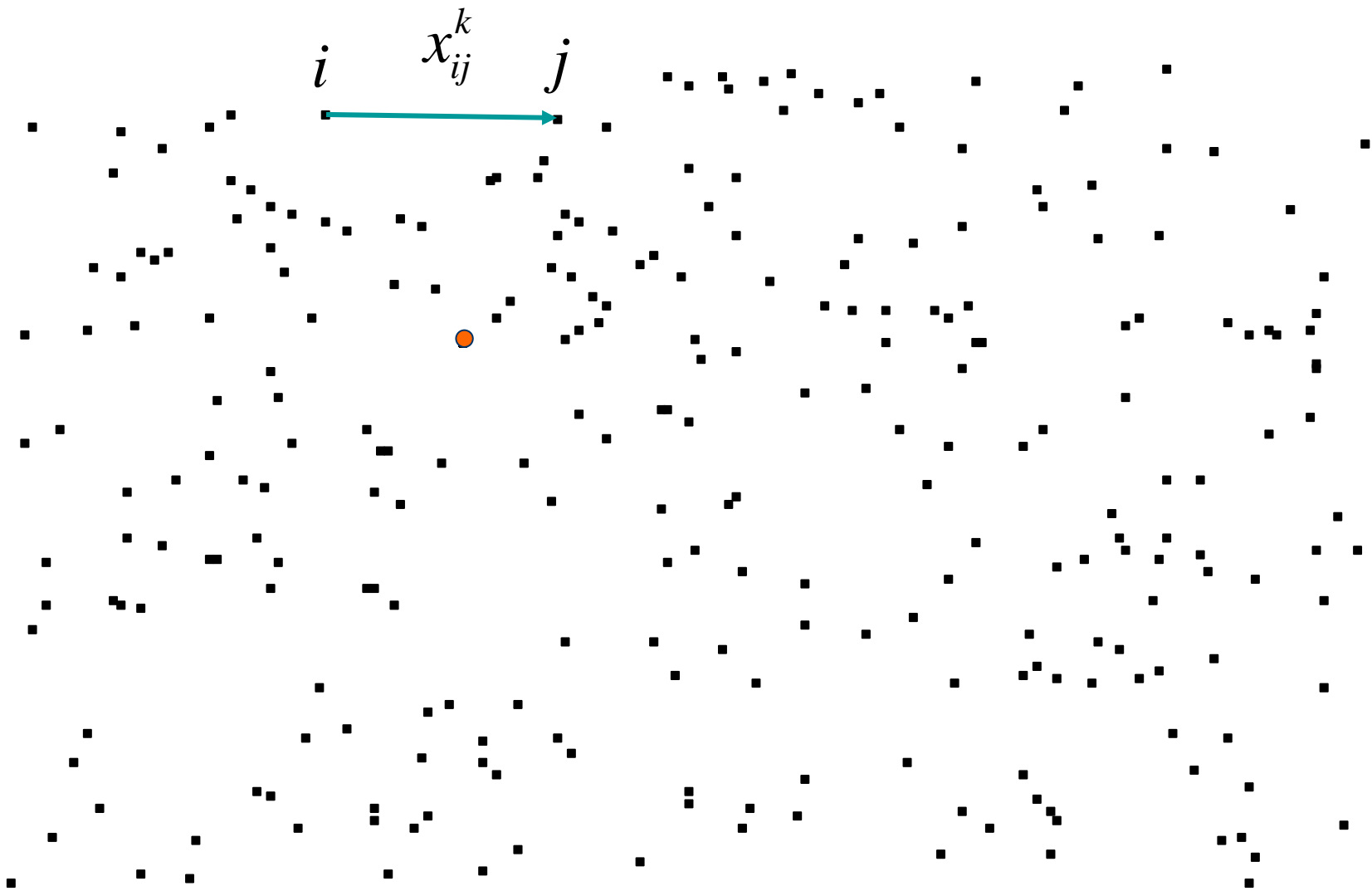
Classical VRP(TW)

- Deliveries from a single depot
- Given customer demand
- Homogeneous fleet
- Sizes/capacities
- Minimize total transportation cost
- (Single time windows)
- More than 1000 references



VRP with Capacity Constraints (CVRP)

- Graph $G=(N,A)$
 - $N=\{0,\dots,n+1\}$ Nodes
 - 0 Depot, $i\neq 0$ Customers
 - $A=\{(i,j): i,j\in N\}$ Arcs
 - $c_{ij}>0$ Transportation Costs
- Demand d_i for each Customer i
- V set of identical Vehicles each with Capacity q
- Goal
 - Design a set of Routes that start and finish at the Depot - with minimal Cost.
 - Each Customer to be visited only once (no order splitting)
 - Total Demand for all Customers not to exceed Capacity
 - Cost: weighted sum of Driving Cost and # Routes
- DVRP – distance/time constraint on each route
- VRPTW – VRP with time windows
- Pickup and Delivery
 - Backhaul – VRPB(TW)
 - Pickup and delivery VRPPD(TW)
 - PDP



A mathematical model for VRPTW (Network Flow Formulation)

$$\text{minimize } \sum_{k \in V} \sum_{(i,j) \in A} c_{ij} x_{ij}^k \quad (1) \quad \text{minimize cost}$$

subject to:

$$\sum_{k \in V} \sum_{j \in N} x_{ij}^k = 1, \quad \forall i \in C \quad (2) \quad \text{each customer 1 time}$$

$$\sum_{i \in C} d_i \sum_{j \in N} x_{ij}^k \leq q, \quad \forall k \in V \quad (3) \quad \text{Capacity}$$

$$\sum_{j \in N} x_{0j}^k = 1, \quad \forall k \in V \quad (4) \quad \text{k routes out of depot}$$

$$\sum_{i \in N} x_{ih}^k - \sum_{j \in N} x_{hj}^k = 0, \quad \forall h \in C, \quad \forall k \in V \quad (5) \quad \text{flow balance for each customer}$$

$$\sum_{i \in N} x_{i,n+1}^k = 1, \quad \forall k \in V \quad (6) \quad \text{k routes into depot (redundant)}$$

$$x_{ij}^k (s_i^k + t_{ij} - s_j^k) \leq 0, \quad \forall (i,j) \in A, \quad \forall k \in V \quad (7) \quad \text{sequence and driving time}$$

$$a_i \leq s_i^k \leq b_i, \quad \forall i \in N, \quad \forall k \in V \quad (8) \quad \text{arrival time in time window}$$

$$x_{ij}^k \in \{0,1\}, \quad \forall (i,j) \in A, \quad \forall k \in V \quad (9) \quad \text{arc (i,j) driven by vehicle k}$$

Variables
-arrival time

Arc Decision
variables

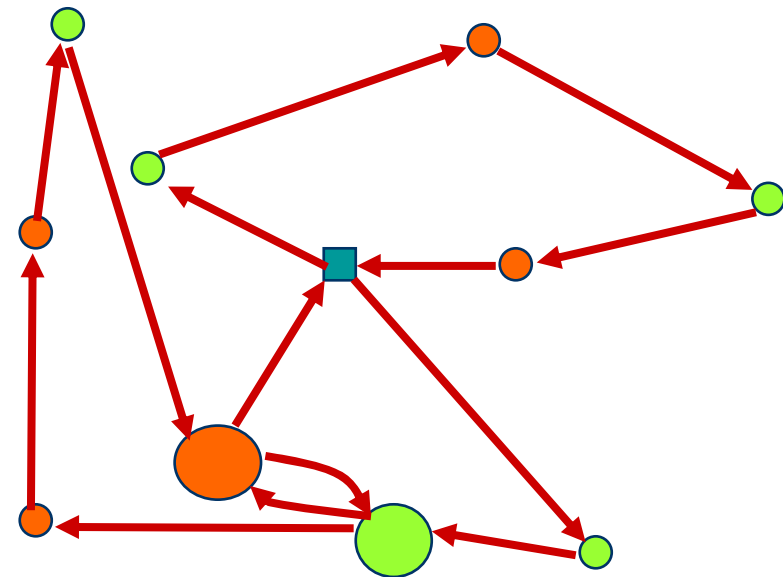
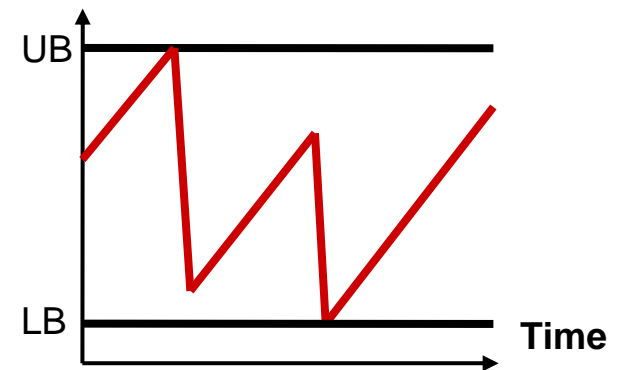
VRP Research in general

- Since 1959
- Much harder than the TSP
- Thousands of papers
- More popular than ever
- Important vehicle for development of generic methods
- One of the great successes of Operations Research
- Industry of tools for transportation optimization
- Quick dissemination and exploitation of scientific advances
- The road is short from scientific to practical improvements

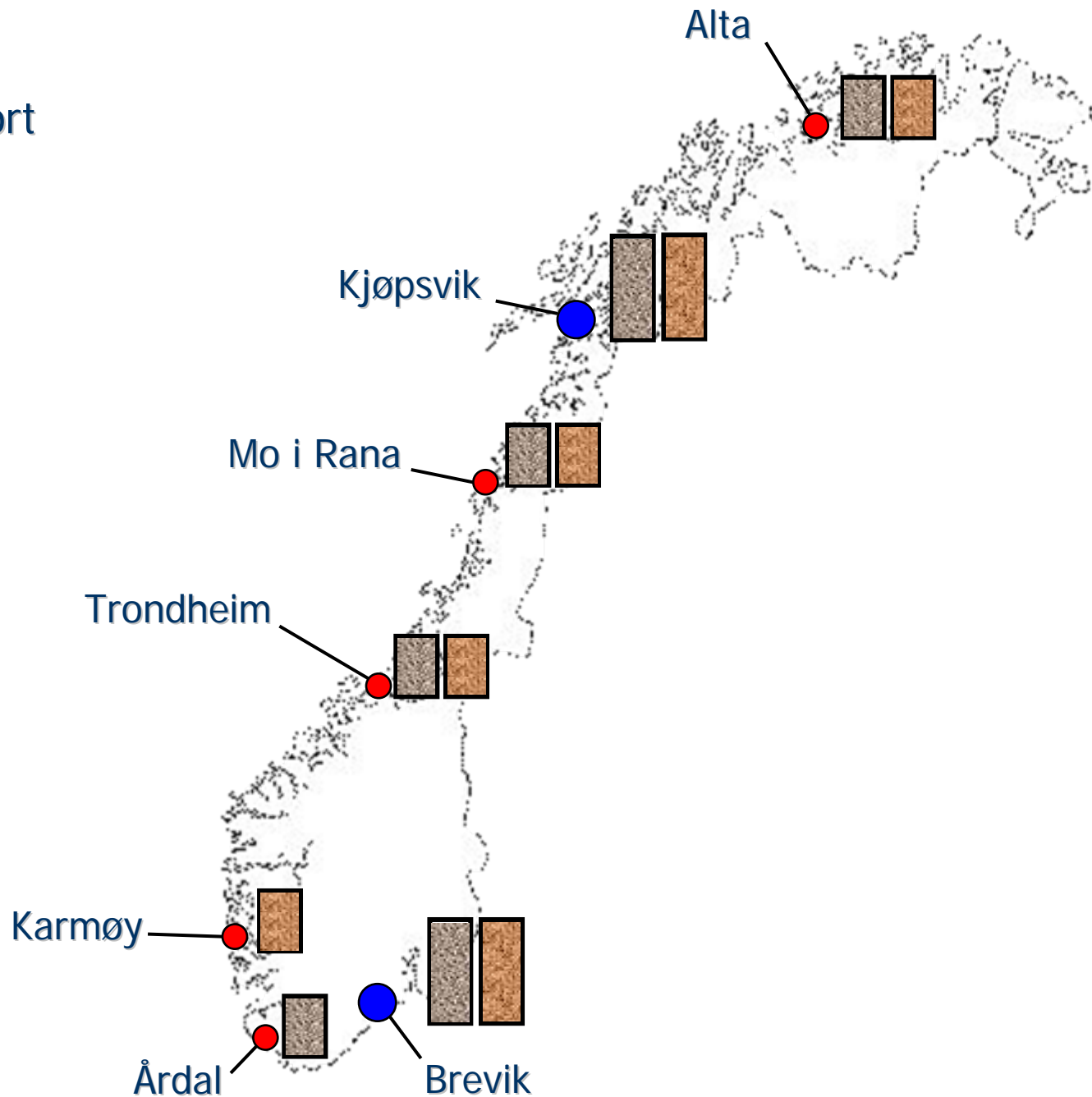
Inventory routing problem (IRP)

- Inventories with capacities
- Production/consumption rate
- Heterogeneous fleet
- Design routes that minimize the transportation cost without interrupting production and consumption of the products
- No pickup and delivery pairs
- Quantity loaded unknown
- Number of visits unknown

Inventory level, production



- Production port
- Consumption port
- Product 1
- Product 2



Practical applications - IRP

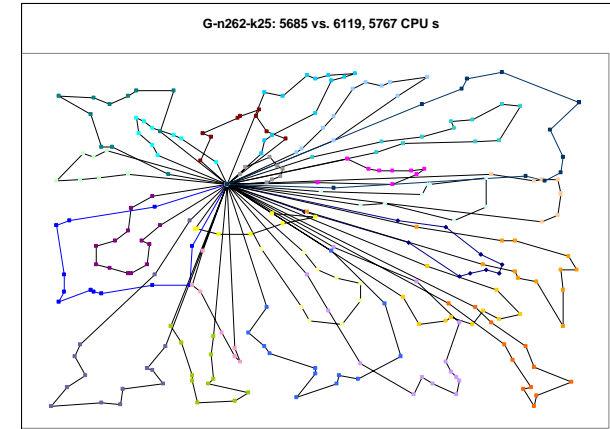
- Both road-based and maritime transportation
 - One/multiple products
 - VRP and PDP structure (with and without depot)
 - Variable production/consumption rate
 - Stochastic demand/production
 - Combining inventory routing with other planning aspects (production, allocation,..)
- Industry cases
 - Ammonia – Yara
 - LNG - Suez Energy International, StatoilHydro, RasGas, QuatarGas
 - Cement - Norcem
 - Fuel oil - Hydro Texaco
 - Animal fodder - Landbruksdistribusjon, Felleskjøpet



- Daily charter rate USD 60,000
- Shipload of LNG worth USD 10,000,000
- Purchase price LNG tanker USD 150,000,000

Fleet composition

- VRP, PDP (or IRP) structure
- Variable heterogeneous vehicle fleet
 - capacities
 - acquisition costs....
- **Objective:** find a fleet composition and a corresponding routing plan that minimizes the sum of routing and vehicle acquisition/depreciation/rental costs



Practical applications – Fleet composition

- Both road-based and maritime transportation
 - Strategic and tactical fleet dimensioning
 - One/multiple products
 - VRP and PDP structure (with and without depot)
 - Stochastic demand and price/cost structure
- Industry cases
 - Cars - Høegh Autoliners
 - LNG – Statoil
 - Dairy products - Tine Midt-Norge
 - Newspapers - Aftenposten, Dagbladet
 - Ice cream - Henning Olsen, Diplom is
 - local distribution - Linjegods
 - Chemicals – Broström Tankes (now Maersk)
 - Cement – Norcem
 - Animals Norsk Kjøtt, Gilde

Research approach

- Mathematical formulations for industrially relevant variants of inventory routing and fleet composition problems
- Analysis
- Solution methods
 - Exact methods (Column generation and Lagrangian relaxation)
 - Bounds, relaxations and reductions
 - Approximative methods (heuristic column generation, metaheuristics)
 - Hybrid methods (combining exact methods and metaheuristics)
- Prototype solvers
- Computational experiments on instances from literature and industry

Relevance to eScience

- Mathematics
 - mathematical modelling
 - polyhedral theory
 - mathematical programming methods
- Computing science, informatics
 - conceptual modelling
 - search methods
 - decision support systems
- Applications
- Numerics
- High-performance computing
 - computational experiments
 - automated code generation for metaheuristics

Summary

- Challenges in industry and the public sector
 - coordination
 - activities, time, resources
 - planning, design
- Computationally hard DOPs often at the core
- There is a strong need for more powerful methods
- Many challenges, promising research avenues
- Application oriented and scientifically challenging
- eScience
- Norway has a strong position
 - good scientists
 - good access to application cases
 - good infrastructure
 - good funding opportunities
- The road is short from scientific to practical improvements

Conclusion

Applied research in discrete optimization deserves further funding in eVITA



Optimization-based decision support within healthcare and transportation

eVITA Scientific Meeting
Geilo, Norway January 28, 2010
Geir Hasle, SINTEF ICT

