Adaptive Transportation Systems

with a Holistic Representation of Supply and Demand

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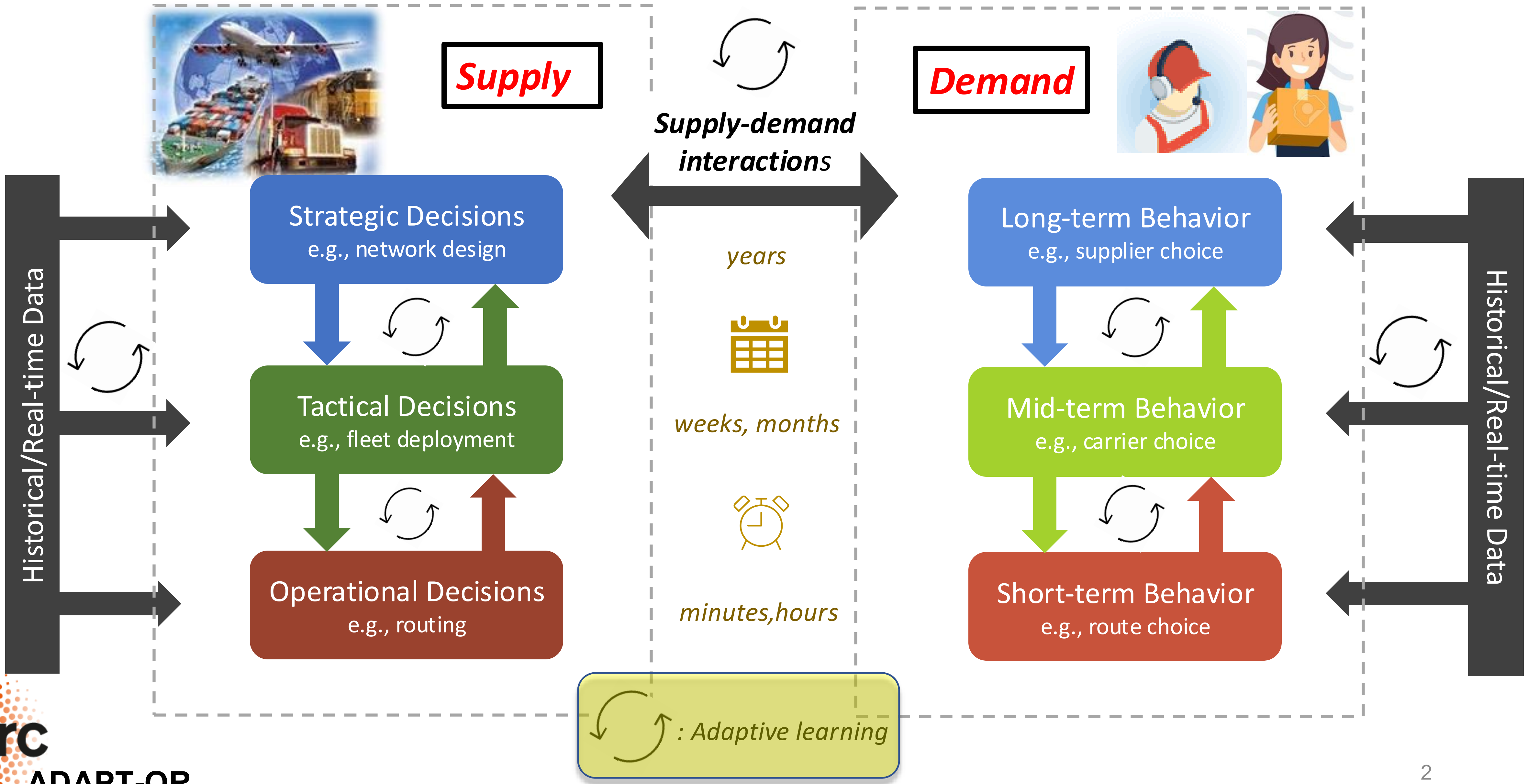
Adaptive Transportation Systems



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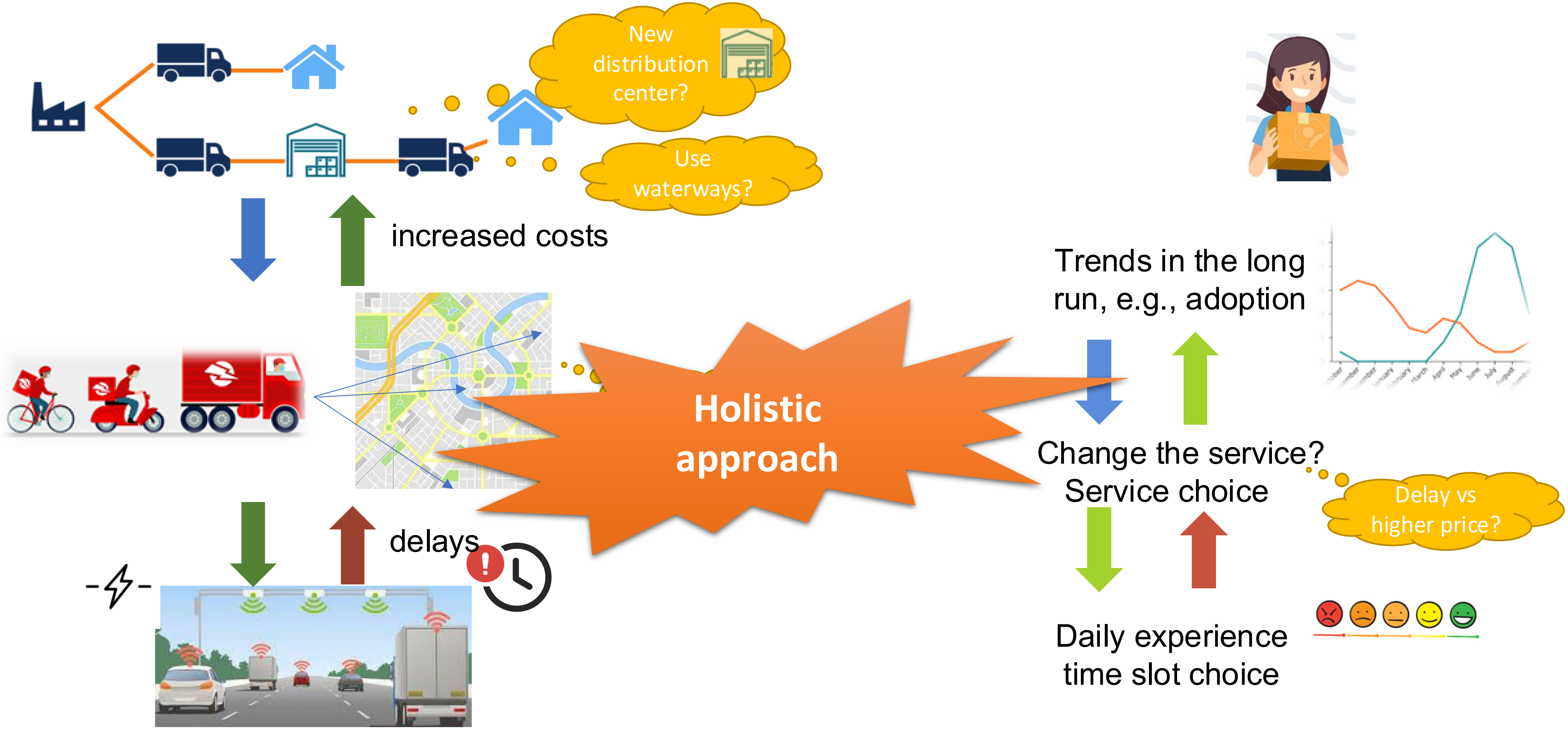
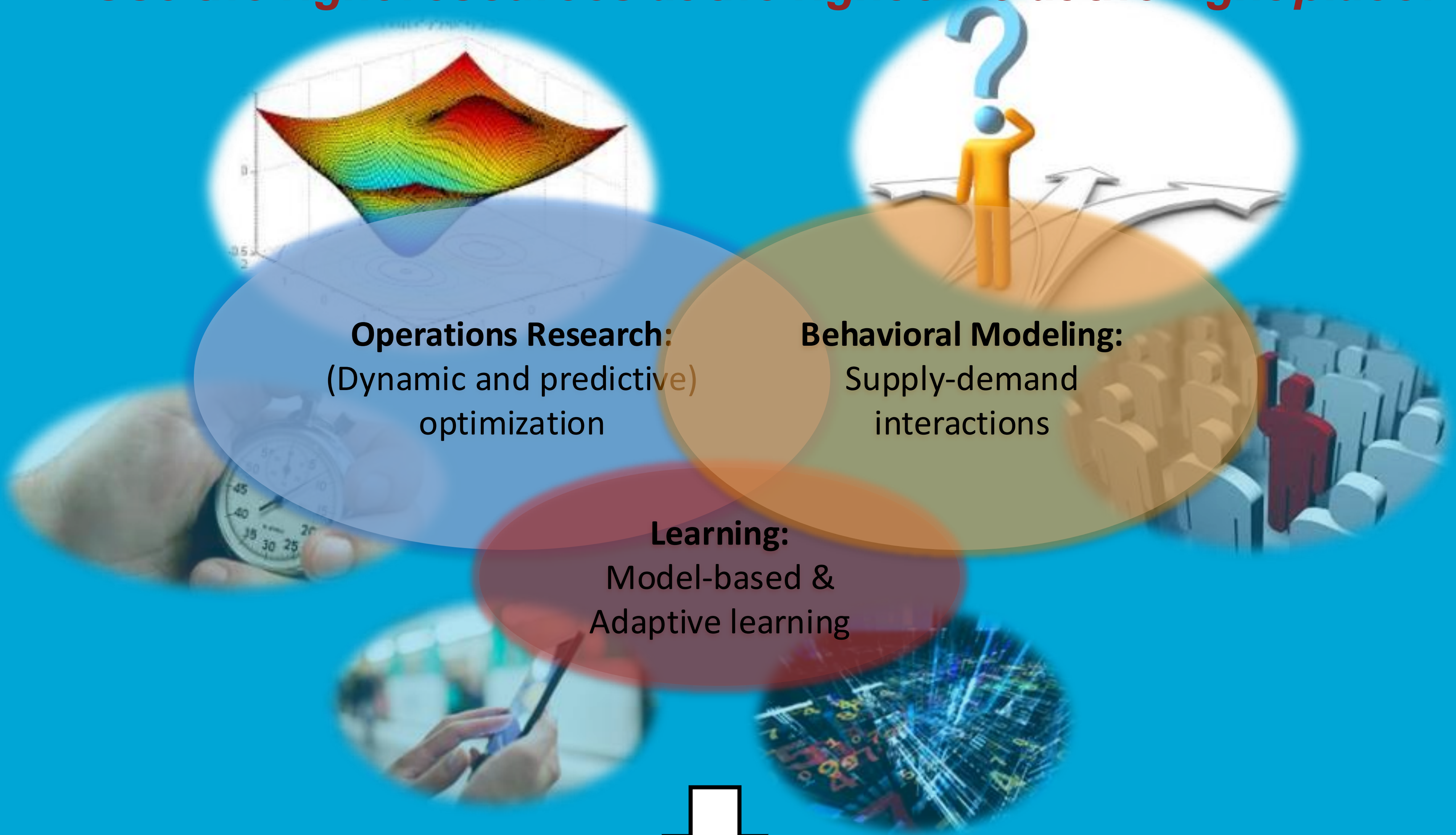
ADAPT-OR

The idea behind



How to develop these capabilities?

Use the right resources at the right time at the right place!



ADAPTIVE TRANSPORTATION & LOGISTICS

Application Areas

Mobility

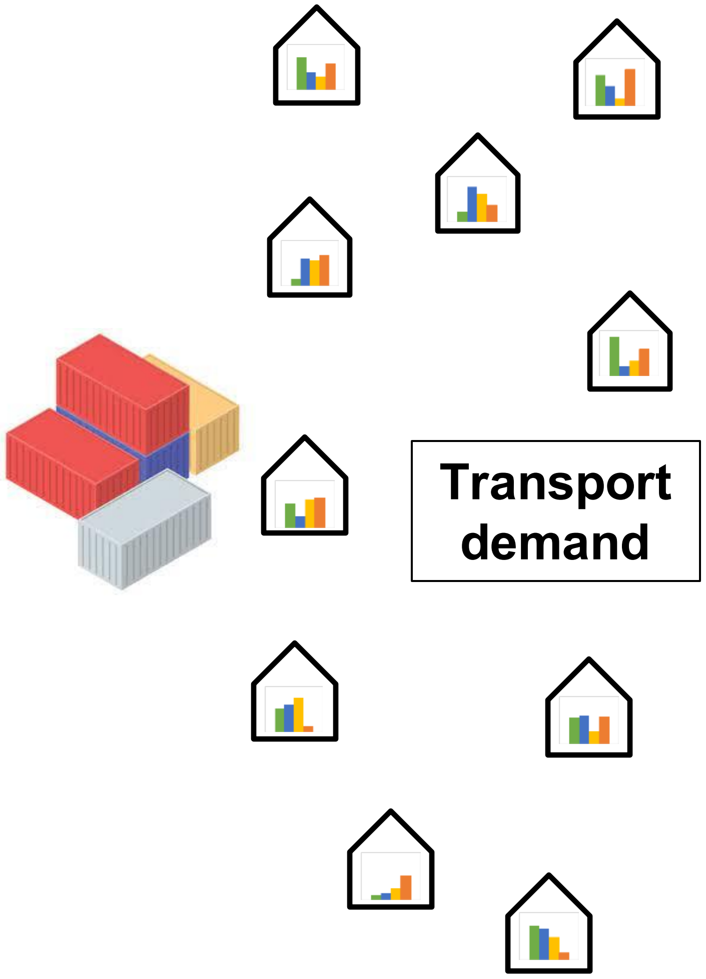
City Logistics

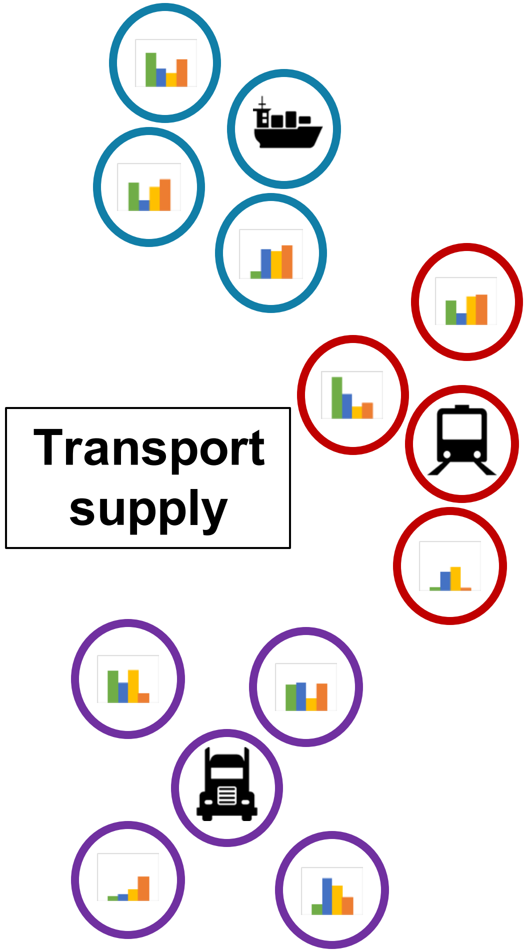
Inland waterways

Last-mile delivery

Intermodal transport

Case for today: Intermodal transport / Synchromodal transport





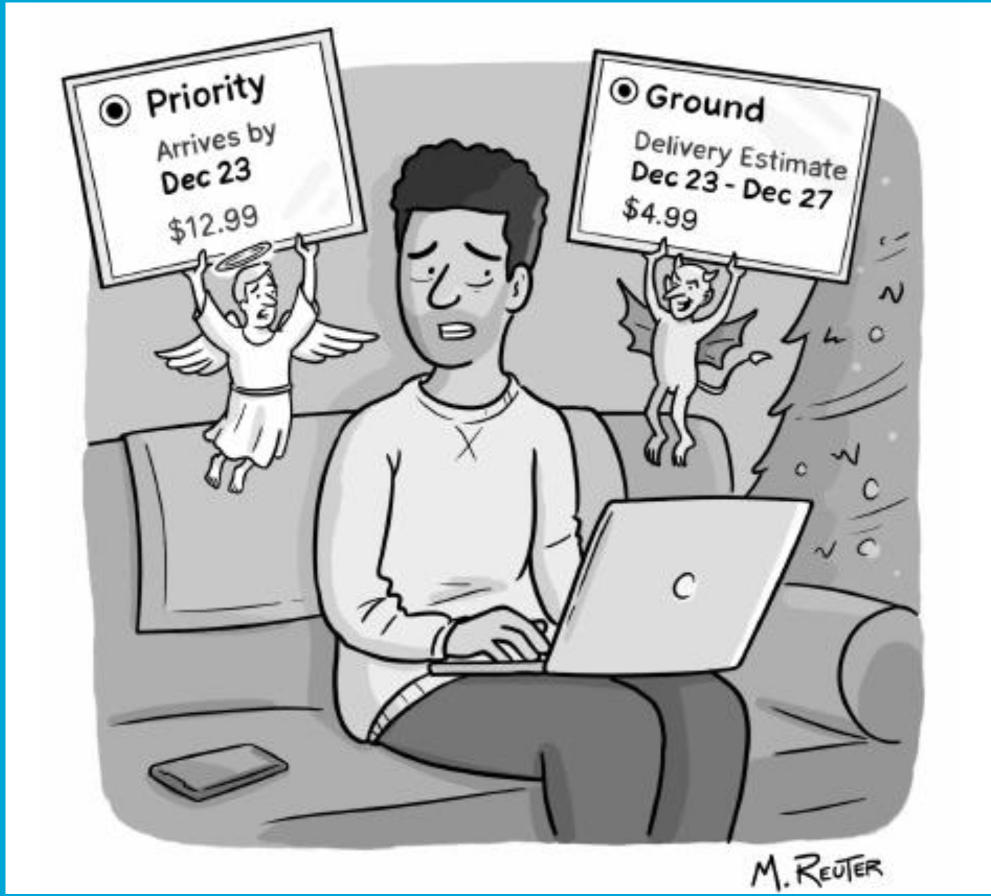
Plan for today

- Choice-based service network design and pricing
  - Tactical level: service network design – mode choice
  - Optimization and behavioral modeling
- Model-assisted reinforcement learning for synchromodal transport
  - Operational level: routing, replanning (+ mode choice)
  - Optimization and learning (+ behavioral modeling)
- Inverse optimization and beyond…

Choice-Driven Service Network Design and Pricing (CD-SNDP)

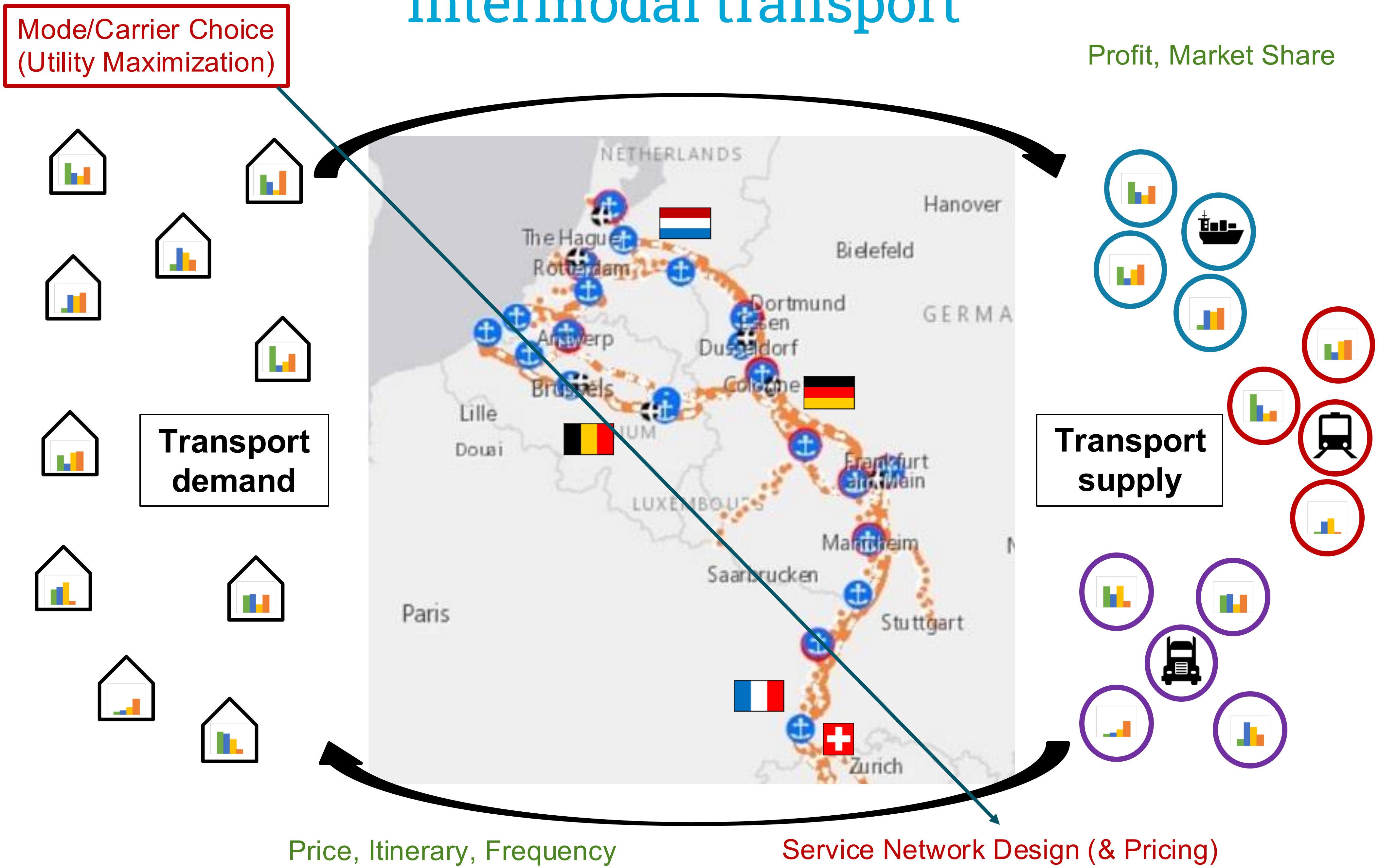
PhD work of

Adrien Nicolet

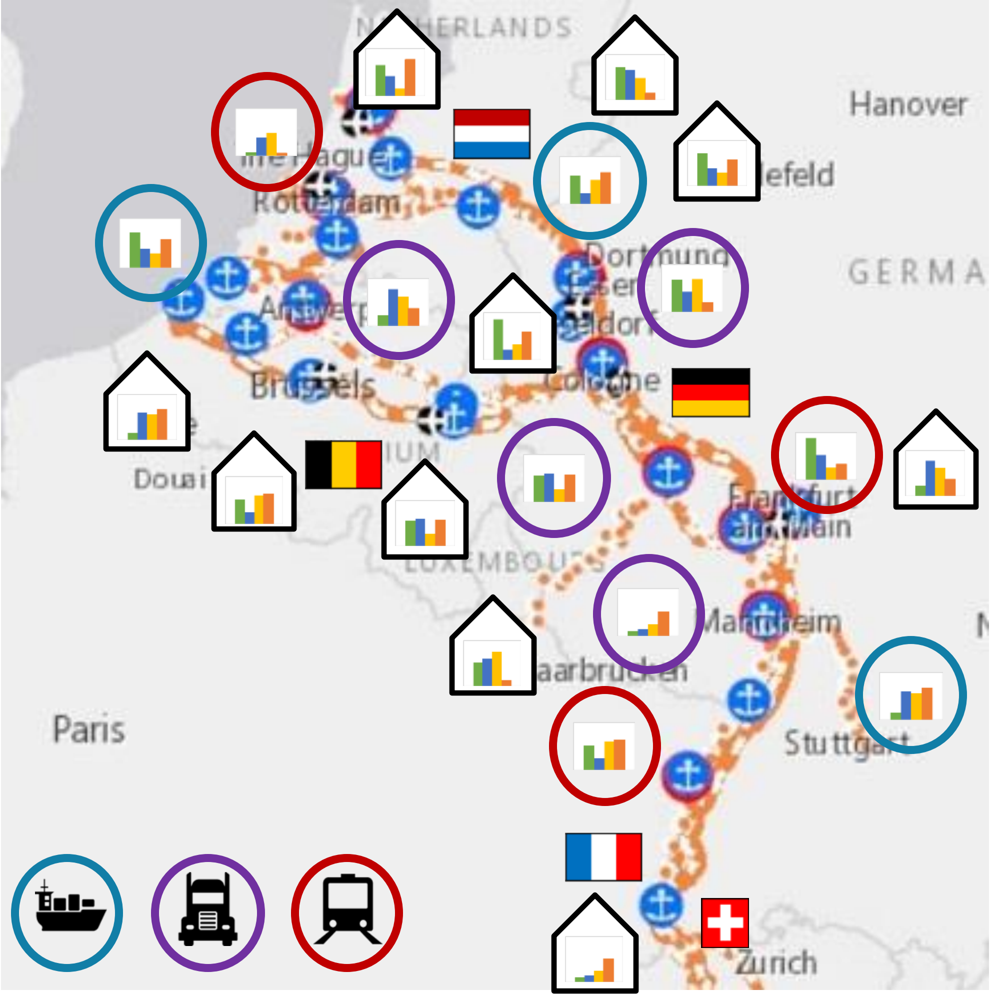


Nicolet, A. and B. Atasoy. "A choice-driven service network design and pricing including heterogeneous behaviors." Transportation Research Part E: Logistics and Transportation Review 191 (2024)

Intermodal transport

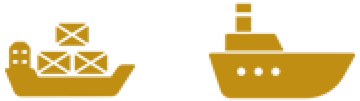


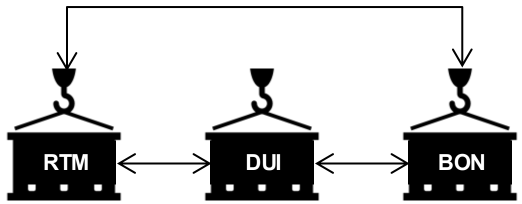
Challenge



- Very complex system
  - Many ports/terminals
  - Involves different countries
  - 3 different transport modes
  - Many operators with various objectives
  - Numerous shippers exhibiting different behavior
  - Relationships between these actors

Notation

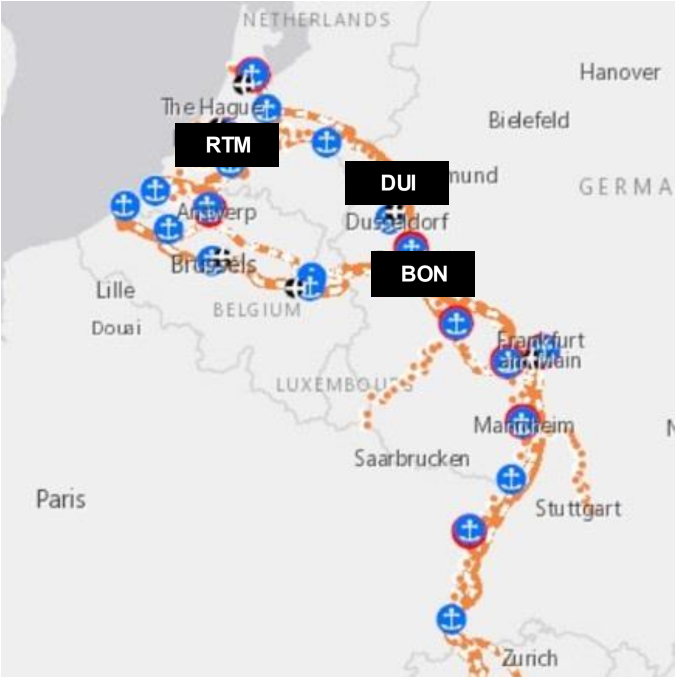




Sets:	
$\mathcal{N}$	Set of terminals (indices: i, j)
$\mathcal{A}$	Set of arcs (i, j)
$\mathcal{K}$	Set of vehicle types (index: k)
$\mathcal{S}$	Set of potential services (index: s)
$\mathcal{L}_s$	Set of legs of service $s \in \mathcal{S}$ (index: l_s)
$\mathcal{H}$	Set of competing alternatives (index: h)
Parameters:	
V_k	Number of vehicles of type k in the operator's fleet
Q_k	Capacity of vehicle type k [TEUs]
W_{sk}	Maximum number of cycles of service s that can be performed by vehicle type k
c_{sk}^{FIX}	Fixed cost of operating service s with vehicle type k [€]
c_{ijsk}^{VAR}	Variable cost of transport between i and j with service s and vehicle type k [€/TEU]
δ_{ijl_s}	Dummy parameter equal to 1 if container traveling from i to j uses service leg l_s, 0 otherwise
D_{ij}	Aggregated transport demand of shippers between i and j [TEUs]
U_{ij}^{O}	Utility of using the operator's services between i and j
U_{ij}^{h}	Utility of using competing alternative h between i and j
Variables:	
v_{sk}	Number of vehicles of type k assigned to service s by the operator
f_{sk}	Frequency of service s operated with vehicle type k
p_{ij}	Price charged by the operator to shippers wanting to transport goods from i to j [€/TEU]
x_{ijsk}	Cargo volume using service s operated with vehicle type k between i and j [TEUs]
z_{ij}^{h}	Cargo volume using competing alternative h between i and j [TEUs]

UL

LL



Potential Services

Formulation

$$\max_{v,f,p,x,z} \sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} p_{ij} x_{ijsk} - \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} c_{sk}^{\mathrm{FIX}} f_{sk} - \sum_{(i,j)\in\mathcal{A}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} c_{ijsk}^{\mathrm{VAR}} x_{ijsk}$$

UL profit maximization

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}} v_{sk} \leq V_k \qquad \forall k \in \mathcal{K}$$

Fleet size

$$f_{sk} \leq W_{sk} v_{sk} \qquad \forall s \in \mathcal{S},\ \forall k \in \mathcal{K}$$

Cycle time feasibility

$$\sum_{(i,j)\in\mathcal{A}} \delta_{ijl_s} x_{ijsk} \leq Q_k f_{sk} \qquad \forall l_s \in \mathcal{L}_s,\ \forall s \in \mathcal{S},\ \forall k \in \mathcal{K}$$

Available capacity

$$x_{ijsk} \leq \sum_{l_s\in\mathcal{L}_s} \delta_{ijl_s} D_{ij} \qquad \forall (i,j) \in \mathcal{A},\ \forall s \in \mathcal{S},\ \forall k \in \mathcal{K}$$

OD included in service

$$\begin{aligned} & p_{ij} \geq 0 && \forall (i,j) \in \mathcal{A} \\ & v_{sk} \in \mathbb{N} && \forall s \in \mathcal{S},\ \forall k \in \mathcal{K} \\ & f_{sk} \in \mathbb{N} && \forall s \in \mathcal{S},\ \forall k \in \mathcal{K} \end{aligned}$$

where x and z solve:

$$\max_{x,z} \sum_{(i,j)\in\mathcal{A}} \left(\sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} U_{ij} x_{ijsk} + \sum_{h\in\mathcal{H}} U_{ij}^h z_{ij}^h \right)$$

LL utility maximization

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} x_{ijsk} + \sum_{h\in\mathcal{H}} z_{ij}^h = D_{ij} \qquad \forall (i,j) \in \mathcal{A}$$

Satisfied demand

$$\begin{aligned} & x_{ijsk} \geq 0 && \forall (i,j) \in \mathcal{A},\ \forall s \in \mathcal{S},\ \forall k \in \mathcal{K} \\ & z_{ij}^h \geq 0 && \forall (i,j) \in \mathcal{A},\ \forall h \in \mathcal{H} \end{aligned}$$

Utility functions

$$U_{ijr}^{O} = \alpha^{\mathrm{IWT}} + \beta_a^{\mathrm{Inter}} a_{ij}^{\mathrm{IWT}} + \beta_q^{\mathrm{IWT}} q_{ij} + \beta_c^{\mathrm{Inter},r} (\boldsymbol{p_{ij}} + \mathrm{VoT} t_{ij}^{\mathrm{IWT}}) + \beta_f^{\mathrm{Inter}} \boldsymbol{f_{ij}} + \epsilon_{ijr}^{O}$$

$$U_{ijr}^{h=\mathrm{IWT}} = \alpha^{\mathrm{IWT}} + \beta_a^{\mathrm{Inter}} a_{ij}^{\mathrm{IWT}} + \beta_q^{\mathrm{IWT}} q_{ij} + \beta_c^{\mathrm{Inter},r} (p_{ij}^{\mathrm{IWT}} + \mathrm{VoT} t_{ij}^{\mathrm{IWT}}) + \beta_f^{\mathrm{Inter}} f_{ij}^{\mathrm{IWT}} + \epsilon_{ijr}^{\mathrm{IWT}}$$

$$U_{ijr}^{h=\mathrm{Rail}} = \alpha^{\mathrm{Rail}} + \beta_a^{\mathrm{Inter}} a_{ij}^{\mathrm{Rail}} + \beta_c^{\mathrm{Inter},r} (p_{ij}^{\mathrm{Rail}} + \mathrm{VoT} t_{ij}^{\mathrm{Rail}}) + \beta_f^{\mathrm{Inter}} f_{ij}^{\mathrm{Rail}} + \epsilon_{ijr}^{\mathrm{Rail}}$$

$$U_{ijr}^{h=\mathrm{Road}} = \alpha^{\mathrm{Road}} + \beta_a^{\mathrm{Road}} a_{ij}^{\mathrm{Road}} + \beta_c^{\mathrm{Road}} (p_{ij}^{\mathrm{Road}} + \mathrm{VoT} t_{ij}^{\mathrm{Road}}) + \epsilon_{ijr}^{\mathrm{Road}}$$

f_{ij} corresponds to the term $\sum_{s \in \mathcal{S}} \sum_{k \in \mathcal{K}} \phi_{ijs} f_{sk}$

Nicolet A, Negenborn RR, Atasoy B, "A logit mixture model estimating the heterogeneous mode choice preferences of shippers based on aggregate data", 2022, *IEEE Open Journal of Intelligent Transportation Systems,* 3:650–661.

Demand simulation

- Expected profits are computed using the knowledge on the utility function
- Idea: simulate demand response to the proposed services and prices using heterogenous population, using Mixed logit model [1].
  - For each OD pair, generate a population of 1000 shippers (i.e. perform 1000 draws of $\beta_{\mathrm{c,INTER}}$ and ε)
  - Compute their utilities based on proposed services and prices
  - Allocate containers (divided equally among the shippers) to the alternative with maximum utility
  - At the end, compute the resulting modal shares and actual profits of the operator

[1] Nicolet A, Negenborn RR, Atasoy B, "A logit mixture model estimating the heterogeneous mode choice preferences of shippers based on aggregate data", 2022, *IEEE Open Journal of Intelligent Transportation Systems,* 3:650–661.

Case study

NOVIMOVE https://novimove.eu

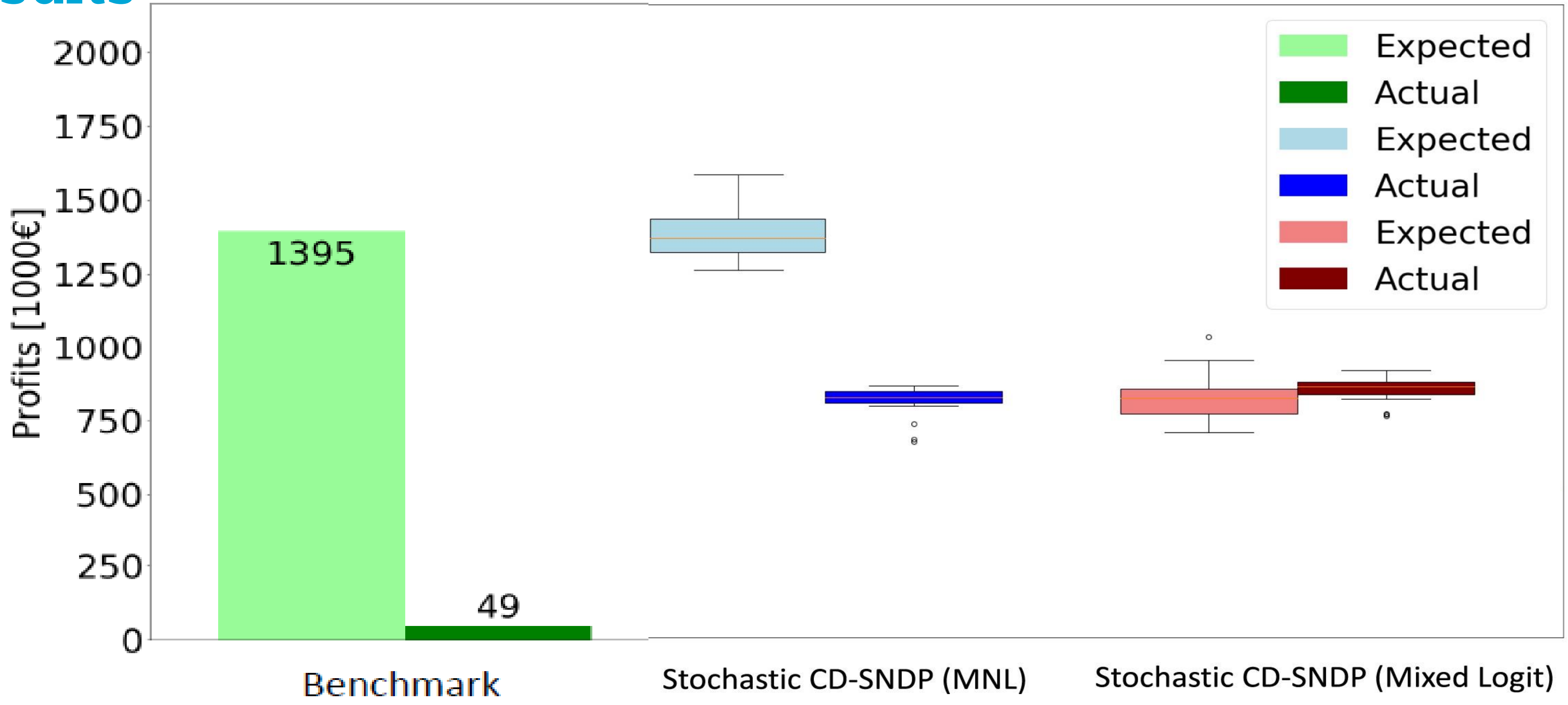
9 nodes network:

- 24 M8 vessels of cap. 180 TEUs
- 18 M11 vessels of cap. 300 TEUs
- Operational time: 120h/week

- Transport demand inputs from NOVIMOVE project [1]
- Cost and time estimation from existing model [2]

[1] Majoor I, et al., "D.2.2: Novimove transport model architecture and data collection", 2021, *Technical report*, NOVIMOVE.
[2] Shobayo P, et al., "Conceptual development of the logistics chain flow of container transport within the Rhine-Alpine corridor", 2021, *European Transport Conference (ETC)*, 1–17.

Results



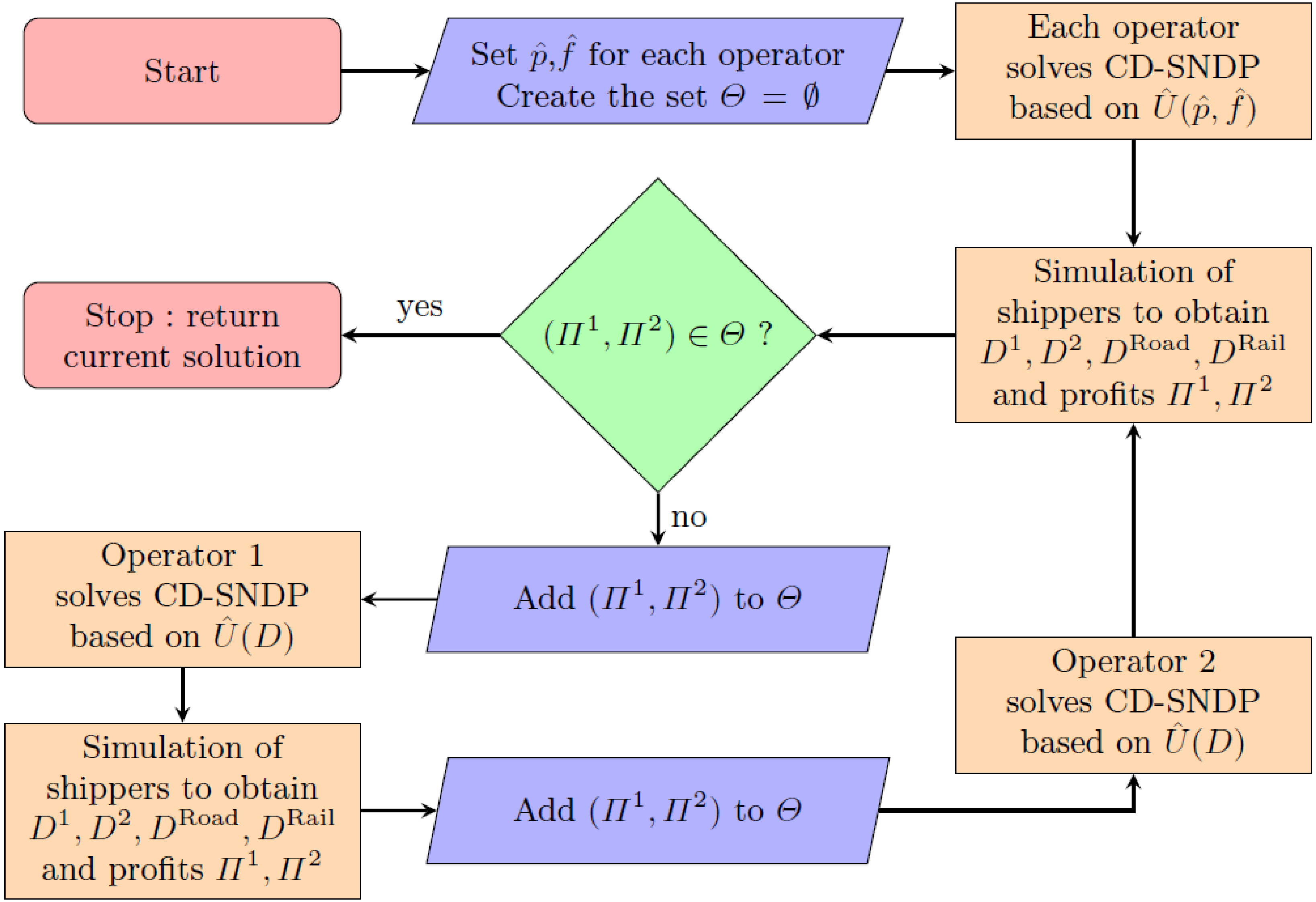
Modal shares	IWT	44% (100%)	37% (39%)	40% (42%)	38%
	Road	44% (0%)	50% (51%)	49% (47%)	55%
	Rail	12% (0%)	13% (10%)	11% (11%)	7%

Limitations

- Full information of the IWT operator
  - About their competitors
  - About the specification of shipper utilities (*even though the exact coefficients are not known*)

- Exogenous and fixed competition
  - No reaction to IWT operator services and prices

Competition concept



$$\hat{U}^h_{ij} = U^1_{ij} + \ln(D^h_{ij}/D^1_{ij})$$

Results on the Rotterdam-Duisburg OD pair
Starting assumption

Each operator has:

- 24 small vessels
- 18 big vessels

	$\hat{p}$: 30	60	90	120	150	180	210	240	270	300
Profit outcomes										
$\hat{f}$ 5	0.05	0.04	0.03	1	1	1	1	1	1	1
$\hat{f}$ 20	0.09	0.05	0.05	0.05	0.03	1	1	1	1	1
$\hat{f}$ 35	-	0.21	0.09	0.05	0.05	0.05	0.03	1	1	1
Final prices (Operator 1\Operator 2)										
$\hat{f}$ 5	133\130	146\143	134\130	286\0	283\0	284\0	284\0	284\0	284\0	284\0
$\hat{f}$ 20	100\97	127\125	138\135	137\134	134\130	288\0	284\0	284\0	284\0	284\0
$\hat{f}$ 35	-\-	80\78	100\97	127\125	138\135	137\134	134\130	288\0	284\0	284\0
Final frequencies (Operator 1\Operator 2)										
$\hat{f}$ 5	35\35	35\35	35\35	35\0	35\0	35\0	35\0	35\0	35\0	35\0
$\hat{f}$ 20	35\35	35\35	35\35	35\35	35\35	35\0	35\0	35\0	35\0	35\0
$\hat{f}$ 35	-\-	35\35	35\35	35\35	35\35	35\35	35\35	35\0	35\0	35\0
Final IWT share										
$\hat{f}$ 5	68%	66%	66%	28%	28%	28%	28%	28%	28%	28%
$\hat{f}$ 20	75%	68%	67%	68%	66%	28%	28%	28%	28%	28%
$\hat{f}$ 35	0%	79%	75%	68%	67%	68%	66%	28%	28%	28%

77%

Information level

Each operator has:

- 24 small vessels
- 18 big vessels
- $\hat{f} = 20$
- $\hat{p} = 60$

		IWT operator 2	
		Limited	Full
		Profit outcomes	
IWT operator 1	Limited	0.05	0.05
	Full	1	0.06
		Final prices	
IWT operator 1	Limited	127\125	164\164
	Full	152\0	127\127
		Final frequencies	
IWT operator 1	Limited	35\35	35\35
	Full	35\0	35\35
		Final IWT share	
IWT operator 1	Limited	68%	61%
	Full	50%	68%

Asymmetry of information is reducing the overall market share

Conclusions & Future Work

- Competition concept to address the limitations of CD-SNDP
  - Reaction of competitor and imperfect information
- Equilibrium solution highly depends on the assumptions
  - Need of careful validation

- Inclusion of more players → a more realistic agent-based framework
- Inclusion of dynamic pricing, e.g., due to water level changes
- Consideration of Revenue Management

A Model-Assisted Reinforcement Learning for Synchromodal Transport

PhD work of

Yimeng Zhang

Earlier PhD students

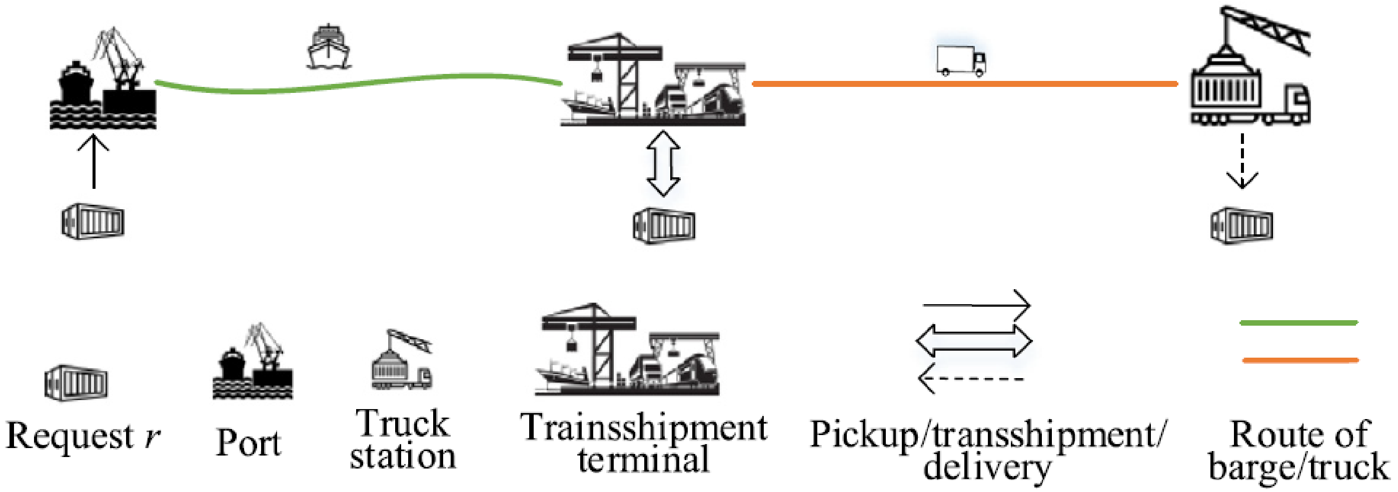
Wenjing Guo

Rie Larsen

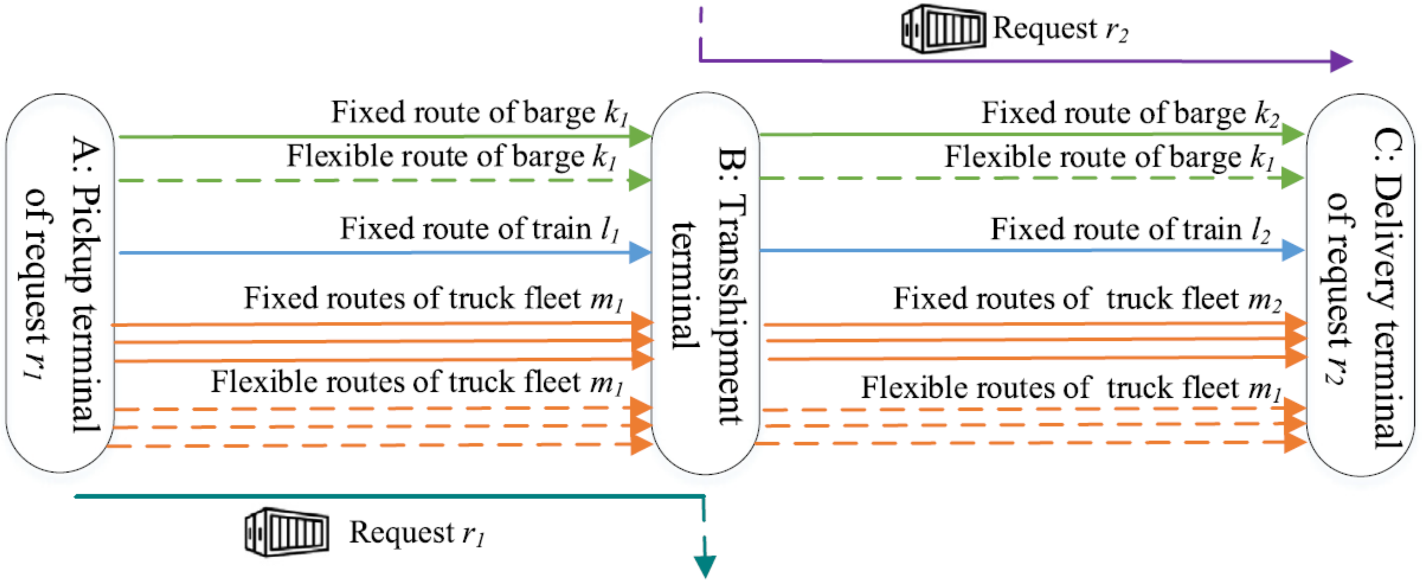
TUDelft

Zhang, Y., Negenborn, R.R., & Atasoy, B. (2023). Synchromodal freight transport re-planning under service time uncertainty: An online model-assisted reinforcement learning. *Transportation Research Part C: Emerging Technologies*, 156

Introduction



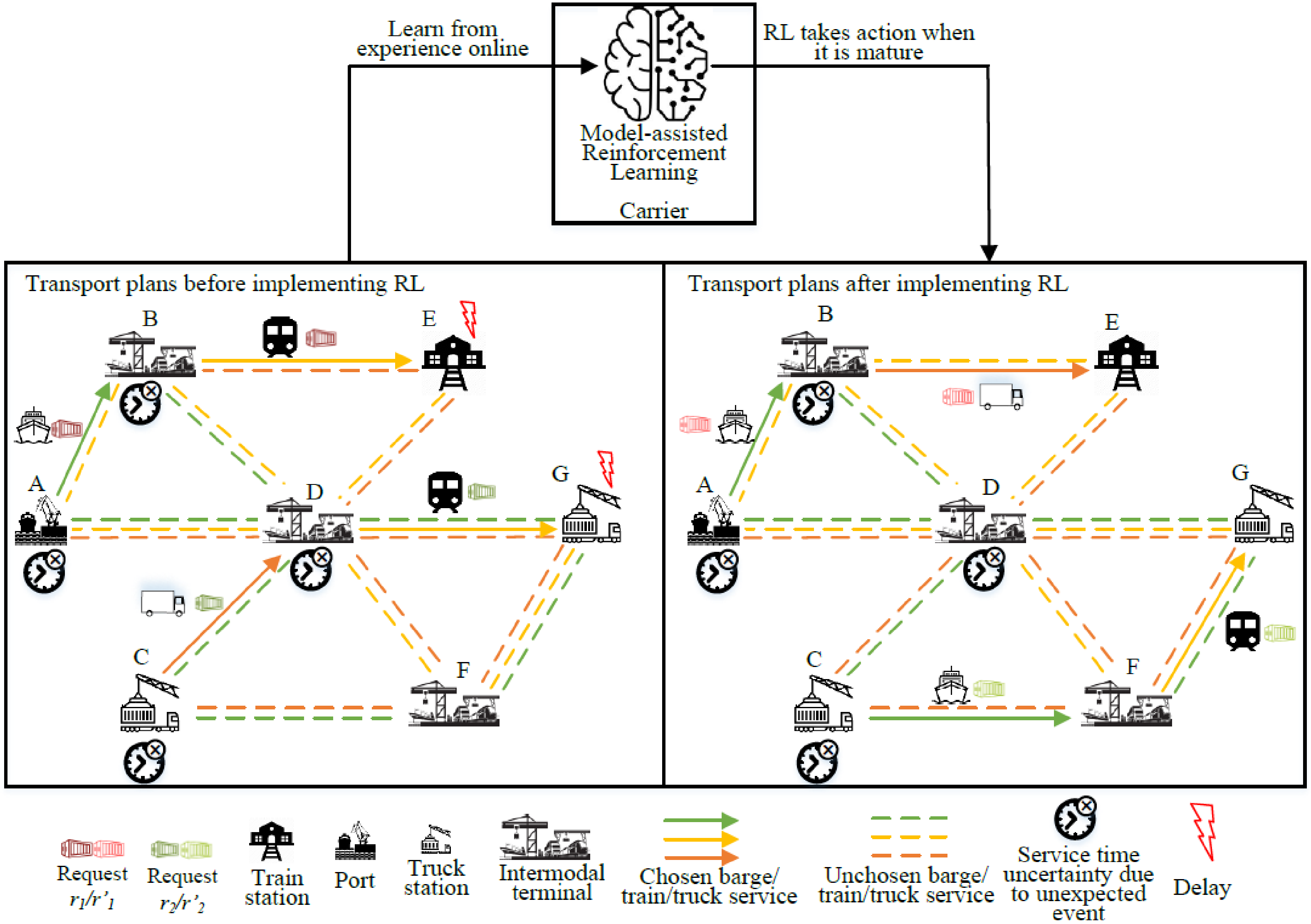
Transshipment between multiple transport modes



Multiple types of services (fixed and flexible services)

Introduction

Service time uncertainty at the terminals



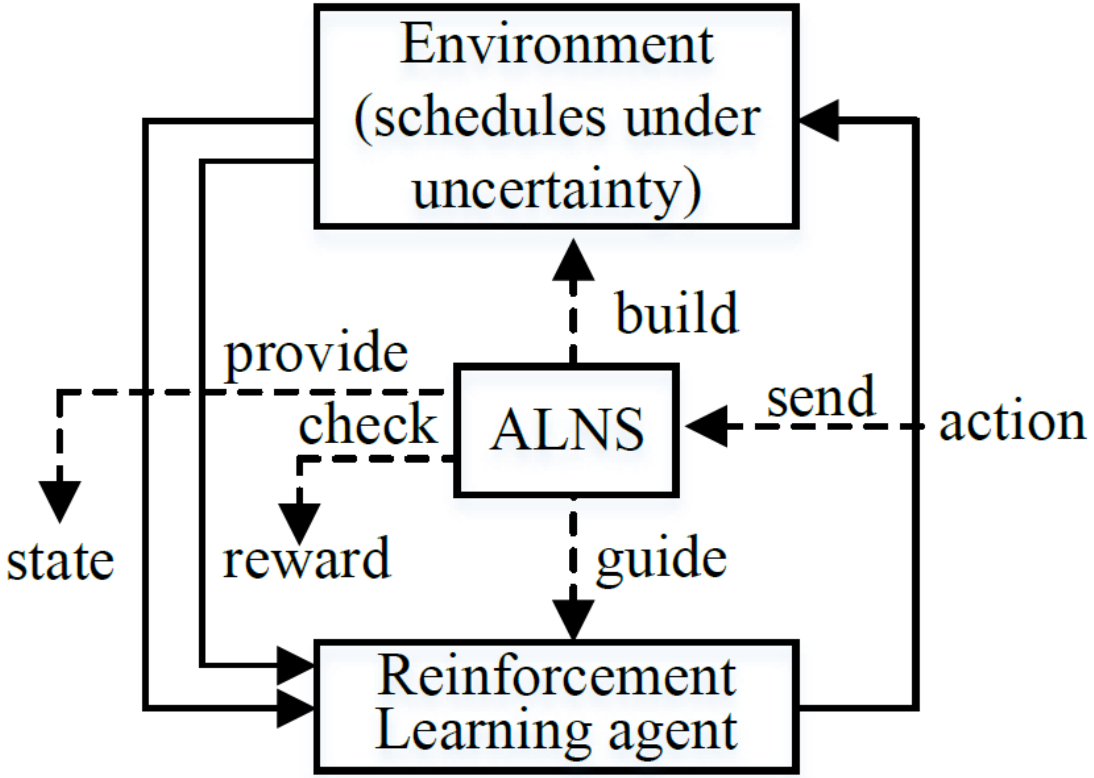
Reinforcement Learning (RL):
learn from the experience and adjust the routes and schedules to avoid delay when unexpected events happen.

Modeling framework

- Initial transport plan by ALNS

When there is a disturbance / disruption:

- Identify the set of affected requests
- Take action
  - (Benchmark) Waiting strategy
  - (Benchmark) Average duration strategy
  - RL strategy - *when mature enough*
- Rewards are provided by ALNS

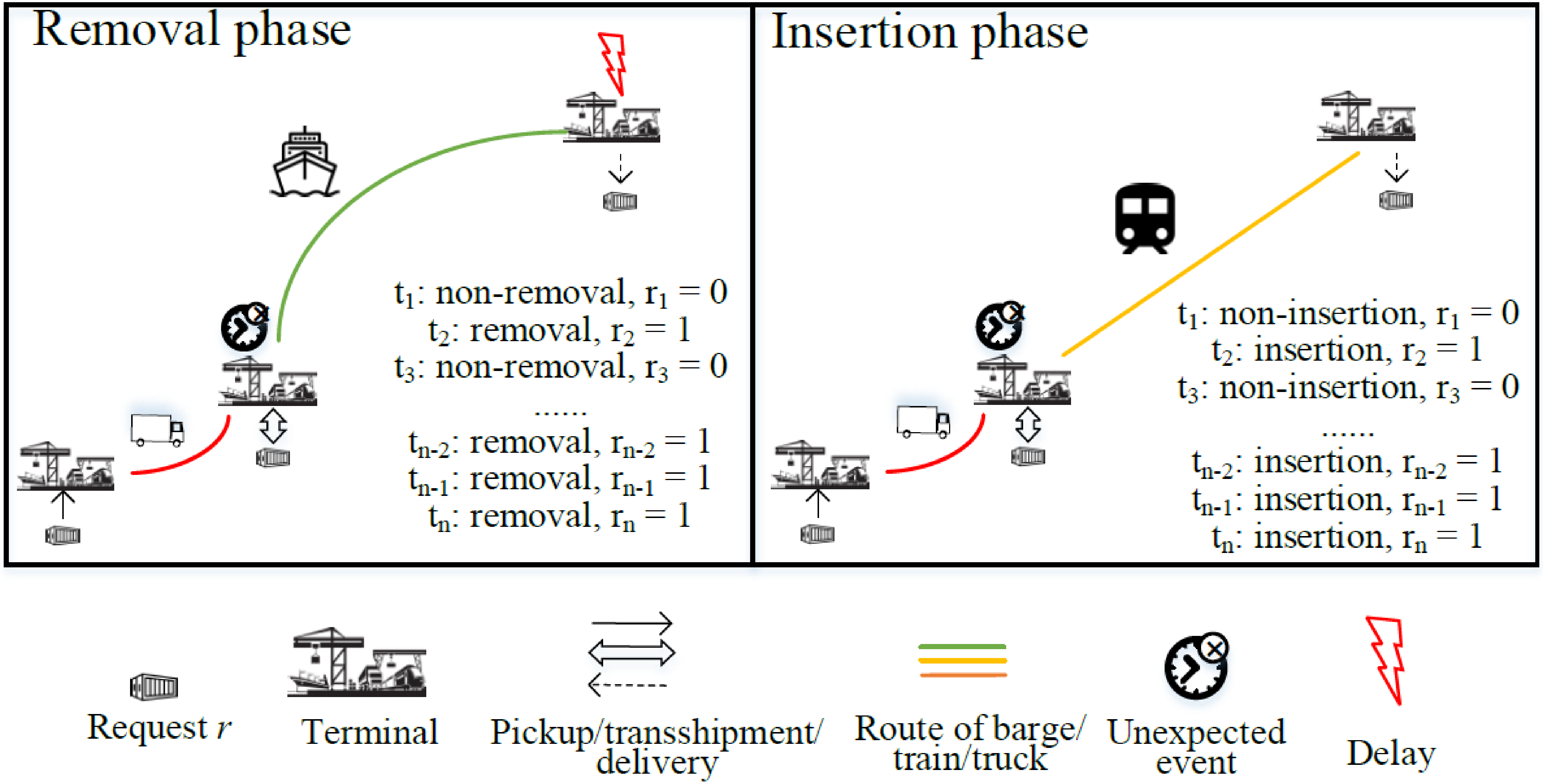


Zhang, Y., Guo, W., Negenborn, R. R., & Atasoy, B. (2022). Synchromodal transport planning with flexible services: Mathematical model and heuristic algorithm. Transportation Research Part C: Emerging Technologies, 140, 103711.

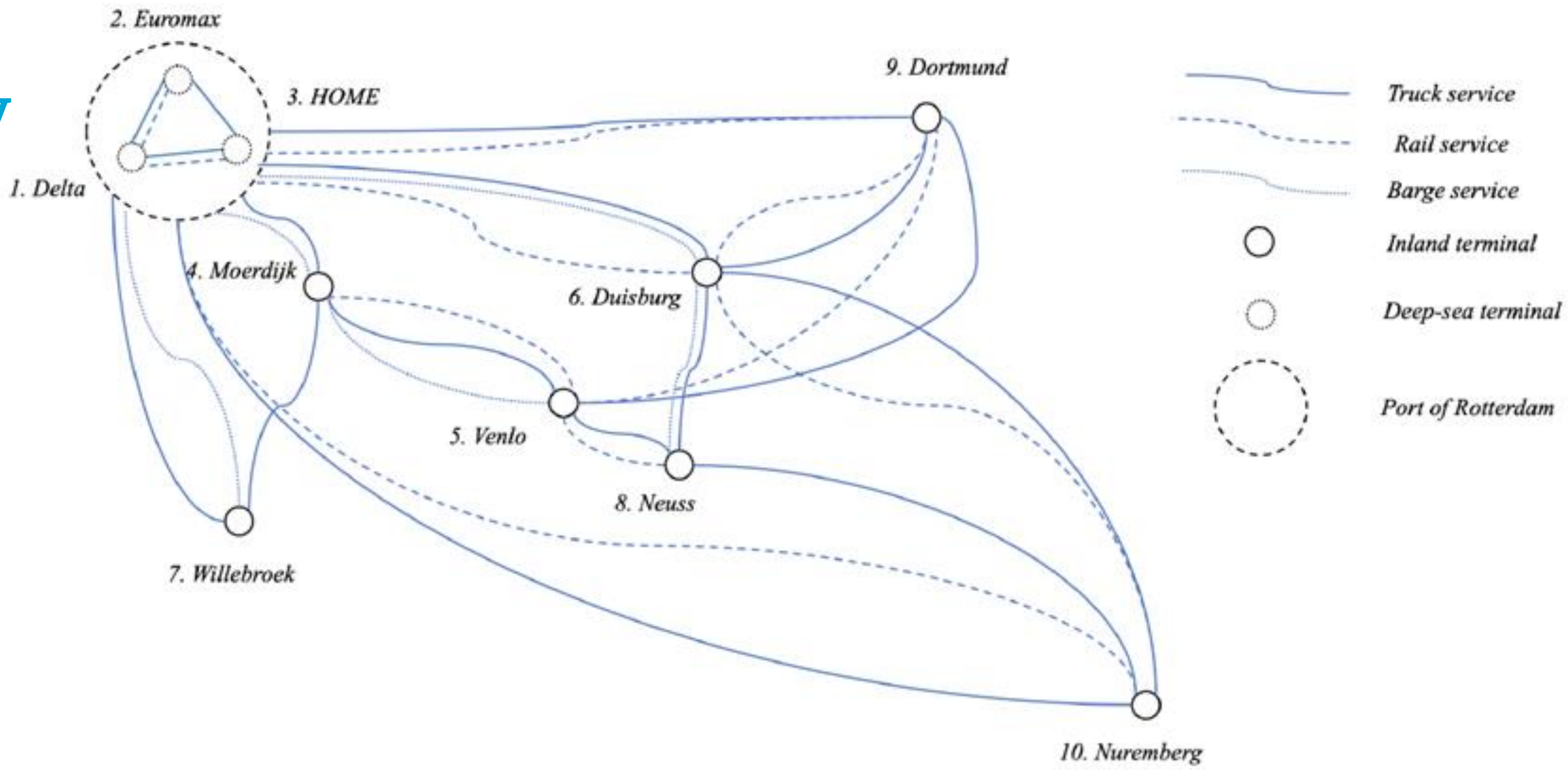
RL methodology

- RL learns how to replan, rather than the distribution of unexpected events
- State: current time, passed terminals, travel time between terminals, delay tolerance
- Action:
  - Removal phase: removal or waiting
  - Insertion phase: insertion or not
- Reward: 1 if the right action is taken, 0 otherwise
  - Right action :
    - the action is removal/not-insert and there is delay when the event finishes
    - the action is waiting/insertion and there is no delay when the event finishes

RL methodology



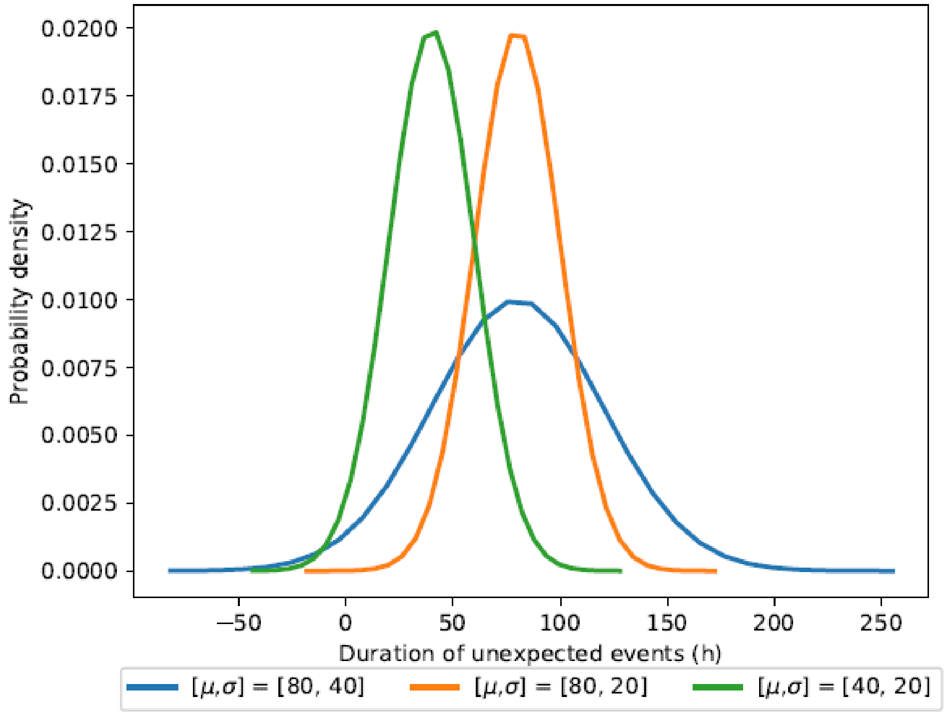
Case study

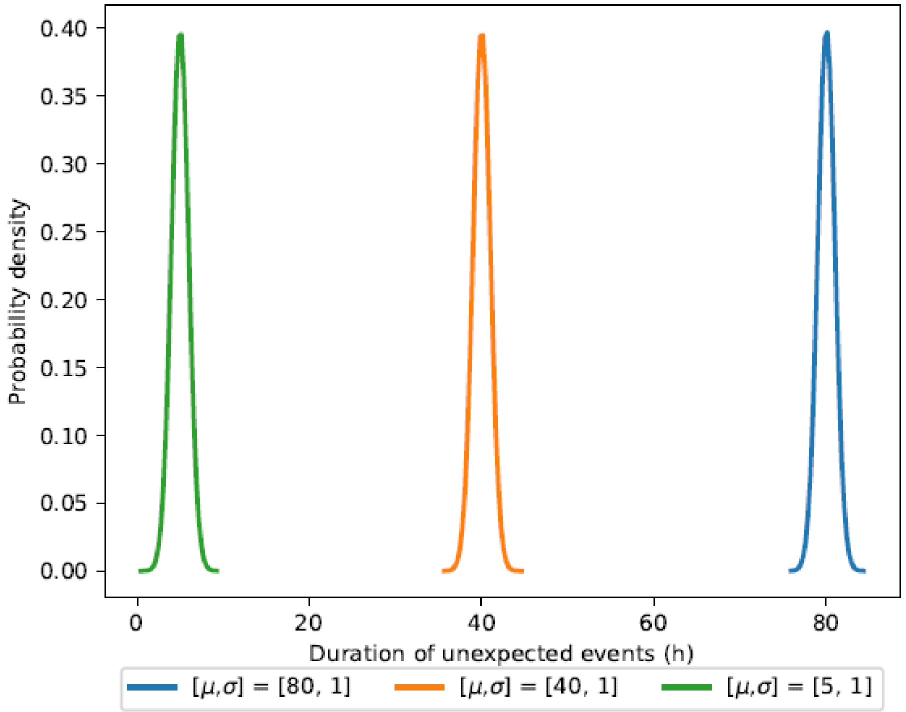


European Gateway Services (EGS) network in the Rhine-Alpine corridor:

- 3 terminals in the Port of Rotterdam
- 7 inland terminals in The Netherlands, Belgium, and Germany
- a total of 116 services: 49 barges, 33 trains, and 34 truck services
- tested with 5, 10, 20, 30, 50, and 100 shipment requests

Case study





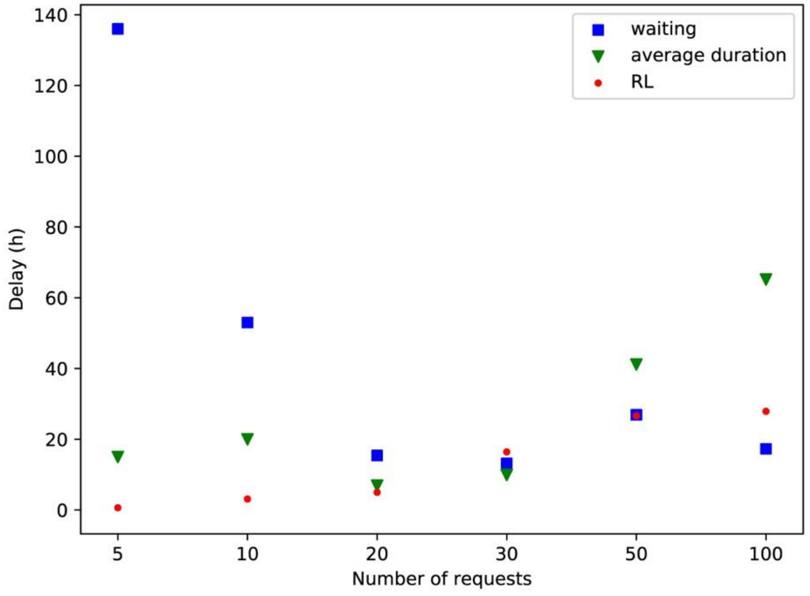
Scenarios

- Disturbances - Severe disturbances – Disruptions (*distributions are not known to RL*)
- Different terminals with different types of events
- Each terminal has multiple types of events

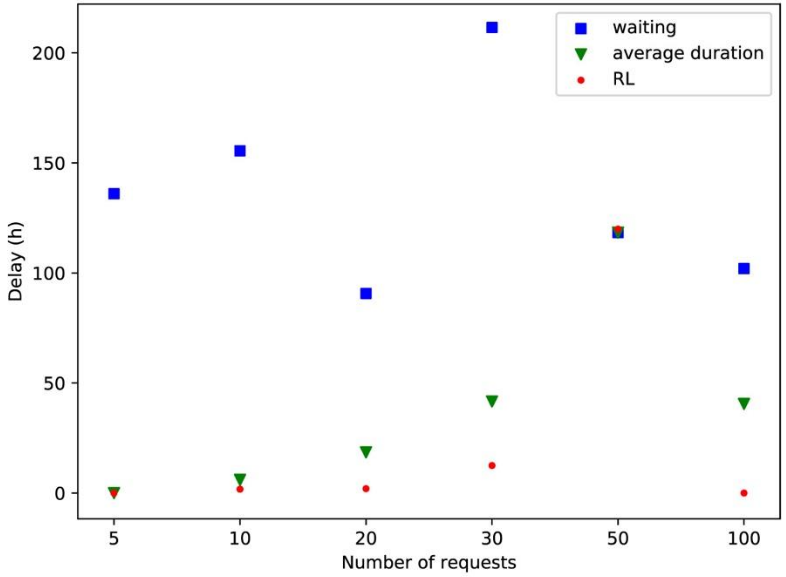
Case study

Results with one type of event per terminal

- The delay of RL strategy is better than the benchmarks
  - 80% of the time better than both
  - 20% of the time better than only one
- Average improvement in delay:
  - 54% wrt waiting
  - 10% wrt average duration



(c) severe disturbances with medium variations ([40,20])



(d) disruptions ([80,1])

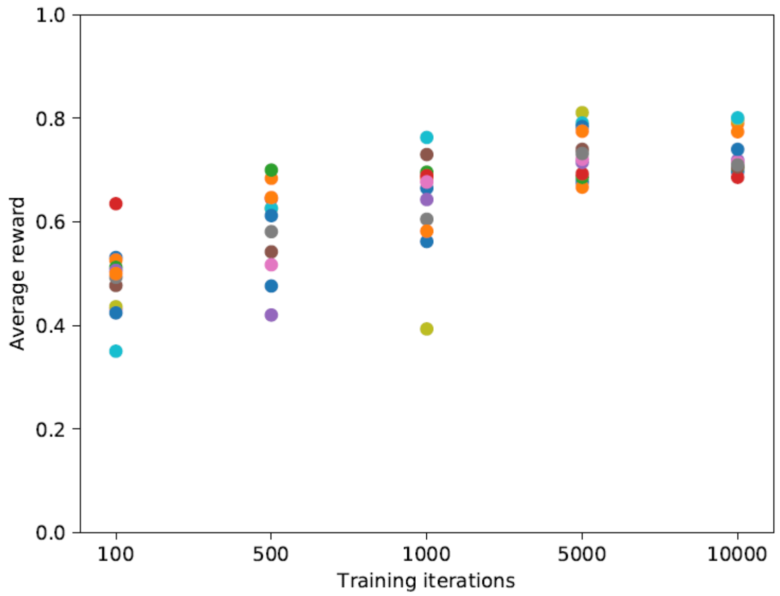
Case study

With the possibility of multiple events at a given terminal

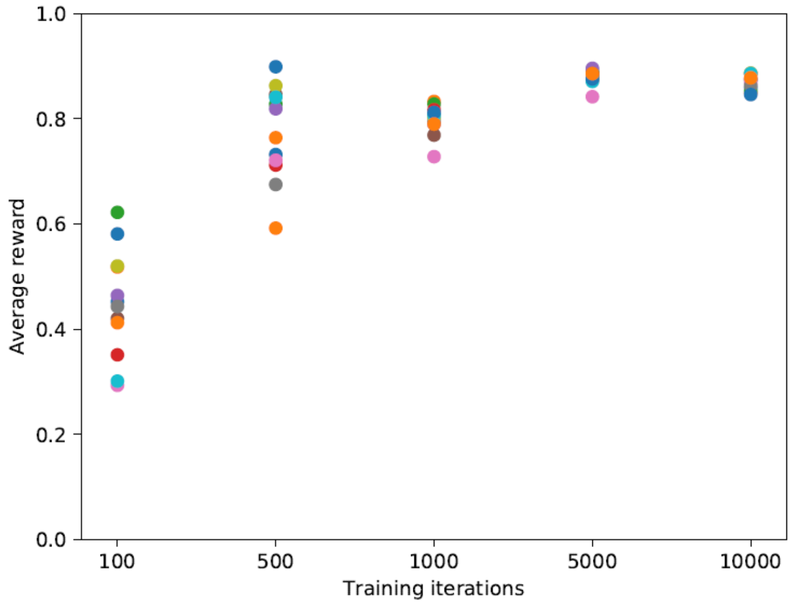
- RL is enriched with severity label information

Severity levels of events:

- Level 1: duration ≤ 20
- Level 2: duration ∈ (20, 40]
- Level 3: duration ∈ (40, 60]
- Level 4: duration ∈ (60, 80]
- Level 5: duration ∈ (80, 100]
- Level 6: duration > 100



(c) Six events without severity levels



(d) Six events with severity levels

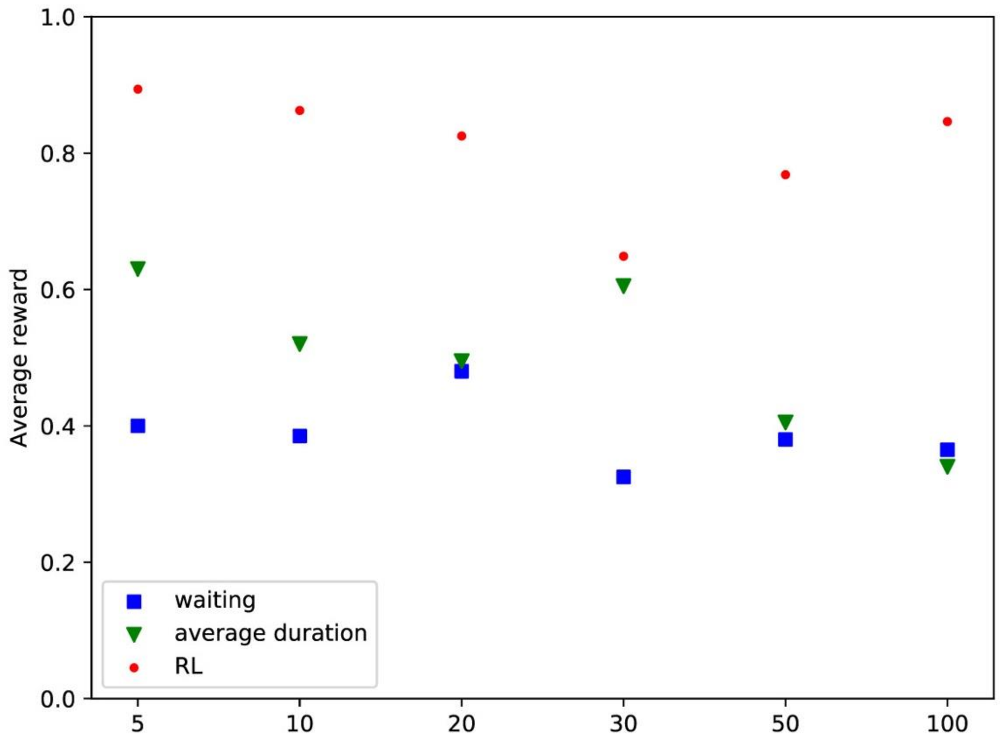
Case study

Note: the total training time needed can change from 1-2 hours to 48 hours across different instances/scenarios

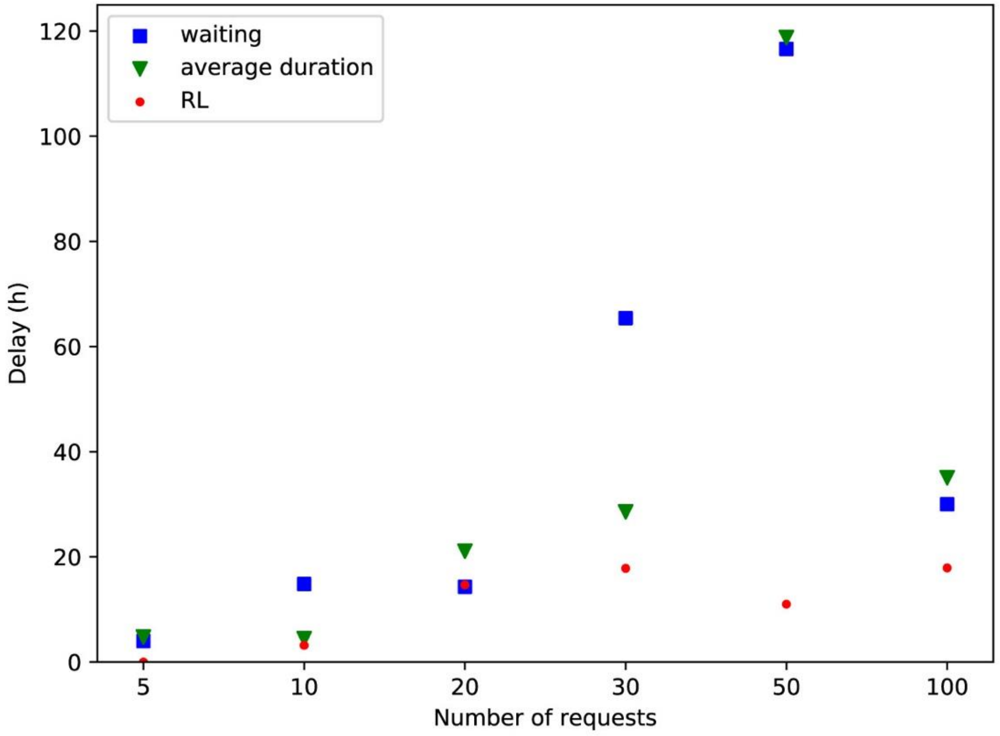
- Average improvement in delay:
  - 53% wrt waiting
  - 29% wrt average duration

Other transport performance metrics

- Average cost savings of 44%
- Average waiting time reduction of 25%



(b) six events [5, 1], [80, 5], [40, 5], [5, 1], [40, 20], [80, 40]



(b) six events [5, 1], [80, 5], [40, 5], [5, 1], [40, 20], [80, 40]

Ongoing & Future Work

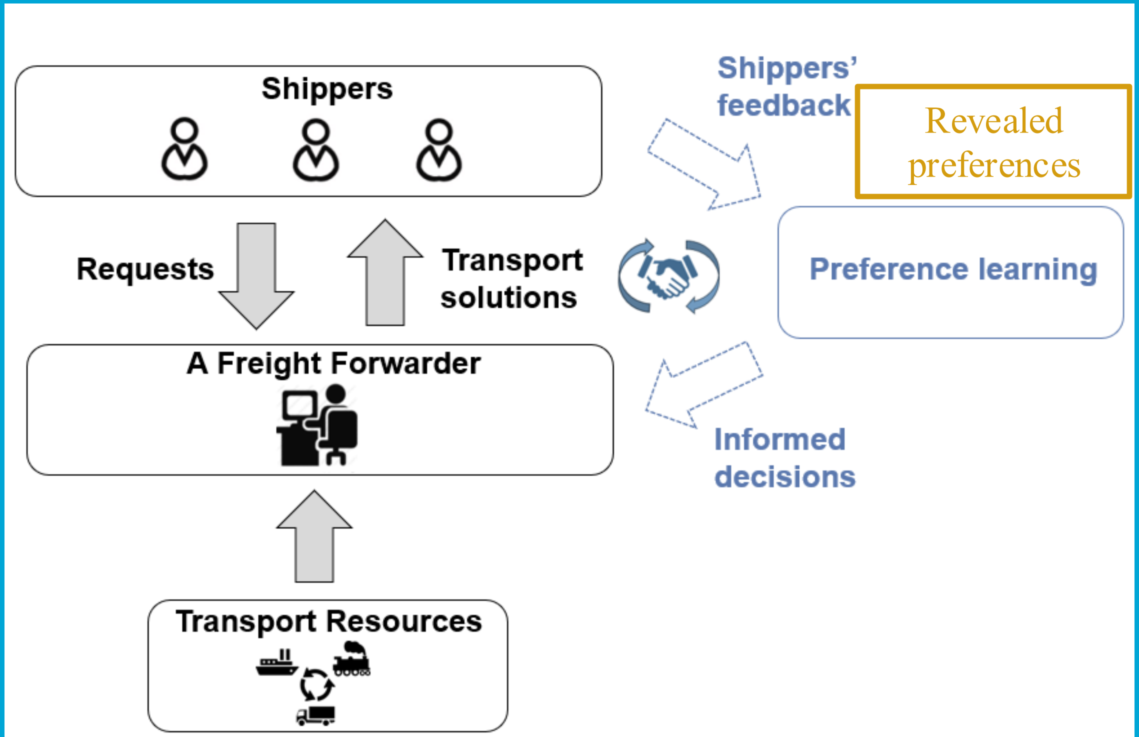
- Different reward functions
  - Continuous functions reflecting better the cost
- Different types of uncertainty
  - Travel time uncertainty, demand uncertainty
- Decentralized decision making
  - Considering different actors (LSPs, operators…)
- Incorporation of behavior

Integrated Synchromodal Transport Planning and Preference Learning

In collaboration with

Mingjia He, ETH

Yimeng Zhang, TU Delft



TU Delft

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References (intermodal / synchromodal transport)

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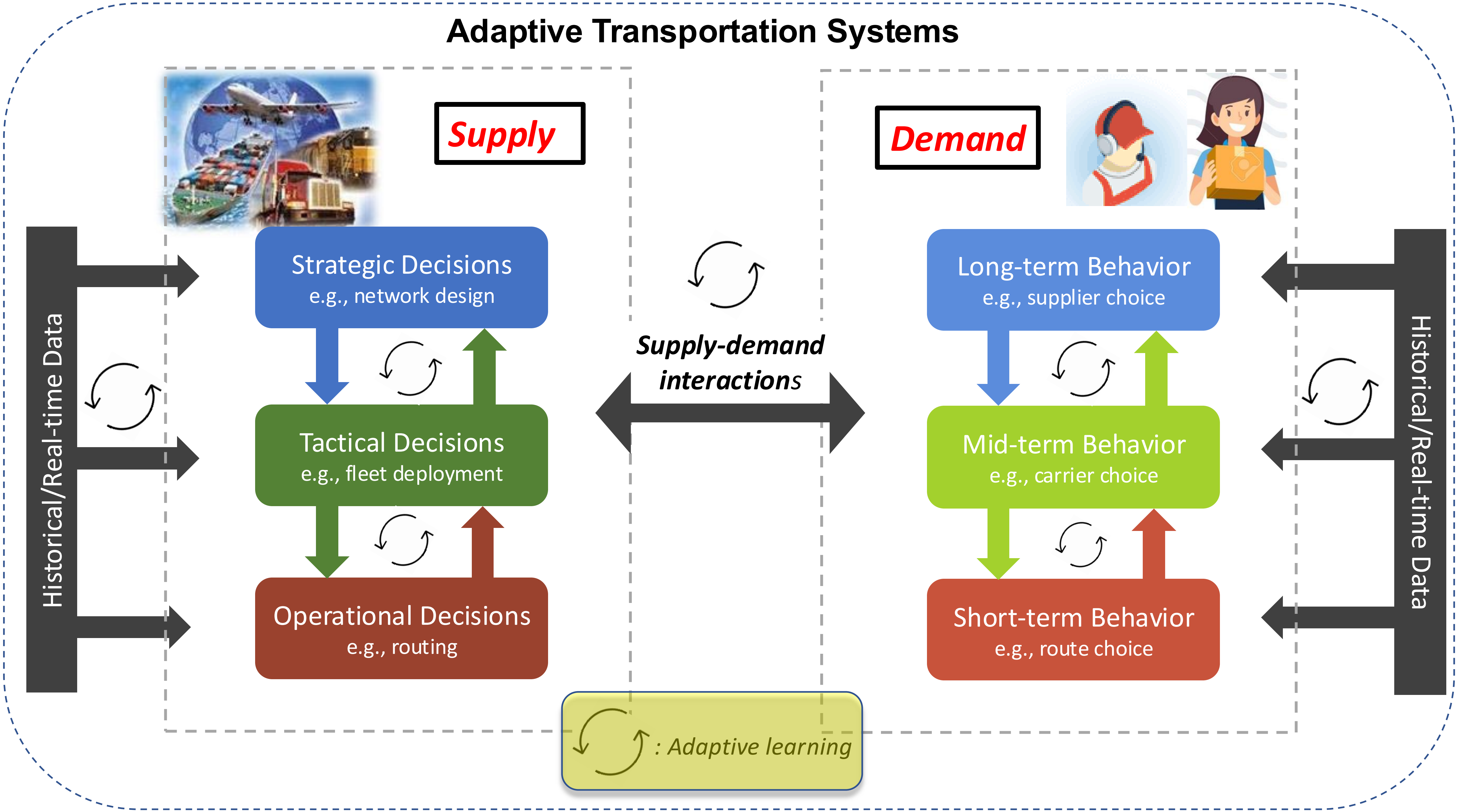

Adaptive Transportation Systems
Supply
Demand
Historical/Real-time Data
Strategic Decisions
e.g., network design
Tactical Decisions
e.g., fleet deployment
Operational Decisions
e.g., routing
Supply-demand interactions
Long-term Behavior
e.g., supplier choice
Mid-term Behavior
e.g., carrier choice
Short-term Behavior
e.g., route choice
Historical/Real-time Data
: Adaptive learning

Some interesting questions

Having information from earlier realizations of the operations…

- Can we learn the cost of reliability (to be incorporated already at the tactical level)?
- Can we embed learning in the decision making directly, where the underlying models for user behavior and transport system characteristics are embedded?
- Can we better quantify the trade-off between the cost of delays for example and the cost of embedding buffers upfront?

Can optimization + learning also help to handle the complexity of choice-based optimization?

Inverse Optimization

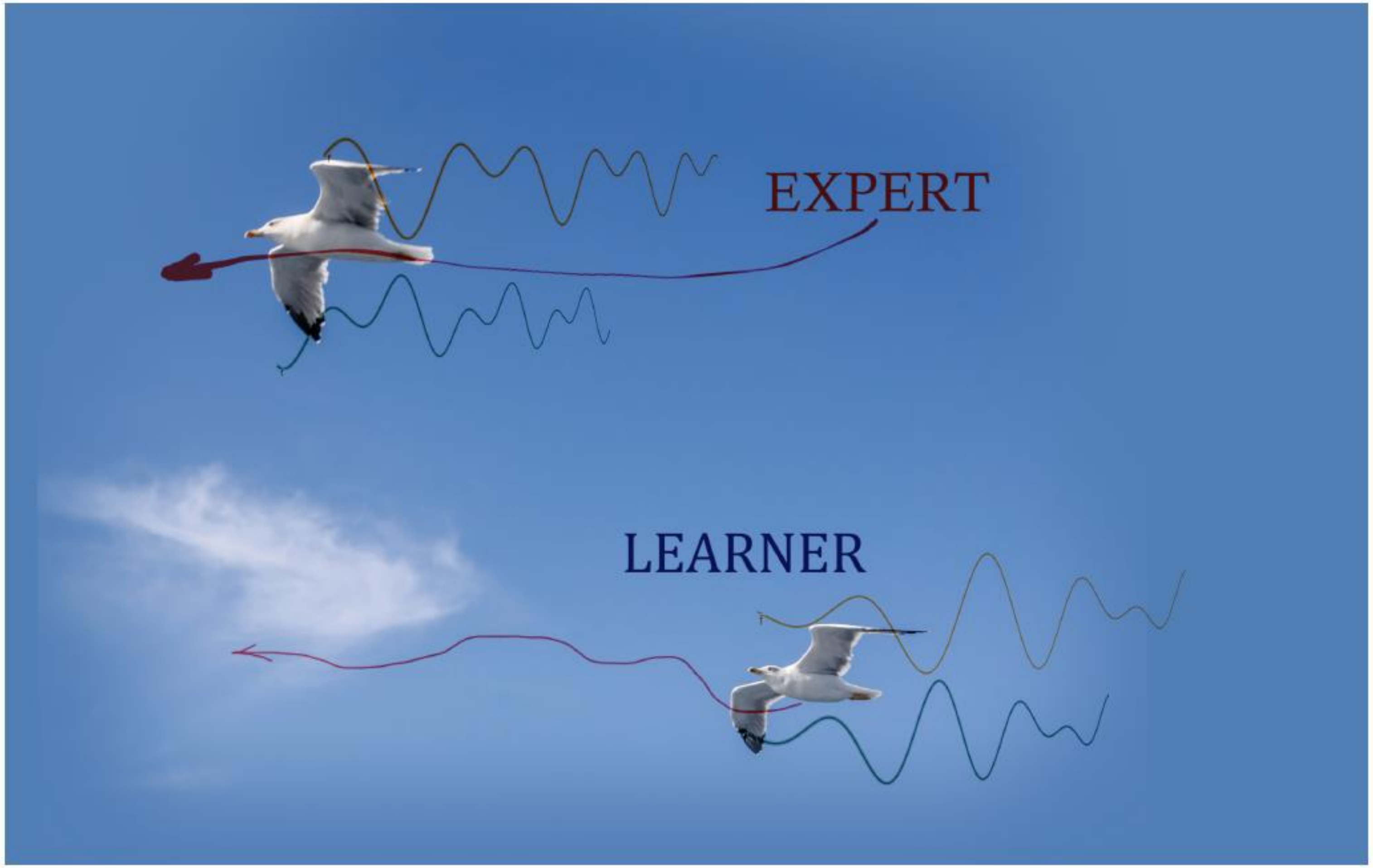
in collaboration with:

Pedro Zattoni Scroccaro

Peyman Mohajerin Esfahani

TU Delft

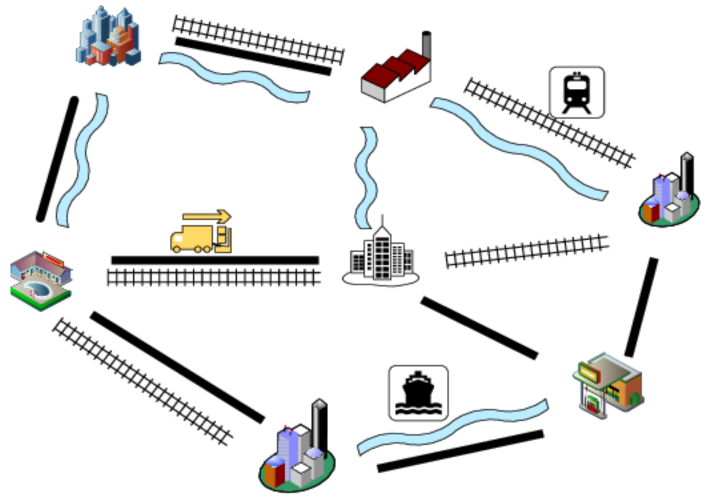
Inverse Optimization



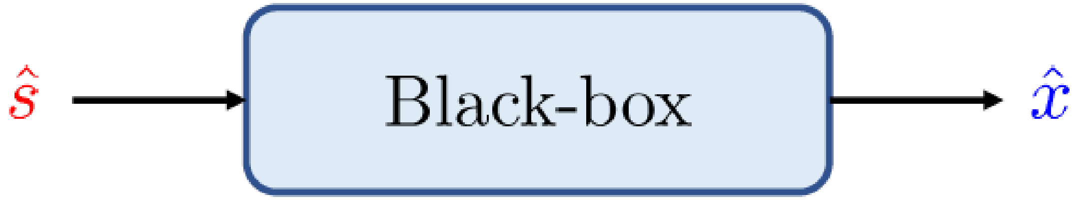
Inverse Optimization

Given a signal (input), the **expert** computes its response (output) by <u>optimizing an unknown cost</u>

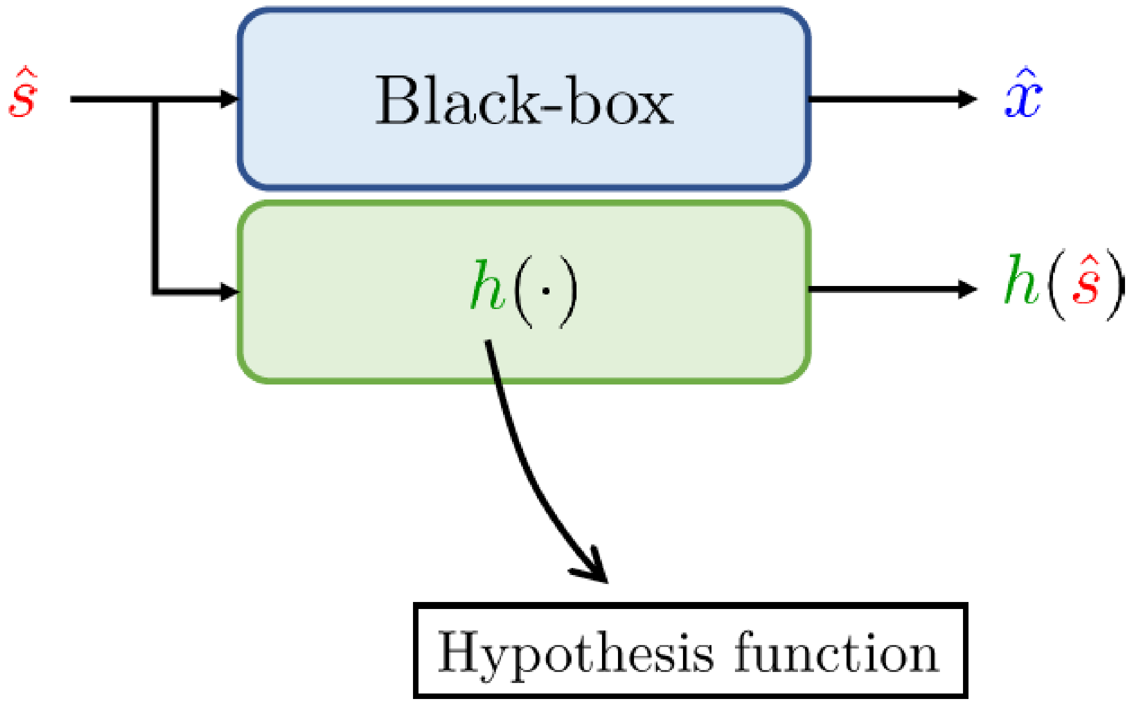
$$\hat{x} = \arg \min_{x \in \mathbb{X}(\hat{s})} F(\hat{s}, x)$$



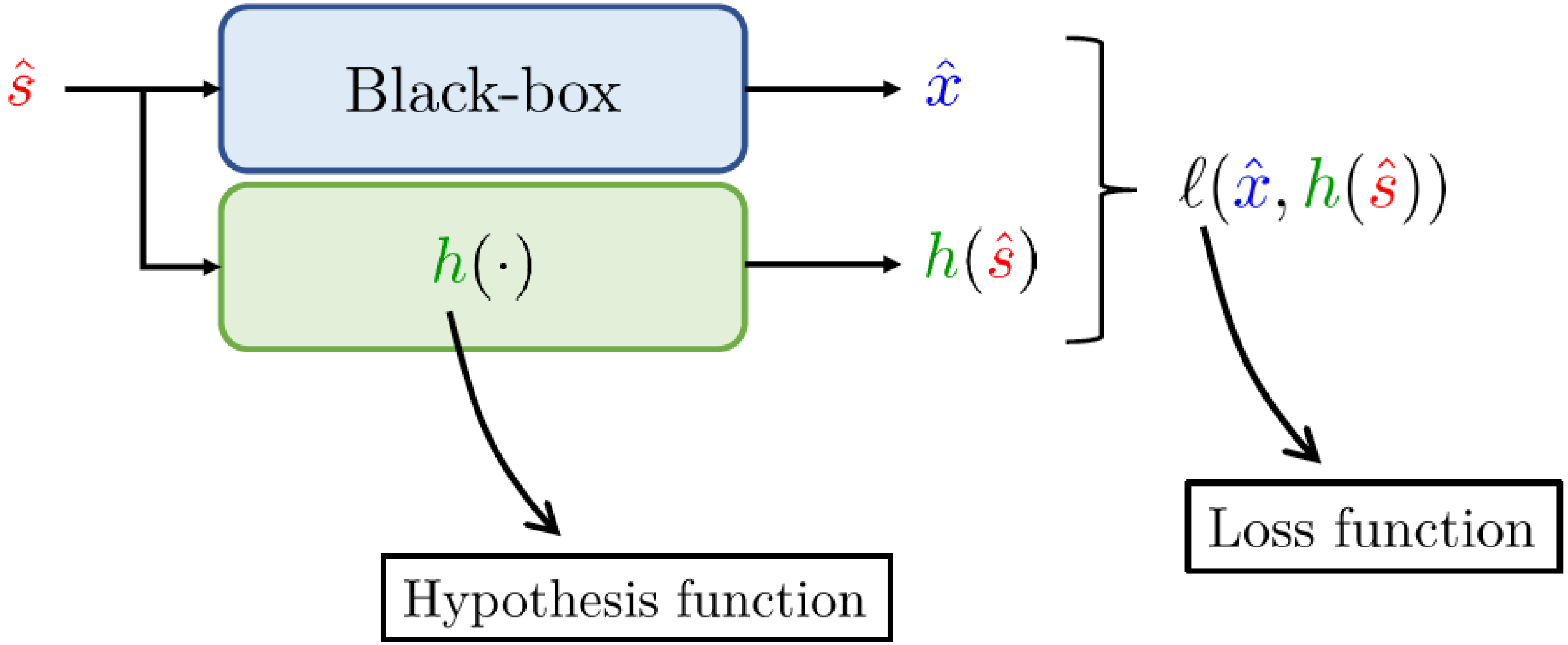
Supervised learning point of view



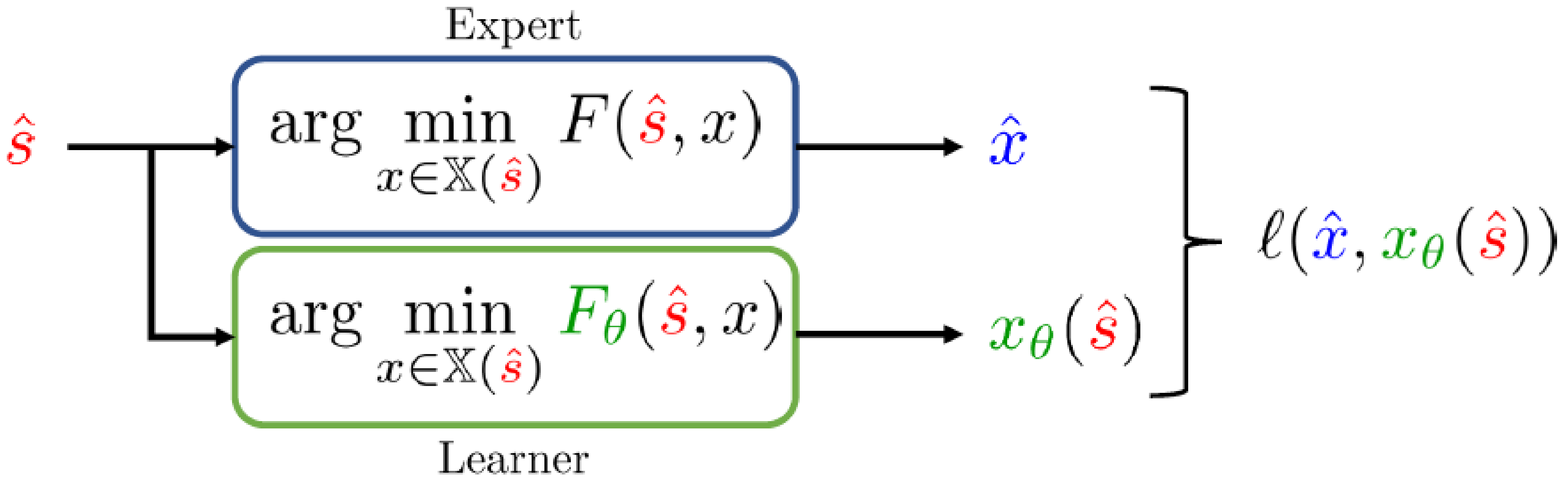
Supervised learning point of view



Supervised learning point of view



Supervised learning point of view



- $F(\hat{s}, x)$ is the unknown cost of the expert

Inverse Optimization Overview

- Training dataset: $\{(\hat{s}_1, \hat{x}_1), \ldots, (\hat{s}_N, \hat{x}_N)\}$

- Choose hyphothesis space: $\{F_\theta \mid \theta \in \Theta\}$

- Optimize loss: $\min_{\theta \in \Theta} \ \kappa \mathcal{R}(\theta) + \frac{1}{N} \sum_{i=1}^{N} \ell(\hat{x}, x_\theta(\hat{s}))$

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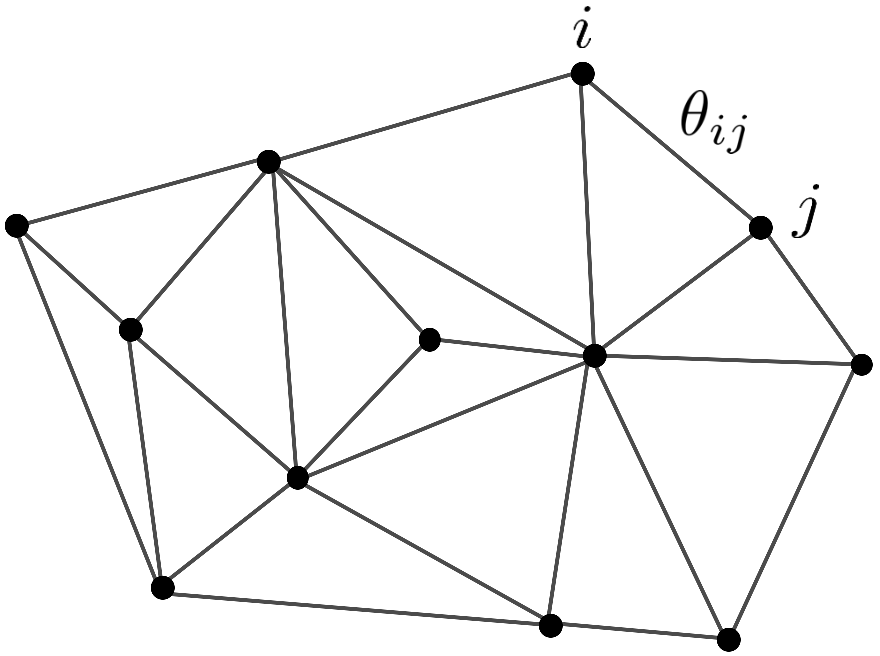
Routing Problems



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Inverse Optimization for Routing Problems

Expert

$$\hat{s} \rightarrow \arg\min_{x \in \mathbb{X}(\hat{s})} F(\hat{s}, x) \rightarrow \hat{x}$$

$$\hat{s} \rightarrow \arg\min_{x \in \mathbb{X}(\hat{s})} F_\theta(\hat{s}, x) \rightarrow x_\theta(\hat{s})$$

Learner

Inverse Optimization for Routing Problems

Demands
Set of customers
Time-windows
…

Expert

$$\arg\min_{x \in \mathbb{X}(\hat{s})} F(\hat{s}, x) \longrightarrow \hat{x}$$

$$\arg\min_{x \in \mathbb{X}(\hat{s})} F_\theta(\hat{s}, x) \longrightarrow x_\theta(\hat{s})$$

Learner

Inverse Optimization for Routing Problems

Demands
Set of customers
Time-windows
…

Expert

$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \theta^{\star}_{ij} x_{ij} \longrightarrow \hat{x}$$

$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \theta_{ij} x_{ij} \longrightarrow x_{\theta}(\hat{s})$$

Learner

TU Delft

Inverse Optimization for Routing Problems

Unkown weights

Expert

Demands
Set of customers
Time-windows
...

$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \boxed{\theta^{\star}_{ij}} x_{ij} \rightarrow \hat{x}$$

$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \theta_{ij} x_{ij} \rightarrow x_{\theta}(\hat{s})$$

Learner

TU Delft

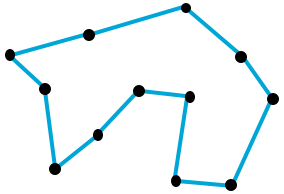
Inverse Optimization for Routing Problems

Demands
Set of customers
Time-windows
...

Expert

$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \theta^{\star}_{ij} x_{ij}$$

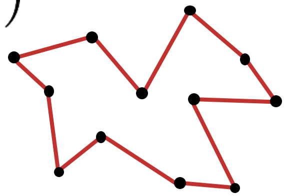
$\hat{x}$



$$\arg\min_{x \in \mathbb{X}(\hat{s})} \sum_{i=1}^{n} \sum_{j=1}^{n} \theta_{ij} x_{ij}$$

Learner

$x_\theta(\hat{s})$



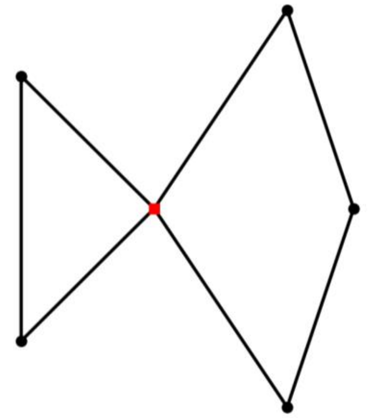
$\ell(\hat{x}, x_\theta(\hat{s}))$

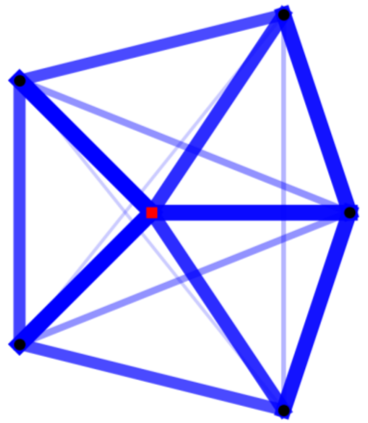
Simple CVRP example

Expert (CVRP)

Demands

$$\arg\min_{x\in\mathbb{X}^{\mathrm{CVRP}}(\hat{s})} \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{K} \boxed{\theta^{\star}_{ij}}\, x_{ijk}$$



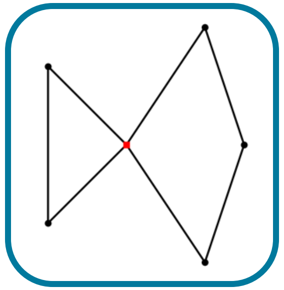


- <u>Gradient descent</u>

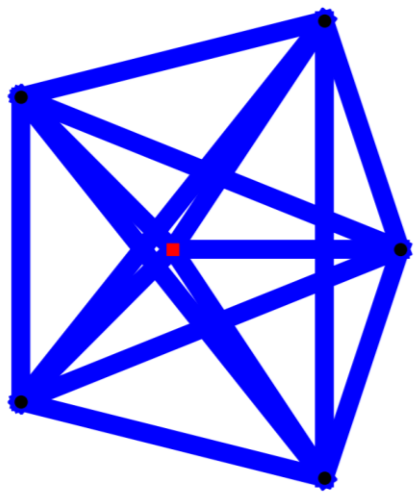
$$\theta^{[t+1]} = \theta^{[t]} - \eta \frac{\partial \ell(\hat{x}, x_{\theta^{[t]}}(\hat{s}))}{\partial \theta}$$

Learning Algorithm

Expert route

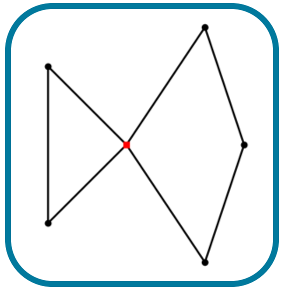


$\theta^{[0]}$



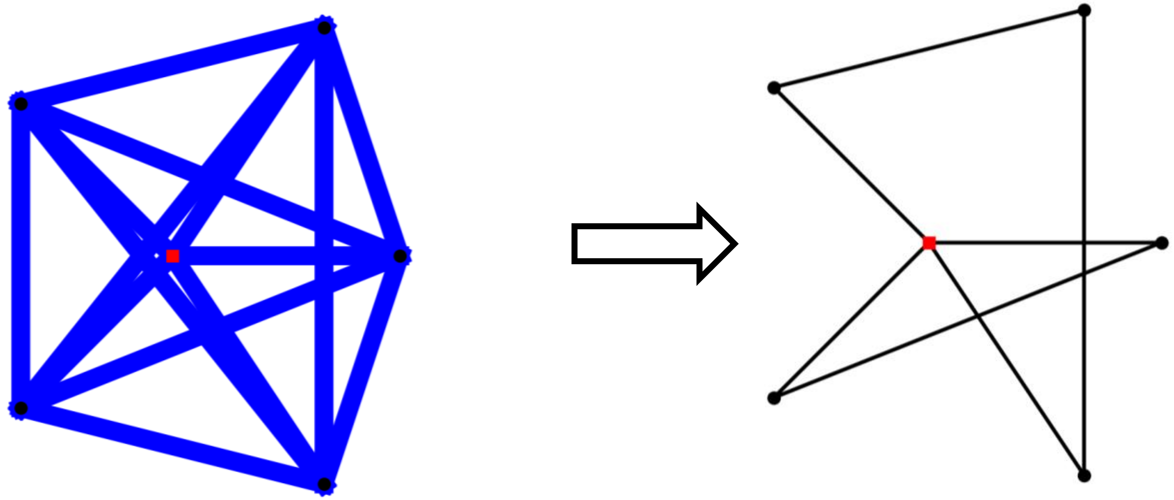
Learning Algorithm

Expert route



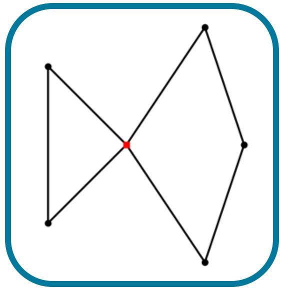
$\theta^{[0]}$

$\mathrm{CVRP}(\theta^{[0]})$

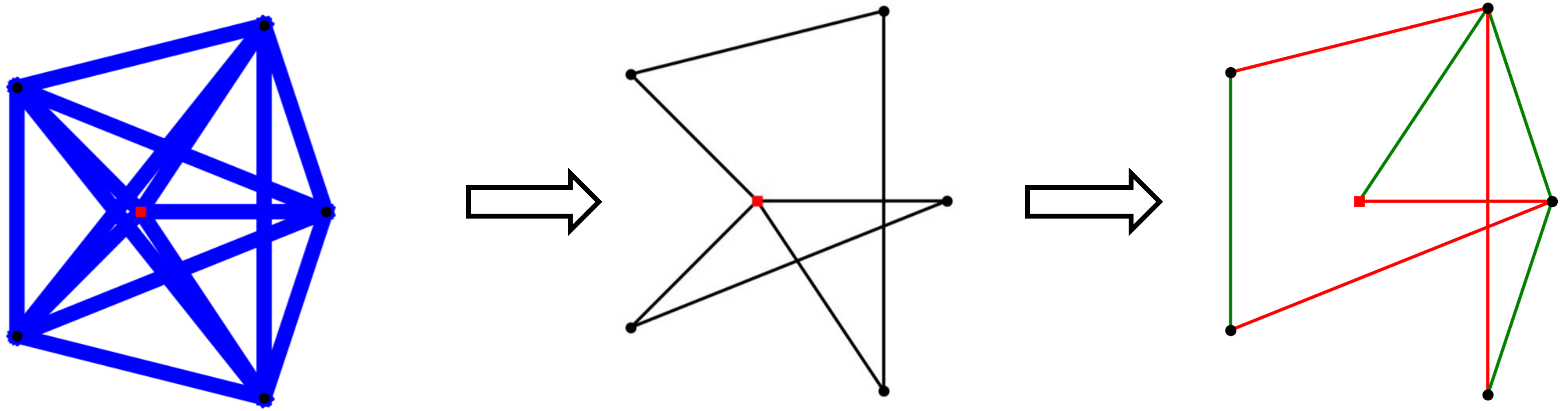


Learning Algorithm

Expert route

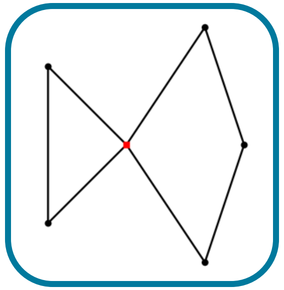


$\theta^{[0]}$ $\mathrm{CVRP}(\theta^{[0]})$ Route difference

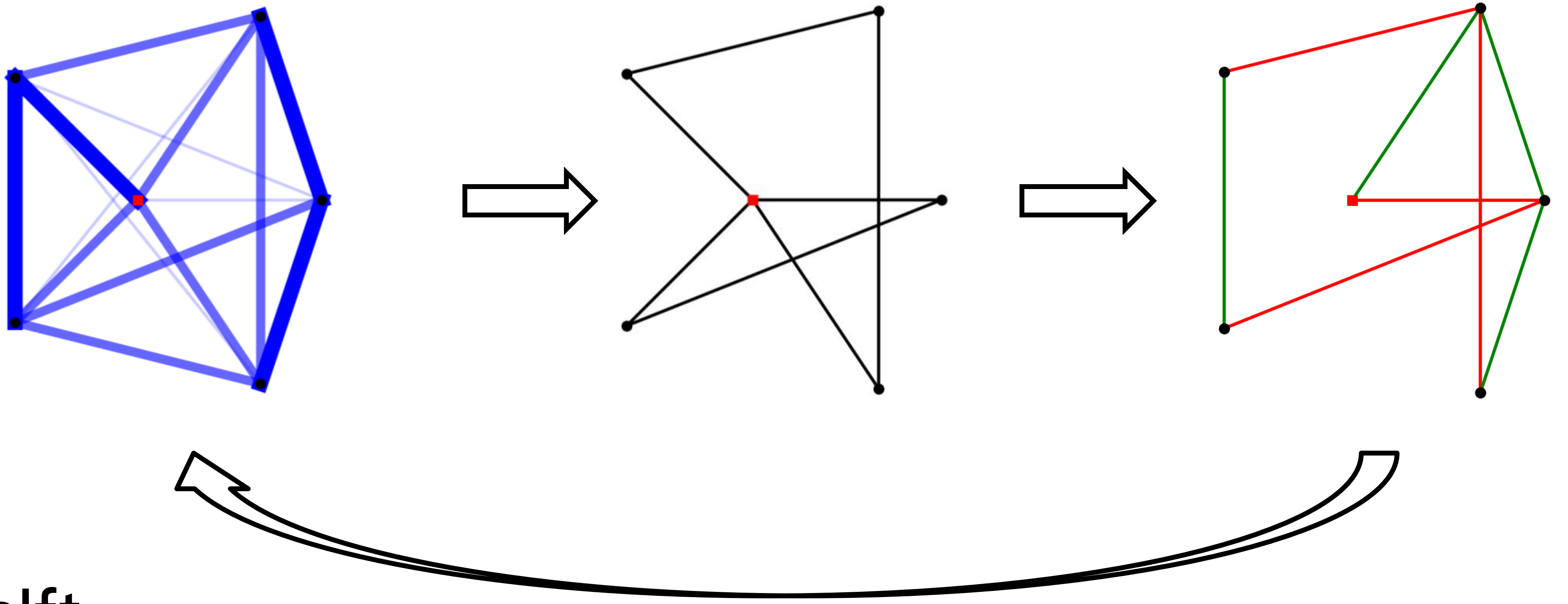


Learning Algorithm

Expert route

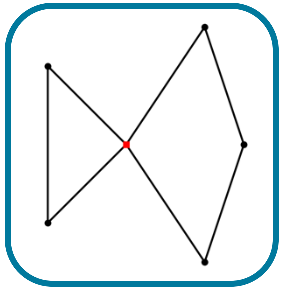


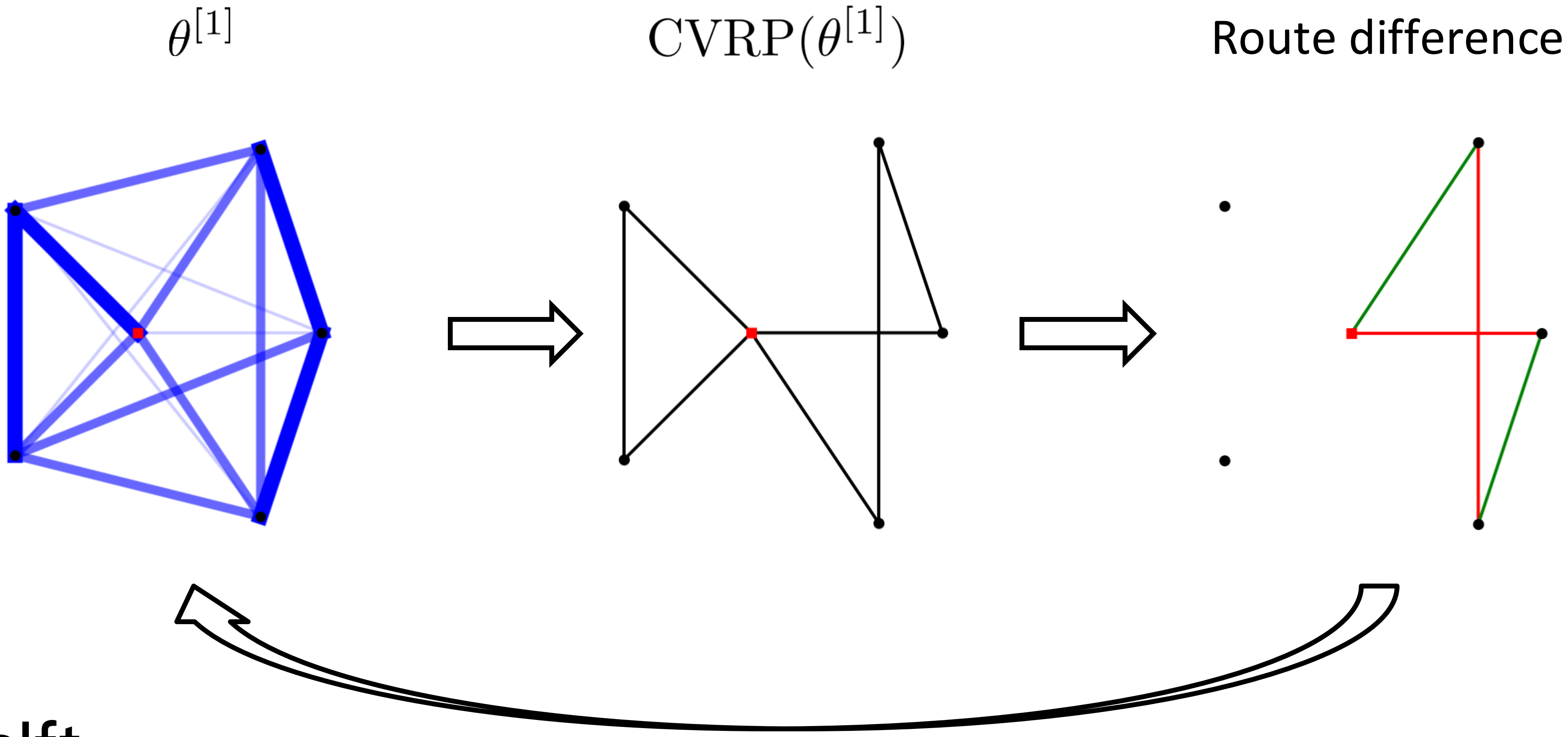
$\theta^{[1]}$ $\mathrm{CVRP}(\theta^{[0]})$ Route difference



Learning Algorithm

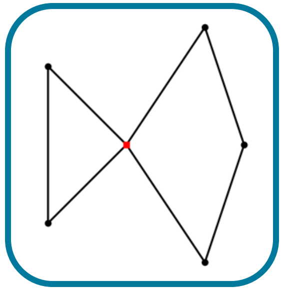
Expert route



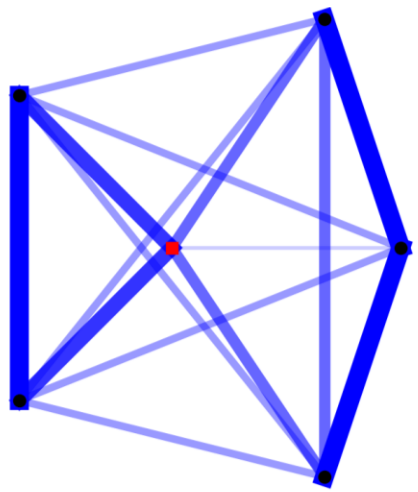


Learning Algorithm

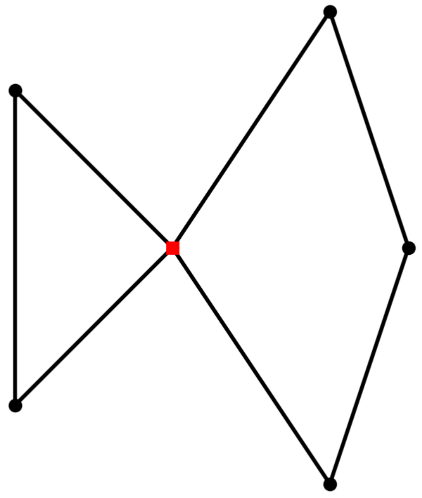
Expert route



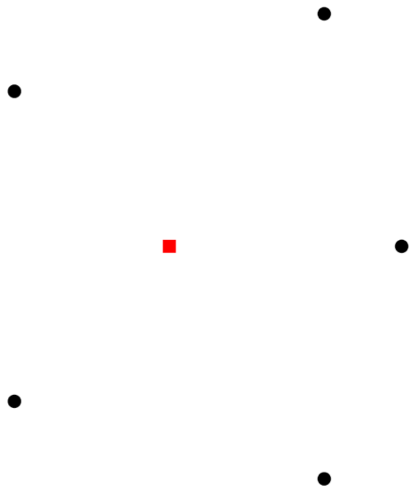
$\theta^{[2]}$



$\mathrm{CVRP}(\theta^{[2]})$



Route difference



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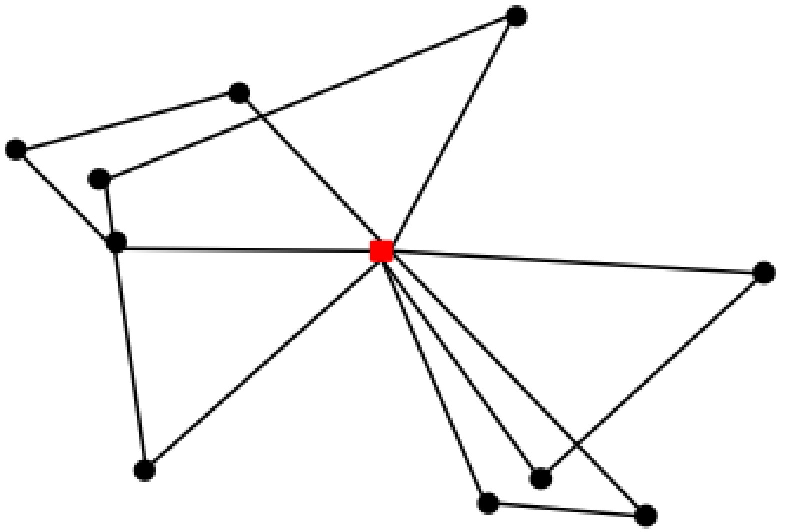
Dynamic Routing Problems
Learn How to Dispatch or Postpone

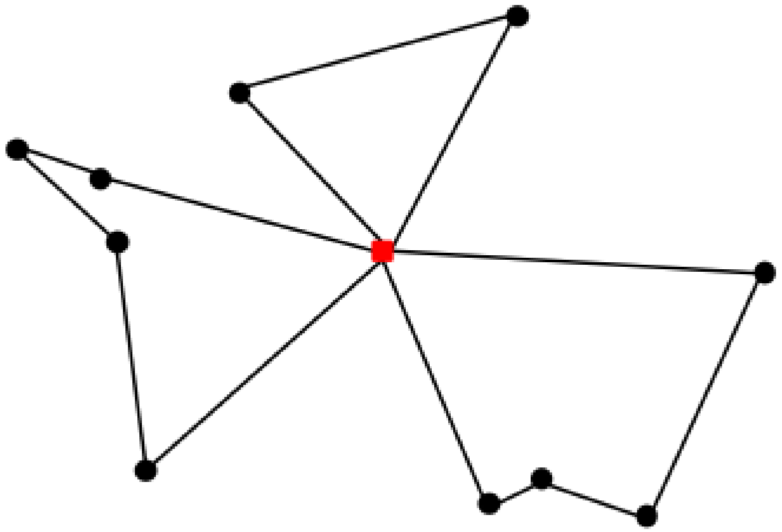
- Dataset of historical examples
- Approach: model the problem as a prize-collecting DVRP* and apply our IO method

Optimal prizes → dynamic routes = best routes in hindsight

Dynamic routes

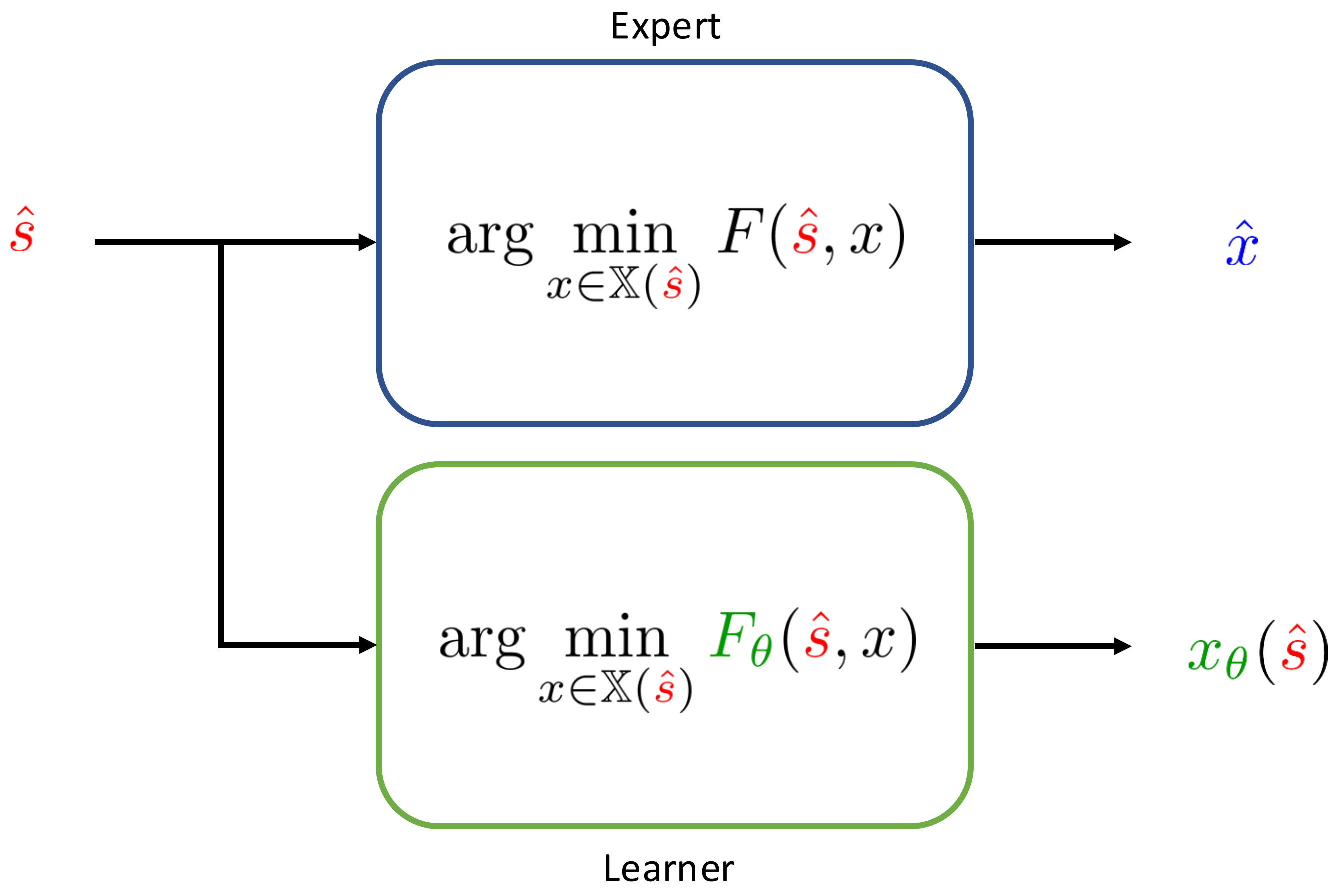


Best routes in hindsight

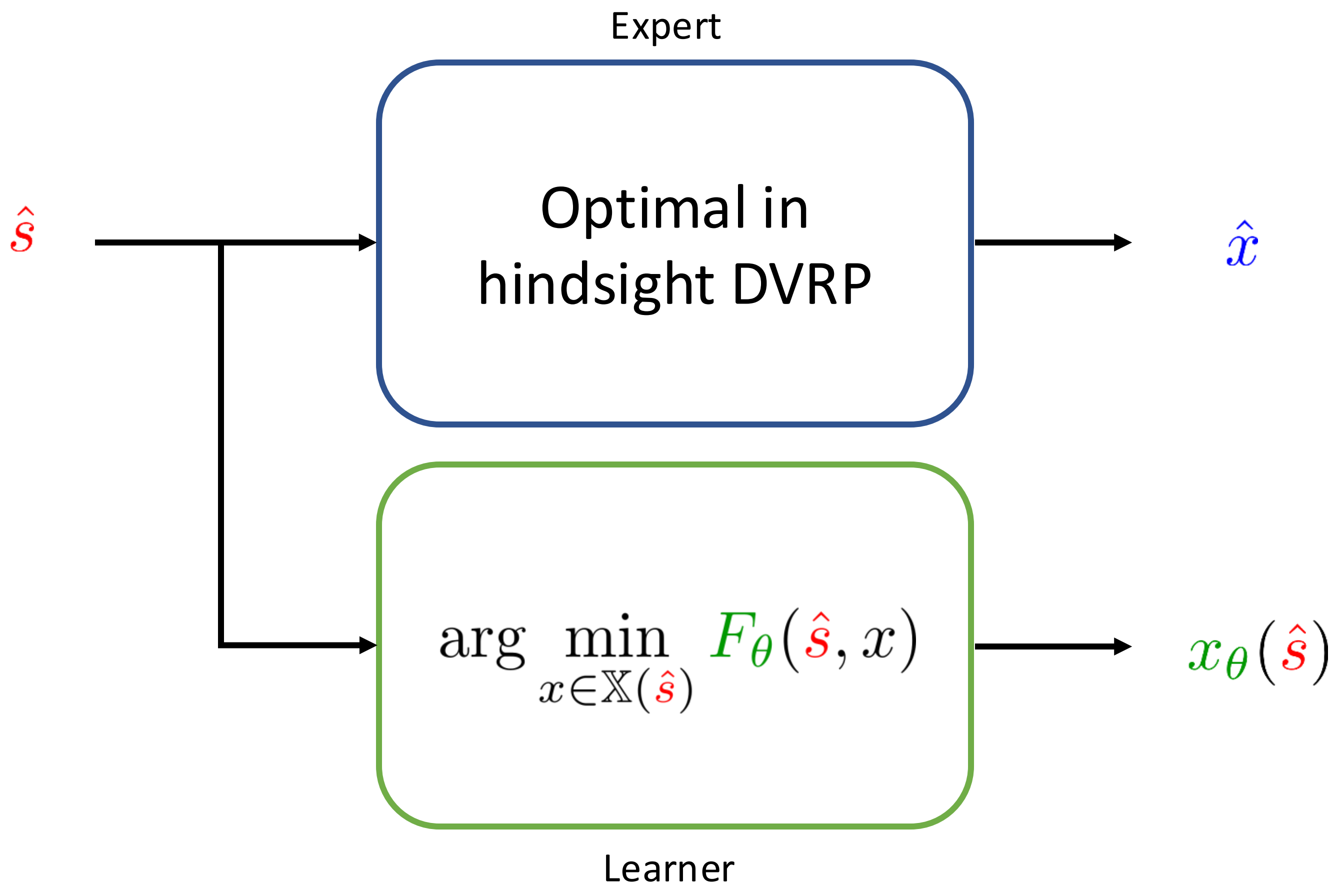


*Baty, Jungel, Klein, Parmentier, Schiffer (2023)

IO for Dynamic VRPS



IO for Dynamic VRPS



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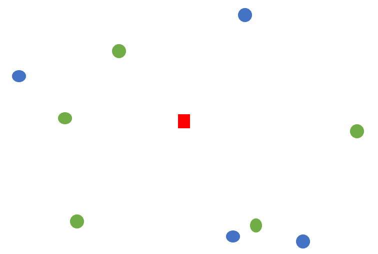
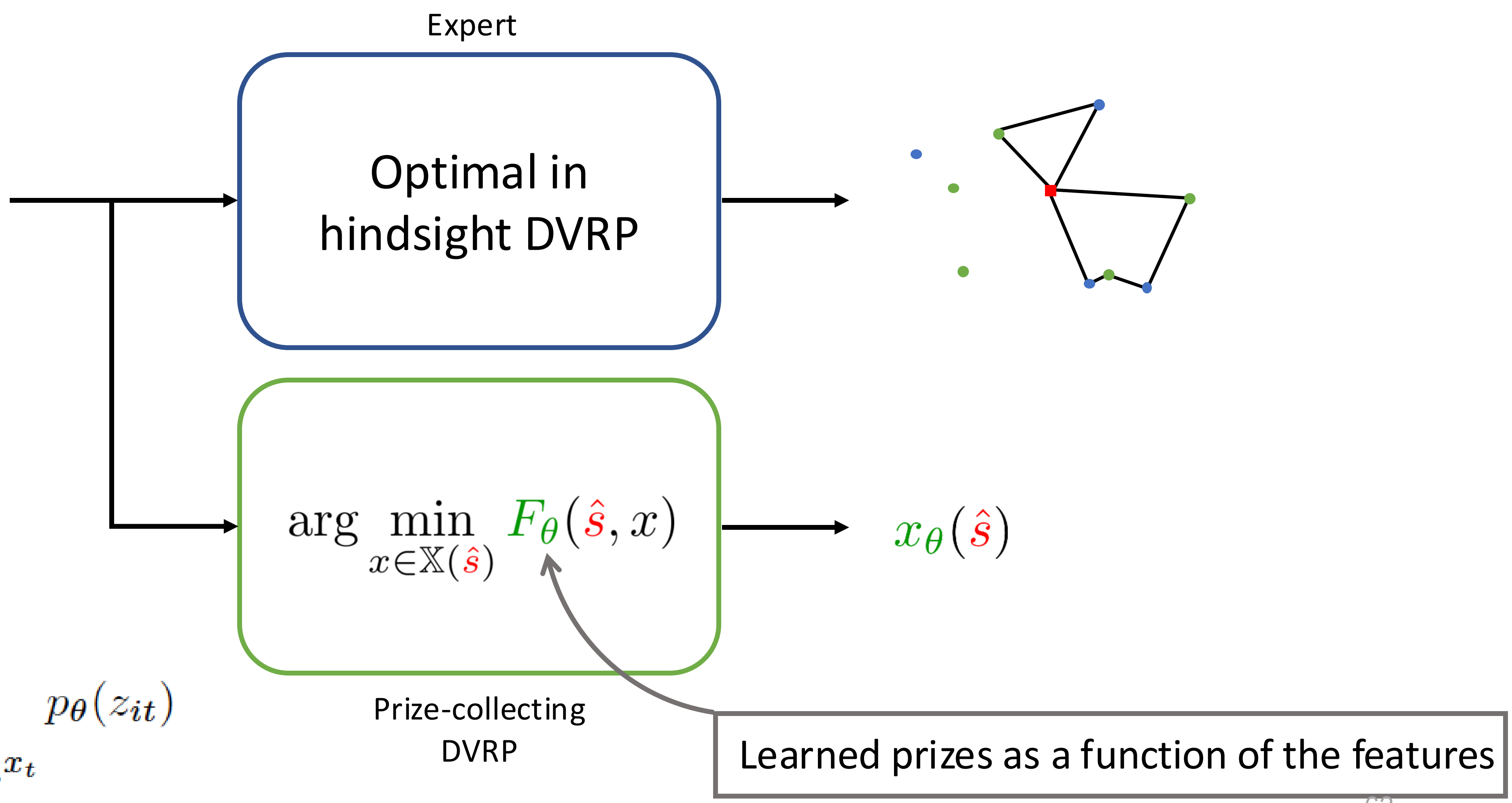
IO for Dynamic VRPS

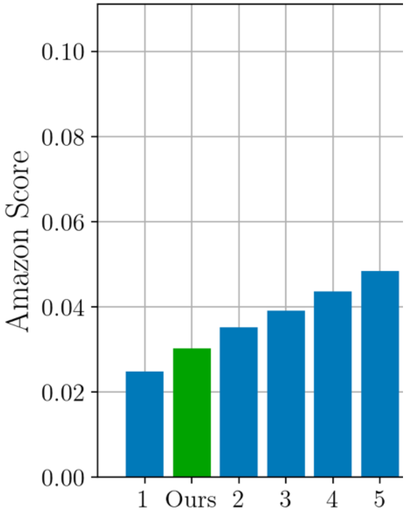




$$
\begin{aligned}
\arg\min_{x_t} \quad & c(x_t) - \sum_{z_{it} \in A_t \setminus x_t} p_\theta(z_{it}) \\
\text{s.t.} \quad & x_t \subseteq A_t,
\end{aligned}
$$

Successful tests

amazon Last-Mile Routing Challenge (2021)



EURO Meets NeurIPS 2022
Vehicle Routing Competition

EURO
THE ASSOCIATION OF EUROPEAN OPERATIONAL RESEARCH SOCIETIES

EWG DSO DATA SCIENCE MEETS OPTIMIZATION

EWG VEROLOG VEHICLE ROUTING AND LOGISTICS

NEURAL INFORMATION PROCESSING SYSTEMS

ORTEC

EAISI EINDHOVEN AI SYSTEMS INSTITUTE

TU/e

TU Delft

References

Generic Theory

Routing problems

Open-source Python code

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- Zattoni Scroccaro, van Beek, Mohajerin Esfahani and Atasoy (2025), "**Inverse Optimization for Routing Problems**", Transportation Science, 59(2): 301-321.
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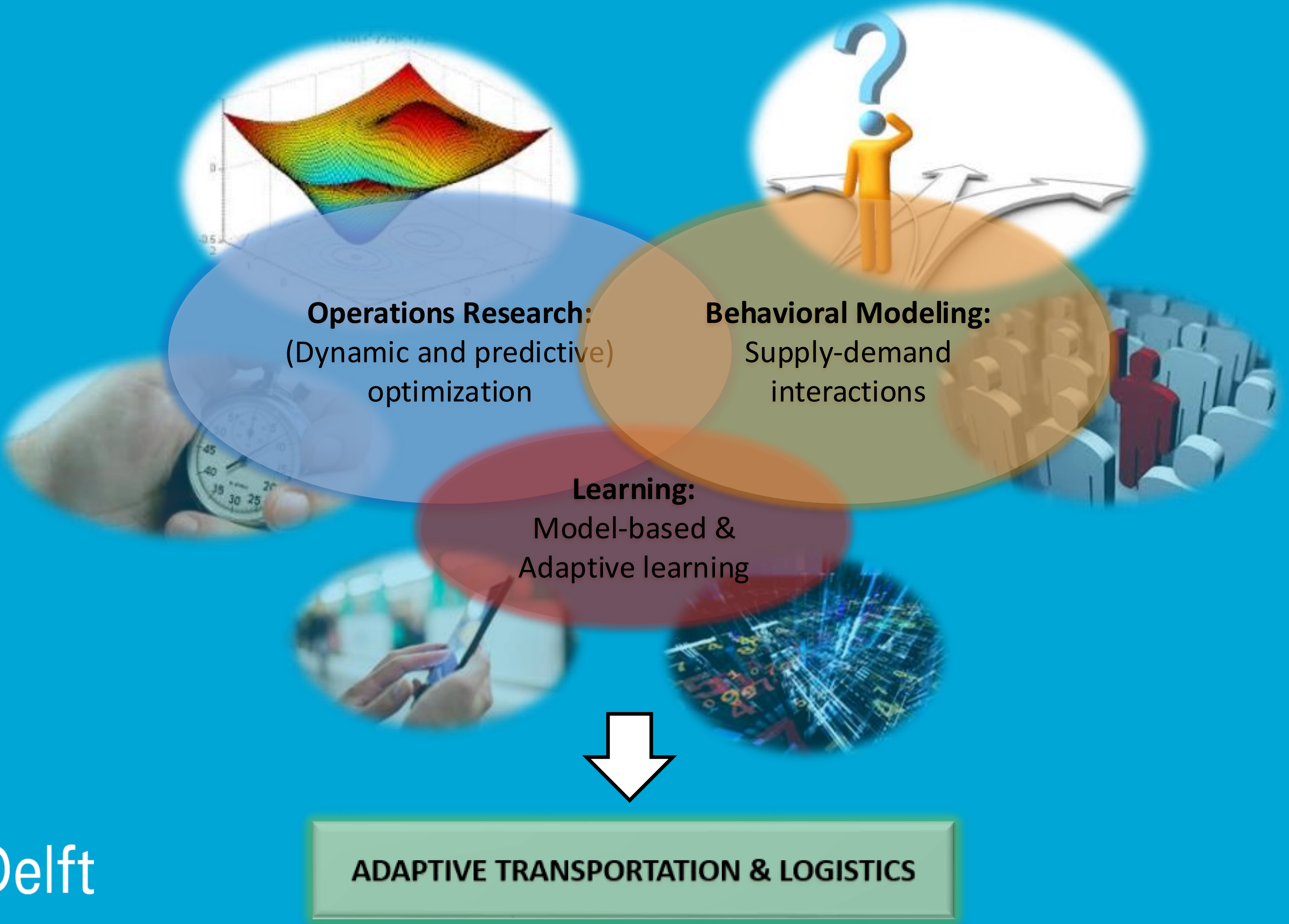
Operations Research:
(Dynamic and predictive)
optimization
Behavioral Modeling:
Supply-demand
interactions
Learning:
Model-based &
Adaptive learning
ADAPTIVE TRANSPORTATION & LOGISTICS