On the development of the Regret-based Dutch National Transport Model

Comparing RRM and RUM models and forecasts

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Motivation and research objectives

Motivation

- Large-scale transport models are widely used to assess the long-term effects of transport policy and infrastructure

- Large-scale transport models* are based on just **one decision rule**: Random Utility Maximization (RUM)

- While the RUM model is very elegant, the assumptions underlying the RUM model may not always be behaviourally realistic: in fact, a vast body of literature shows that people use **variety** of decision rules

→ Currently little is known about the ***robustness*** of the forecasts of large-scale transport model towards the uncertainty associated with the underlying decision rule.

* based on discrete choice models

Motivation and research objectives

Motivation

- Random Regret Minimization (RRM) is one possible alternative to the RUM model.

→ We develop a RRM-based counterpart of the (RUM-based) Dutch National Transport Model (henceforth abbreviated as **LMS**)

Research objectives

1. To learn about the <u>*robustness*</u> of the forecasts of transport model towards the uncertainty associated with the underlying decision rule

2. To see whether it is (technically) feasible to develop non-RUM based large-scale transport models

The strategy

Development phase:

- Identify RUM models in LMS and replace by RRM models

- Re-calibrate the model system

Analysis phase: Comparing RRM and RUM outcomes

<u>Base year</u>

- Base year forecasts (2010)
- Implied demand elasticities

<u>Case study</u>

- Develop forecasts for a future year (2030)

The strategy

Development phase:

- Identify RUM models in LMS and **replace** by RRM models …. **But, not so trivial**

Challenges → New insights on RRM modelling:

→ The need to correct for (variation in) choice set size

→ The effect of the scale parameter in RRM models

→ New RRM models: μRRM model, P-RRM model

→ Methods to reduce the computational burden to estimate RRM models

2014

Together, these development made it possible to develop the Regret-based LMS

Development phase

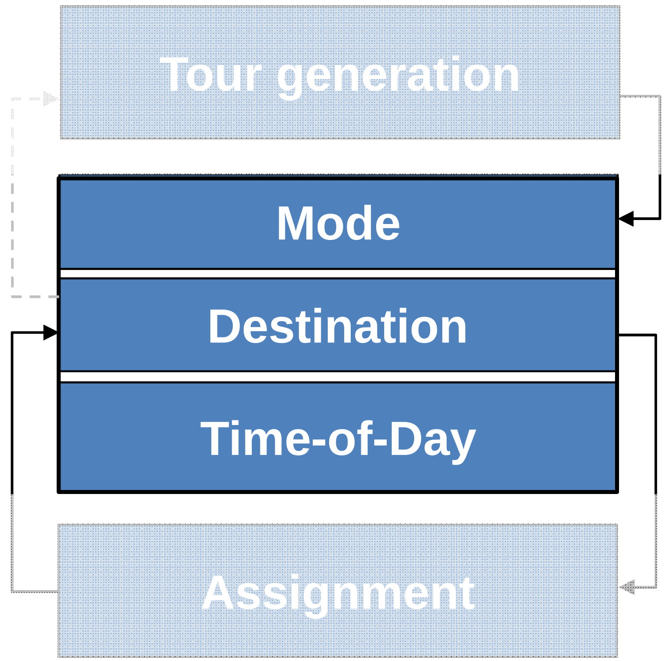
Identify RUM models

The LMS

- Tour-based transport model
- 1406 Transport Analysis Zones
- Enumeration module (SES)

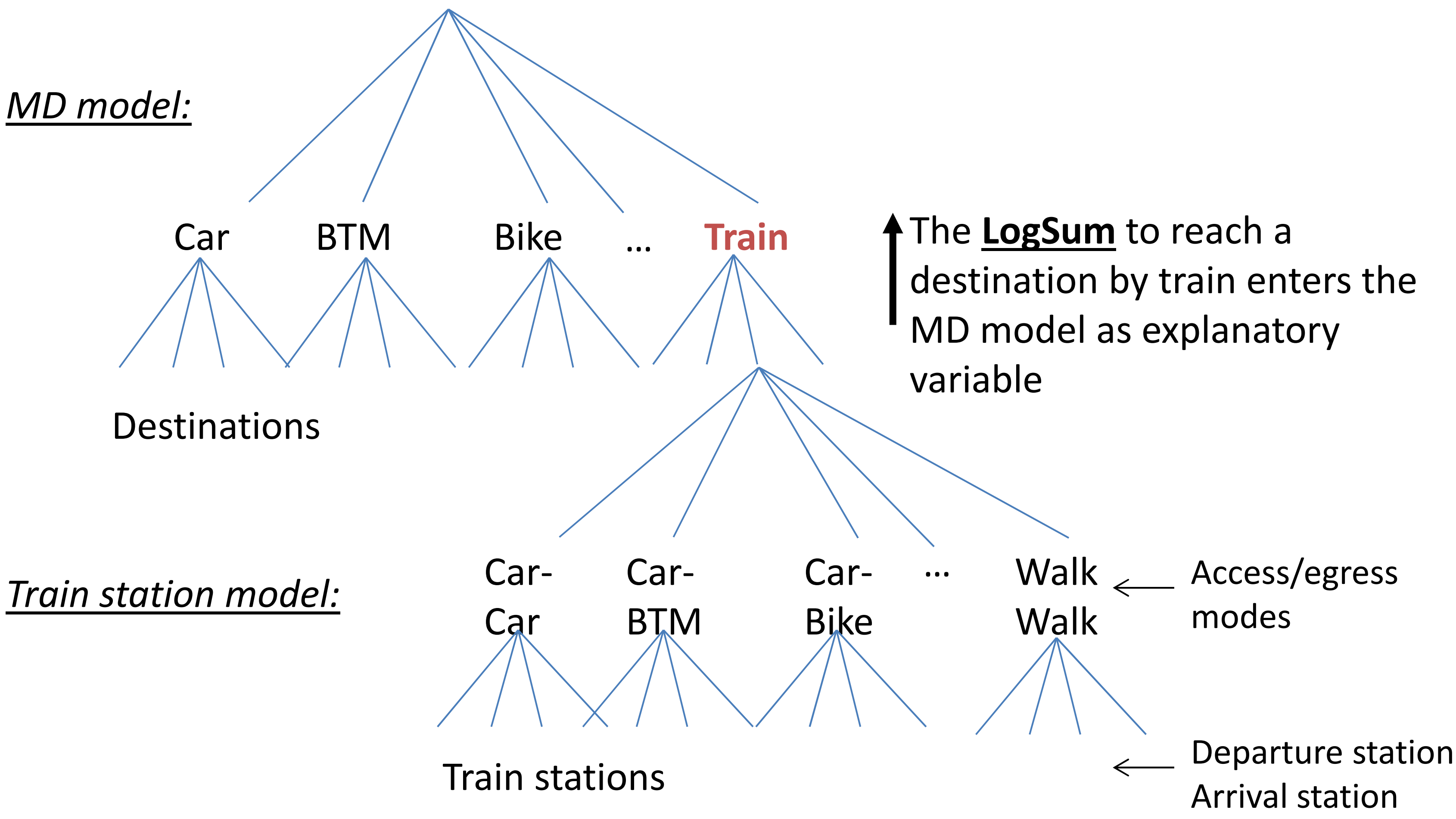
- Tour-generation models: Binary logit
- MD models: Nested Logit
- Assignment: static/pseudo dynamic assignment model

LMS/SES



Identify RUM models

- The MD model has sub model for Train station choices. This model is **sequentially** estimated (rather than jointly estimated)

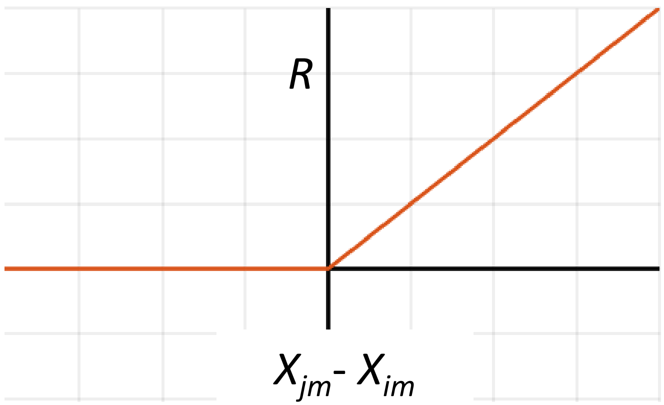


Replace with RRM models

- RUM models have been replaced by P-RRM models

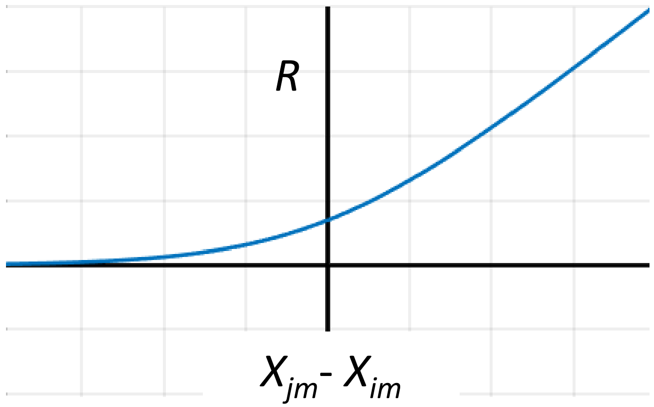
→ The P-RRM model postulates the strongest regret minimizing behaviour
→ Largest *difference* in postulated behaviour between RRM and RUM

P-RRM (2015)



$$R_i = \sum_m \sum_{j \neq i} \max\left(0, \beta_m \left[x_{jm} - x_{im}\right]\right)$$

RRM (2010)



$$R_i = \sum_m \sum_{j \neq i} \ln\left(1 + \exp\left(\beta_m \left[x_{jm} - x_{im}\right]\right)\right)$$

Replace with RRM models

- RUM models have been replaced by P-RRM models

→ The P-RRM model postulates the strongest regret minimizing behaviour

→ Practical advantage: huge reduction in required computational efforts

$$R_i = \sum_m \sum_{j \neq i} \max\left(0, \beta_m \left[x_{jm} - x_{im}\right]\right)$$

↑

In case, that we know the signs of the parameters β_m, then

$$R_i = \sum_m \beta_m \sum_{j \neq i} \max\left(0, \left[x_{jm} - x_{im}\right]\right) \qquad if \qquad \beta_m > 0$$

$$R_i = \sum_m \beta_m \sum_{j \neq i} \min\left(0, \left[x_{jm} - x_{im}\right]\right) \qquad if \qquad \beta_m < 0$$

Replace with RRM models

- RUM models have been replaced by P-RRM models

  → The P-RRM model postulates the strongest regret minimizing behaviour

  → Practical advantage: huge reduction in required computational efforts

$$R_i = \sum_m \beta_m x_{im}^{P-RRM} \qquad where \quad x_{im}^{P-RRM} = \begin{cases} \sum_{j \neq i} \max\left(0, \left[x_{jm} - x_{im}\right]\right) & if \quad \beta_m > 0 \\ \sum_{j \neq i} \min\left(0, \left[x_{jm} - x_{im}\right]\right) & if \quad \beta_m < 0 \end{cases}$$

  - x_{im}^{P-RRM} can be computed prior to the estimation

    → Estimation time ~ Linear additive RUM

  - Regret takes a linear-additive form

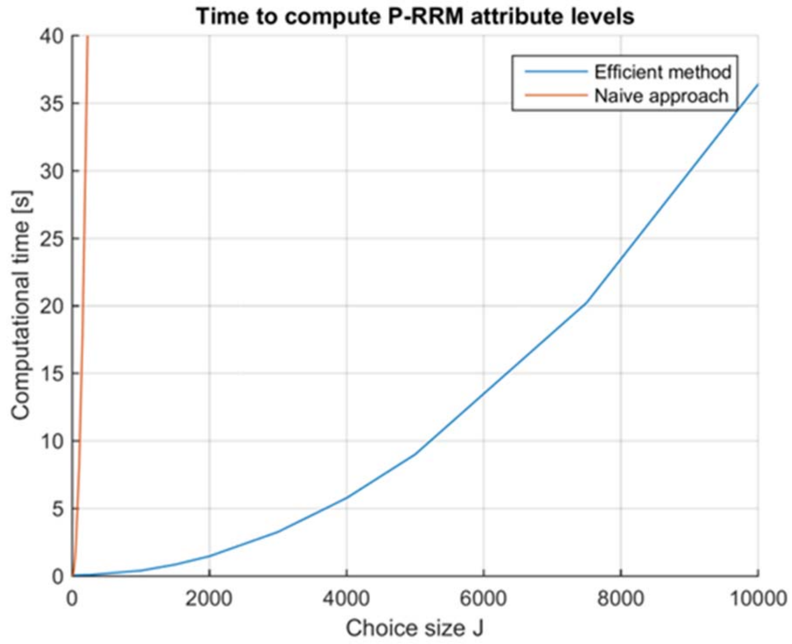
    → Smooth and globally concave LL

→ Moreover, by capitalizing on the linear structure of the P-RRM model we were able to develop techniques to further reduce computational efforts

Replace with RRM models

- RUM models have been replaced by P-RRM models

→ The P-RRM model postulates the strongest regret minimizing behaviour
→ Practical advantage: huge reduction in required computational efforts



→ **Bottom line: feasible computational times ☺**

Replace with RRM models

- For consistent comparison: the model specification of **RUM**-LMS is adopted in the **RRM**-LMS (thus, RRM model specifications not optimized for RRM)

- Regret can only be experienced for *generic attributes*

→ Hybrid Utility-Regret specification: $U_i = V_i - R_i$

Regret attributes	*Utility attributes*
- *Travel cost*	- *ASCs*
- *Travel time*	- *Socio-economic characteristics*
- *Travel distance*	- *Driving license*
- *etc.*	-

→

$$U_i = ASC_{\text{mode}} + D_1 + \ldots + D_k - \sum_m \beta_m \sum_{j \neq i} \max\left(0, \left[x_{jm} - x_{im}\right]\right)$$

$$U_i = ASC_{\text{train}} + \beta_{TrLogSum} \cdot LogSum_i$$

Results

Development phase

Estimation results

	Commute	Business	Education	Shopping	Other	Work-Business	Work-Other	Child-Education	Child-Other
No. obs	33 803	3 100	8 614	24 039	36 206	1 086	652	9 150	8 095
LL RUM	-136 730	-12 305	-24 652	-61 899	-118 272	-4 777	-1 467	-16 074	-21 596
LL RRM	-137 001	-12 334	-24 790	-61 985	-119 847	-4 811	-1 467	-16 071	-21 666
LL_{RUM} - LL_{RRM}	271	29	138	86	1 575	34	0	-4	70
ΔLL/obs	0.008	0.009	0.016	0.004	0.043	0.031	0.000	0.000	0.009

Model fit:

- Difference between LL RUM and LL P-RRM relatively small, especially ΔLL/No. obs
- Moreover, it should be noted that model specifications are optimized for RUM
- Similar results are obtained for the Train station choice models

Estimation results

COMMUTE

MODEL	**RUM**		**P-RRM**	
No. observations	33 803		33 803	
Final LL	-136 730		-137 001	
No. parameters	85		85	
ρ^2	0.495		0.494	
ASC_Car_driver	6.19	(11.86)	5.32	(11.75)
ASC_Car_passenger	-2.64	(-6.05)	-2.63	(-6.73)
ASC_Train	-13.48	(-28.36)	1.19	(2.94)
ASC_Bus_metro_tram	-3.77	(-8.01)	-3.37	(-7.91)
ASC_Cycling	3.58	(7.97)	3.21	(8.06)
Travel Time Car	-0.03	(-37.59)	-0.05	(-40.48)
Travel Time Bus_metro	-0.04	(-20.32)	-0.03	(-19.62)
Travel cost	-0.17	(-20.63)	-0.23	(-25.54)
Distance cycling	-0.19	(-62.73)	-0.23	(-62.92)
Distance walking	-0.87	(-4.35)	-1.00	(-4.41)
IntraCd	-1.09	(-5.73)	-1.10	(-6.16)
IntraPs	-0.29	(-1.36)	-0.30	(-1.44)
IntraBt	-2.54	(-9.18)	-2.59	(-9.68)
TrLogsum	0.74	(45.03)	0.85	(44.74)
CdCBD75	-0.41	(-7.51)	-0.64	(-12.04)
NoWrkDst	-0.02	(-17.54)	-0.02	(-17.42)
PartWrkDst	-0.02	(-27.87)	-0.02	(-28.09)
OVCarCo0	0.43	(2.88)	0.57	(4.27)
CdLicNoCar	-10.85	(-16.53)	-9.54	(-16.83)
CdMale	0.80	(11.27)	0.69	(11.17)
BtMale	-0.96	(-6.07)	-0.86	(-6.17)
CdStudent	-1.21	(-3.68)	-1.08	(-3.76)

ASCs are in same order of magnitude, with the **exception of the ASC for Train**

In line with expectations: RRM en RUM taste parameters are different from one another

Most other constants and dummy variables have the same sign, and by and large the same size.

Including TrLogsum

Results

Analysis phase: Base year

Base year forecasts (tours)

RUM/MON

	Train	Car driver	Car passenger	BTM	Bike	Walk
Education	1.12	0.94	1.04	0.94	1.08	0.85
Commute	1.17	1.07	1.17	1.06	1.14	1.10
Business	0.92	1.15	1.15	1.14	1.28	1.23
Shopping	1.18	1.04	1.14	1.17	1.16	1.03
Other	1.19	1.08	1.18	1.15	1.13	1.00
Total	1.15	1.07	1.16	1.06	1.13	1.02
RMSE	0.15	0.09	0.14	0.13	0.17	0.13

RRM/MON

	Train	Car driver	Car passenger	BTM	Bike	Walk
Education	1.04	0.93	1.03	1.02	1.08	0.84
Commute	1.11	1.07	1.14	1.28	1.13	1.07
Business	0.81	1.17	1.05	1.14	1.21	1.16
Shopping	1.16	1.04	1.13	1.24	1.16	1.03
Other	1.15	1.08	1.18	1.08	1.13	1.01
Total	1.08	1.07	1.15	1.16	1.13	1.01
RMSE	0.14	0.10	0.12	0.18	0.15	0.11

RRM/RUM

	Train	Car driver	Car passenger	BTM	Bike	Walk
Education	0.93	0.99	0.99	1.09	1.00	0.99
Commute	0.95	1.00	0.98	1.20	0.99	0.98
Business	0.88	1.02	0.91	1.00	0.94	0.95
Shopping	0.99	1.00	0.99	1.06	1.00	1.00
Other	0.97	1.00	1.00	0.94	1.00	1.00
Total	0.94	1.00	0.99	1.09	1.00	1.00

Base year forecasts (tours)

RUM/MON

	Train	Car driver	Car passenger	BTM	Bike
Education	1.12	0.94	1.04	0.94	1.08
Commute	1.17	1.07	1.17	1.06	1.14
Business	0.92	1.15	1.15	1.14	1.28
Shopping	1.18	1.04	1.14	1.17	1.16
Other	1.19	1.08	1.18	1.15	1.13
Total	1.15	1.07	1.16	1.06	1.13
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RMSE	0.14	0.10	0.12	0.18	0.15

RRM/RUM

	Train	Car driver	Car passenger	BTM	Bike
Education	0.93	0.99	0.99	1.09	1.00
Commute	0.95	1.00	0.98	1.20	0.99
Business	0.88	1.02	0.91	1.00	0.94
Shopping	0.99	1.00	0.99	1.06	1.00
Other	0.97	1.00	1.00	0.94	1.00
Total	0.94	1.00	0.99	1.09	1.00

Differences between RUM-LMS and RRM-LMS mostly small…

But at several occasions considerable

In particular for:

- **Train**
- **BTM**
- **Business**

Elasticities

Elasticities of passenger kilometres

	Commute		Business		Education		Shopping		Other		Total	
	RUM-RRM		RUM-RRM		RUM-RRM		RUM-RRM		RUM-RRM		RUM-RRM	
Car driver Cost	-0.51	-0.53	-0.17	-0.10	-	-	-0.46	-0.52	-0.29	-0.37	-0.41	-0.44
Car driver time	-0.88	-0.82	-0.88	-0.75	-1.54	-1.54	-1.35	-1.26	-1.32	-1.18	-1.02	-0.93
Car passenger time	-1.50	-1.48	-1.05	-0.91	-1.68	-1.82	-1.93	-1.90	-1.55	-1.49	-1.59	-1.54
BTM Cost	-0.55	-0.65	-0.12	-0.08	-	-	-0.54	-0.67	-0.24	-0.29	-0.30	-0.36
BTM in-vehicle time	-0.81	-0.80	-0.88	-0.94	-1.03	-1.10	-0.96	-0.86	-0.81	-0.80	-0.90	-0.92
Train Cost	-0.91	-0.97	-0.07	-0.09	-	-	-0.99	-0.96	-0.69	-0.70	-0.59	-0.63
Train time	-0.74	-0.81	-0.41	-0.51	-1.02	-1.13	-0.50	-0.52	-0.45	-0.47	-0.77	-0.84
Train Frequency	0.70	0.16	0.51	0.11	0.47	0.16	0.29	0.09	0.25	0.10	0.57	0.15

- Many elasticities are by and large of similar size under RUM and RRM: $\Delta E<|0.1|$
- However, there are substantial differences in Train frequency elasticities

Results

Analysis phase: Case study

Case study High Frequency Rail

- High Frequency Rail (HFR) scenario involves a substantial increase intensity of trains on main trajectories

- Motivations to choice this case study:
  - Pragmatic: relatively little efforts needed to implement scenario
  - Political: not so sensitive topic (anymore)
  - Expect relatively large differences

- Given our research objective, absolute levels are not relevant. Therefore, we look at the difference in the percentage increase:

$$\%\Delta Q = \frac{Q_{HFR}^{2030} - Q_{NO\ HFR}^{2030}}{Q_{Base}^{2010}}$$

Case study High Frequency Rail

Δ%Passenger kilometres RUM

	Train	Car driver	Car passenger	BTM	Bike	Walk	Total
Education	0.15	-0.02	-0.01	-0.03	-0.01	-0.01	0.05
Commute	0.26	-0.01	-0.01	-0.03	-0.02	-0.02	0.03
Business	0.16	0.00	-0.01	-0.01	-0.01	-0.01	0.01
Shopping	0.12	0.00	0.00	0.00	0.00	0.00	0.01
Other	0.08	0.00	0.00	0.00	0.00	0.00	0.01
Total	0.20	-0.01	0.00	-0.03	-0.01	0.00	0.02

Δ%Passenger kilometres RRM

	Train	Car driver	Car passenger	BTM	Bike	Walk	Total
Education	0.10	-0.01	-0.01	-0.02	-0.01	-0.01	0.03
Commute	0.15	-0.01	-0.01	-0.01	-0.01	-0.01	0.01
Business	0.08	0.00	0.00	-0.01	0.00	0.00	0.00
Shopping	0.08	0.00	0.00	0.00	0.00	0.00	0.00
Other	0.04	0.00	0.00	0.00	0.00	0.00	0.00
Total	0.12	0.00	0.00	-0.01	0.00	0.00	0.01

Case study High Frequency Rail

- **Observations:**
  - Both models predict a strong increase in train travel demand (in line with expectations)
  - Relative increases across travel purposes are consistent: highest growth for commute, followed by Business and Education

→ The RRM-LMS is **relatively** less sensitive towards the HFR policy than the RUM-LMS

This is especially noteworthy given the fact that the model fits for the RUM and RRM models were by and large the same

Case study High Frequency Rail

- **Explanations:**
  1. **The effect of general (‘across-the-board’) improvements in RRM models**
  2. **Sequential estimation of RRM models**
  3. **…?**

Case study High Frequency Rail

- **Explanations:**
  1. **The effect of general (‘across-the-board’) improvements in RRM models**

  – In RRM models only relative performance matters

    E.g. when all alternatives would become €5 more expensive, regret levels would stay **exactly** the same (all else being equal).

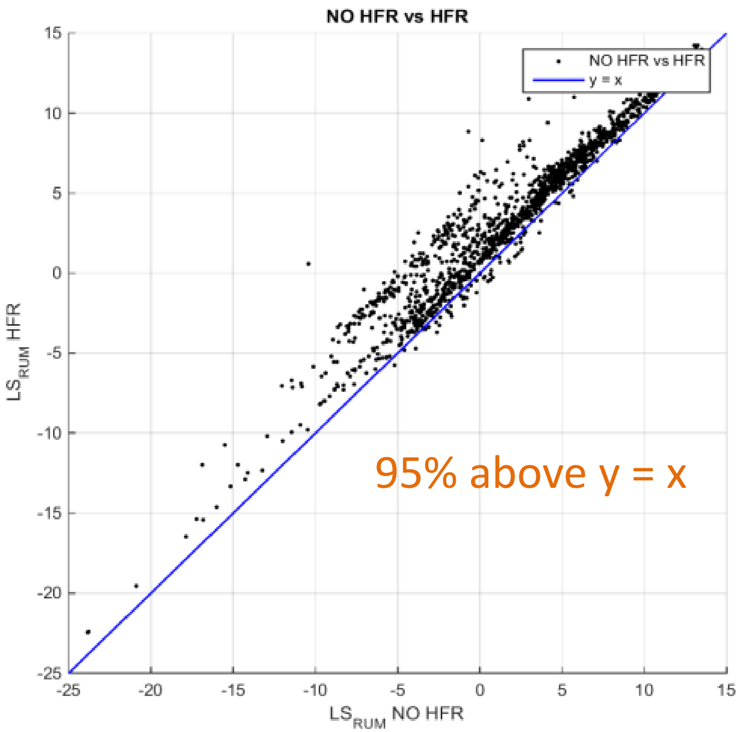
  – Since, the HFR concerns a general improvement, this phenomenon may partly explain the relative insensitivity of the RRM-LMS towards the HFR policy

  – Changes due to the HFR policy enter the Train station model, which, in turn, enter the MD model **via the LogSums**

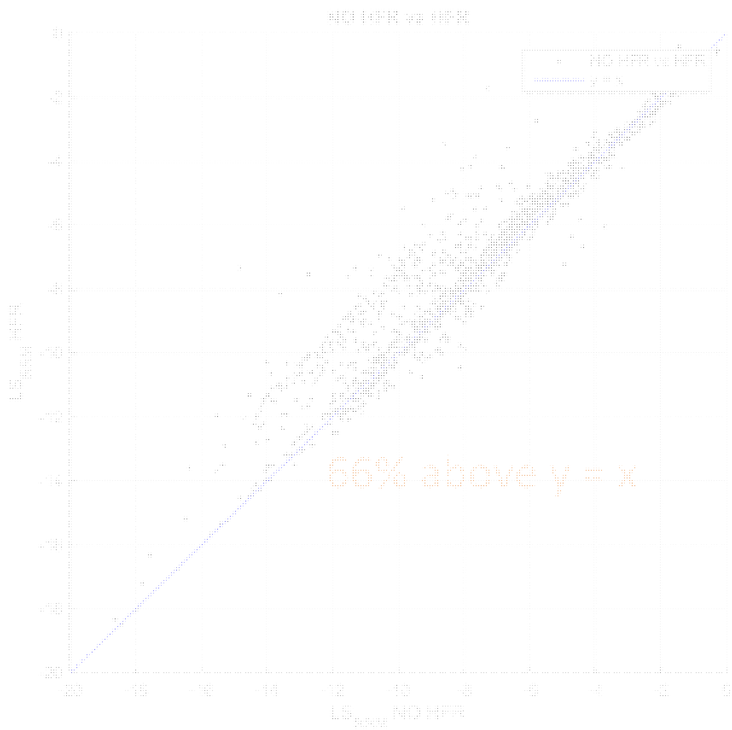
Case study High Frequency Rail

- **Explanations:**
  1. **The effect of general (‘across-the-board’) improvements in RRM models**

RUM



RRM



Case study High Frequency Rail

- **Explanations:**
  2. Sequential estimation of RRM models
  – The sequential estimation approach may not be fully ‘compatible’ with an RRM modelling framework

  – Due to the sequential estimation, an improvement of a Train alternative **<u>only</u>** enters the MD model via the RRM LogSum: it does *not* affect the regret levels of alternatives in the MD model

    → In other words, the regret level of a car alternative is not affected by an improvement of a Train alternative.

  – The sequential estimation may also partly explain the relative insensitivity of the RRM-LMS towards the HFR policy

Conclusions and further research

Conclusions:

- RRM-based large-scale transport models are technically feasible
- We found non-negligible differences in forecasts between RRM and RUM
- These differences can, at least partly, be understood and explained considering the fundamental differences in behavioural premises of the underlying the regret- and utility-based disaggregate choice models

→ **The assumption on the underlying decision rule <u>does</u> <u>matter</u> for the forecasts of large-scale transport models, at least <u>in some cases</u>**

Limitations and further research:

- Due to the complex nature of the LMS, we were not fully able to isolate the effect of the decision rule
- LMS optimized for RRM?

Questions, Ideas, Suggestions?

For details download our working paper

Van Cranenburgh, S., Chorus, C.G. Does The Decision Rule Matter For Large-Scale Transport Models?

www.advancedRRMmodels.com/working-papers

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