Tell us what the future holds, so we may know that you are gods... *(Isaiah 41:23)*

Everyday mathematics and data combine to help us envision what might be

H&S GROUP

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Forecasting the required tank container and trucking capacity for an intermodal logistics service provider

27/08/2019

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TU/E School of Industrial Engineering

Introduction and problem description

Proposed forecasting methodology

Completing the circle: benefits & implementation

Discussion

Introduction and problem description

Proposed forecasting methodology

Completing the circle: benefits & implementation

Discussion

H&S Foodtrans is a logistics service provider engaged in intermodal transportation of liquid foodstuff

Introduction to H&S

Forecasting the required tank container and trucking capacity

Problem statement

Problem statement:

"How can forecasting be used to predict the short-term required **trucking and tank container** capacity for an intermodal logistics service provider?"

To provide an answer to the problem statement, 3 main steps were taken in this research

Research steps

Problem statement

"How can forecasting be used to predict the short-term required **trucking and tank container** capacity for an intermodal logistics service provider?"

Research steps

Step 1

Forecasting the loadings and deliveries based on *historical* data

Step 2

Adjusting the forecast of step 1 by utilizing *advance demand information*

Step 3

Translate the adjusted forecast of step 2 into:

a. A prediction for the required trucking capacity
b. A prediction for the required tank container capacity

Introduction and problem description

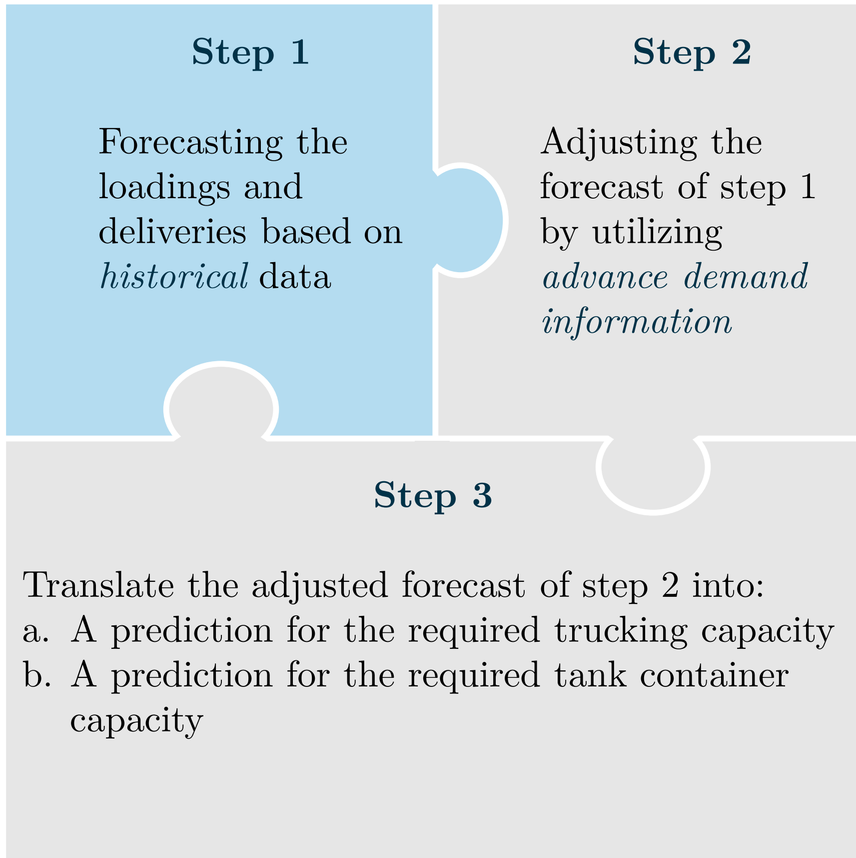
Proposed forecasting methodology

Completing the circle: benefits & implementation

Discussion

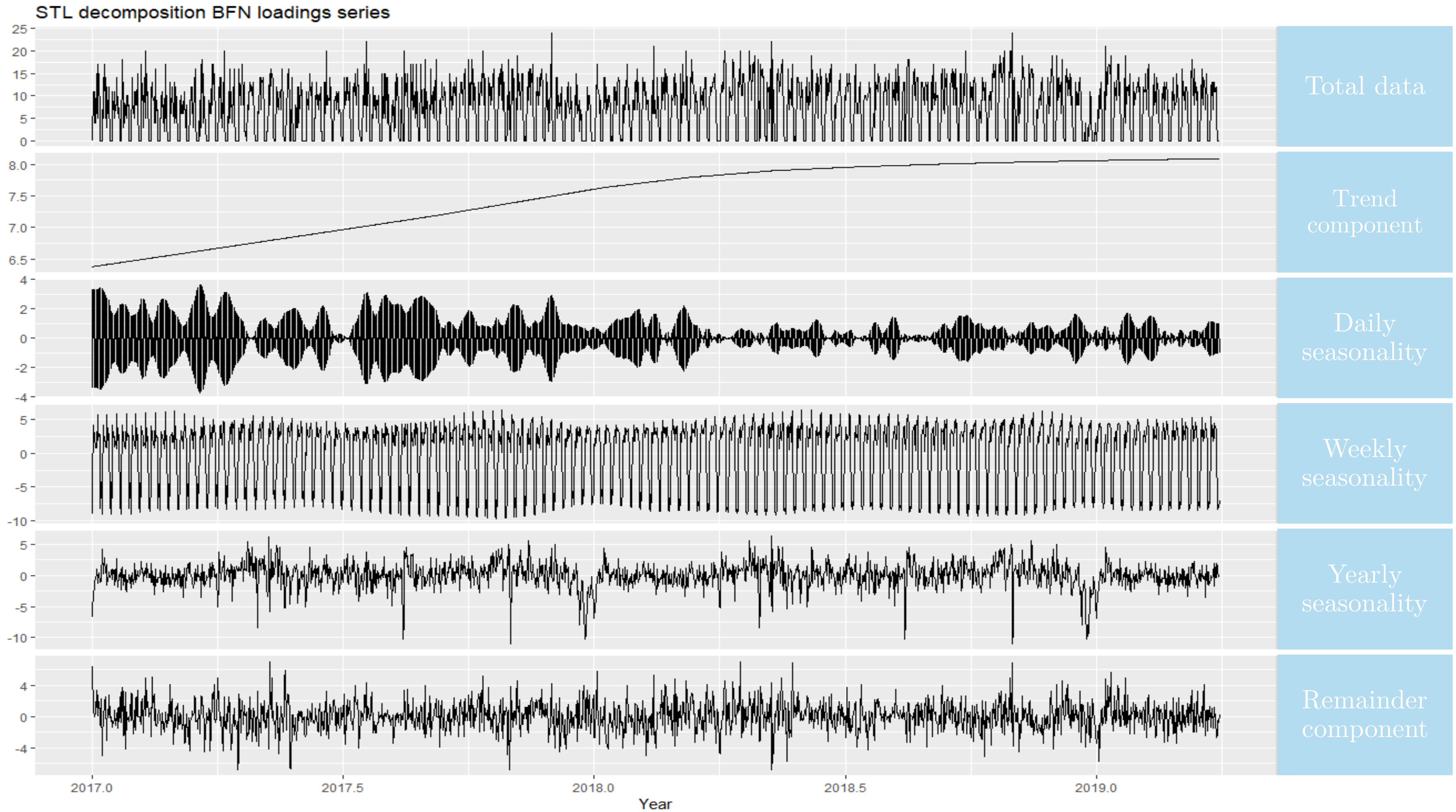
Step 1: How can the number of loadings and deliveries be forecasted from historical data?

Step 1



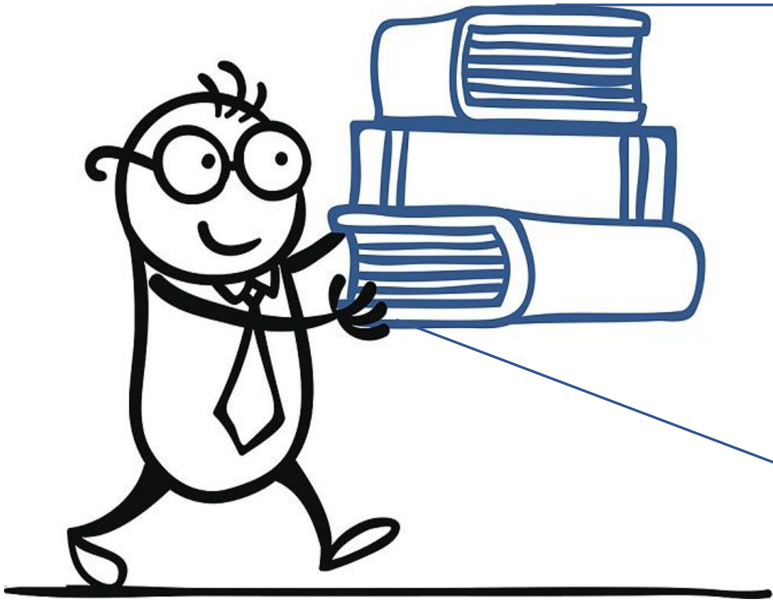
The data exhibits multiple seasonal patterns

STL decomposition BFN loadings series



The literature was consulted to identify forecasting models that can account for time series with multiple (seasonal) components

Literature review



- STL decomposition
- Double exponential smoothing
- Dynamic harmonic regression
- TBATS
- Artificial neural network
- (Simple mean method)

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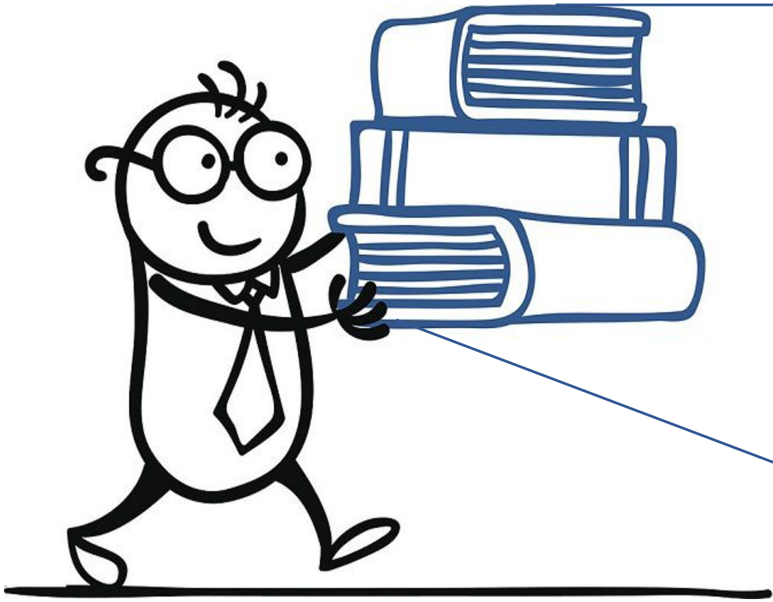

- STL decomposition
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- Simple mean method

Artificial neural networks, Dynamic harmonic regression and the Simple mean method turned out to be the most accurate models in step 1

Best performing models for predicting orders from historical data

Artificial Neural Networks

- \+ Best performing model in most series
- − More difficult to implement for practitioners
- − Lack of explanatory capabilities

Dynamic Harmonic Regression

- \+ Fairly accurate in most series
- \+ Explanatory capabilities (interpretation coefficients)
- − More difficult to implement for practitioners

Simple Mean Method

- \+ Fairly accurate in most series
- \+ Easy to understand for practitioners
- \+ Easy to implement for all planning regions
- \+ Intuitively captures strongest seasonal components

Step 2: How can advance demand information be utilized to enhance the initial forecast of the loadings and deliveries?

Step 2

Step 1

Forecasting the loadings and deliveries based on *historical* data

Step 2

Adjusting the forecast of step 1 by utilizing *advance demand information*

Step 3

Translate the adjusted forecast of step 2 into:

a. A prediction for the required trucking capacity
b. A prediction for the required tank container capacity

Using the Advance Demand Information

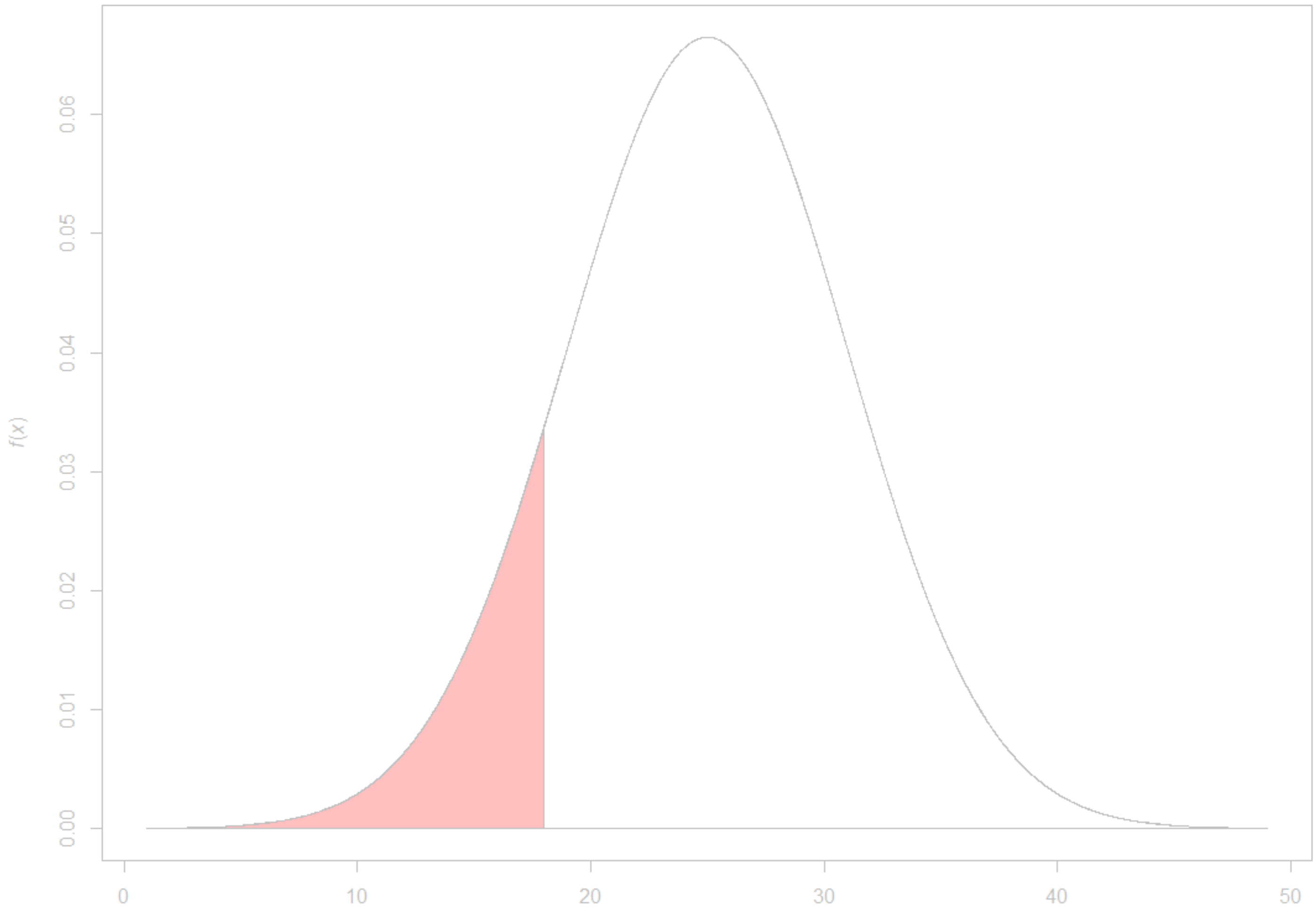
Method 1: Bayesian Adjustment

Intuitive explanation of the idea behind the Bayesian adjustment

Bayesian technique explained

Consider the following situation:

- Today (27/08) we want to forecast the loadings in region x for Friday (30/08)
- The initial forecast equals **25** loadings
- At present, **18** loadings are already in the system for Friday (30/08)



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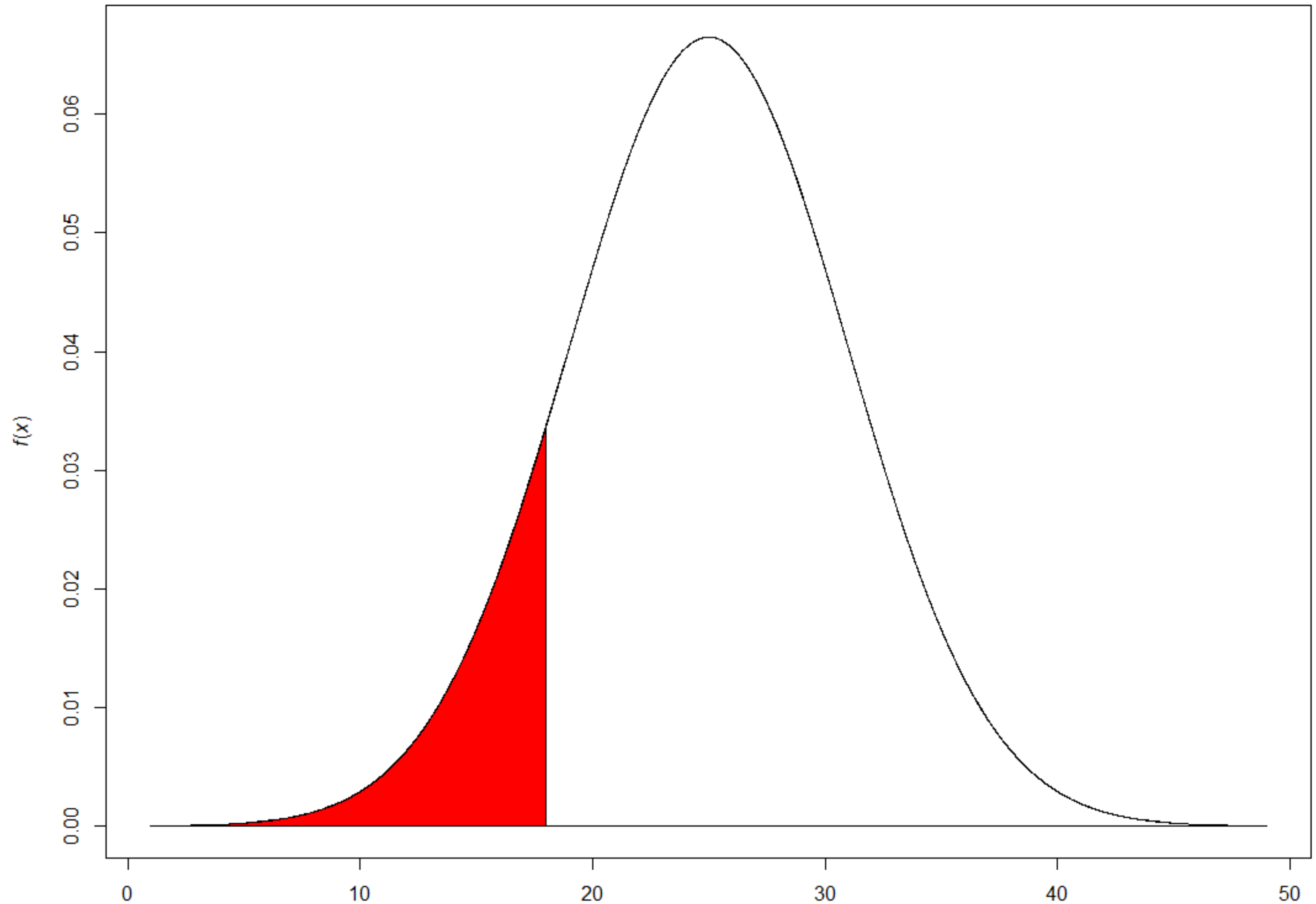

First, the probability distribution for the number of orders (i.e. loadings or deliveries) is estimated

1

Estimate the probability distribution for the number of orders (n) and their corresponding probabilities.

Fit a distribution with mean equal to the initial forecast.

- If the initial forecast is smaller than 10: **Poisson distribution**
- If the initial forecast is greater or equal to 10: **Normal distribution**

Subsequently, the probability that an order for a future time period is already known at present is approximated

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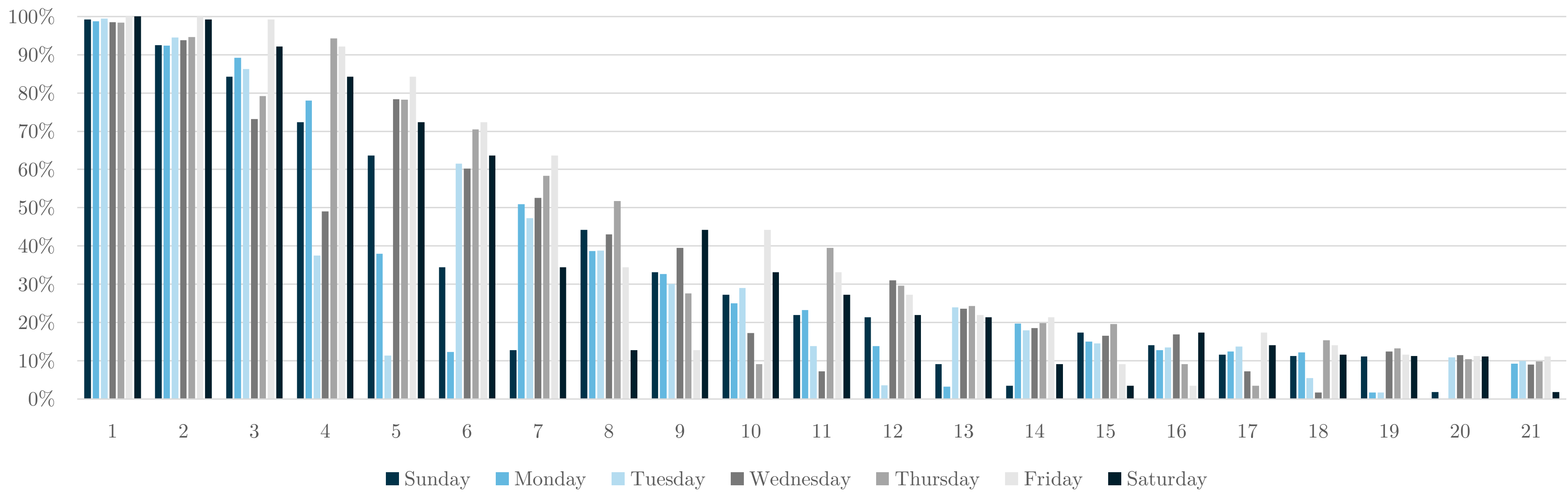
Fit a distribution with mean equal to the initial forecast.

- If the initial forecast is smaller than 10: **Poisson distribution**
- If the initial forecast is larger than 10: **Normal distribution**

2

Estimate the probability that an order for future period τ is already known as of time T

- This probability is denoted by Θ
- Computed separately for each day of the week



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Estimate the probability that an order for future period τ is already known as of time T

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3

Estimate the conditional probability of the advanced number of orders, for each possible value that the number of orders for period τ can take

$$P\langle n_{a\tau} \mid n_j \rangle = \binom{n_j}{n_{a\tau}} {\theta_\tau}^{n_{a\tau}} (1-\theta_\tau)^{n_j - n_{a\tau}}$$

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- If the initial forecast is smaller than 10: **Poisson distribution**
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1	*Estimate the probability distribution for the number of orders (n) and their corresponding probabilities.*	Fit a distribution with mean equal to the initial forecast. • If the initial forecast is smaller than 10: **Poisson distribution** • If the initial forecast is larger than 10: **Normal distribution**
2	*Estimate the probability that an order for future period τ is already known as of time T*	• This probability is denoted by Θ • Computed separately for each day of the week
3	***Estimate the conditional probability of the advanced number of orders, for each possible value that the number of orders for period τ can take***	$P\langle n_{a\tau} \mid n_j \rangle = \binom{n_j}{n_{a\tau}} {\theta_\tau}^{n_{a\tau}} (1-\theta_\tau)^{n_j - n_{a\tau}}$

Fourth, Bayes' Theorem is used to derive the probability of the number of orders, given the advanced number of orders

1	*Estimate the probability distribution for the number of orders (n) and their corresponding probabilities.*	Fit a distribution with mean equal to the initial forecast. • If the initial forecast is smaller than 10: **Poisson distribution** • If the initial forecast is larger than 10: **Normal distribution**
2	*Estimate the probability that an order for future period τ is already known as of time T*	• This probability is denoted by Θ • Computed separately for each day of the week
3	*Estimate the conditional probability of the advanced number of orders, for each number of orders, for each possible value that the number of orders for period τ can take*	$P\langle n_{a\tau} \mid n_j\rangle = \binom{n_j}{n_{a\tau}} {\theta_\tau}^{n_{a\tau}}(1-\theta_\tau)^{n_j - n_{a\tau}}$
4	***Estimate the probability of the number of orders, given the advanced number of orders***	$P\langle n_j \mid n_{a\tau}\rangle = \frac{P\langle n_{a\tau} \mid n_j\rangle * P\langle n_j\rangle}{P\langle n_{a\tau}\rangle}$ where, $P\langle n_{a\tau}\rangle = \sum_j P\langle n_{a\tau} \mid n_j\rangle * P\langle n_j\rangle$

Finally, the expected value of the rescaled distribution is calculated to derive the adjusted forecast

1	*Estimate the probability distribution for the number of orders (n) and their corresponding probabilities.*	Fit a distribution with mean equal to the initial forecast. • If the initial forecast is smaller than 10: **Poisson distribution** • If the initial forecast is larger than 10: **Normal distribution**
2	*Estimate the probability that an order for future period τ is already known as of time T*	• This probability is denoted by Θ • Computed separately for each day of the week
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5	***Estimate the expected number of orders for future period τ***	$E\langle n \mid n_{a\tau}\rangle = \sum_j n_j P\langle n_j \mid n_{a\tau}\rangle$

Summary of the Bayesian adjustment

1	*Estimate the probability distribution for the number of orders (n) and their corresponding probabilities.*	Fit a distribution with mean equal to the initial forecast. • If the initial forecast is smaller than 10: **Poisson distribution** • If the initial forecast is larger than 10: **Normal distribution**
2	*Estimate the probability that an order for future period* τ *is already known as of time T*	• This probability is denoted by Θ • Computed separately for each day of the week
3	*Estimate the conditional probability of the advanced number of orders, for each possible value that the number of orders for period* τ *can take*	$P\langle n_{a\tau} \mid n_j \rangle = \binom{n_j}{n_{a\tau}} {\theta_\tau}^{n_{a\tau}} (1-\theta_\tau)^{n_j - n_{a\tau}}$
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5	*Estimate the expected number of orders for future period* τ	$E\langle n \mid n_{a\tau} \rangle = \sum_j n_j P\langle n_j \mid n_{a\tau} \rangle$

The Bayesian technique significantly improves the initial forecast

Performance Bayesian technique

Type of forecast	Improvement after Bayesian technique
sub-daily (AM / PM) number of loadings and deliveries forecast for **1 week ahead**	Initial forecast was improved by **64%**
daily number of loadings and deliveries forecast for **3 weeks ahead**	Initial forecast was improved by **27%**

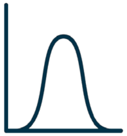
Recall that the output of the Bayesian algorithm is a forecast of the expected number of loadings and deliveries

Recap step 1 and 2

Historical data forecast

Artificial Neural Network

Dynamic Harmonic Regression



Simple Mean Method

Bayesian algorithm

Output

The forecasted number of **loadings** and **deliveries** in a certain region in a given period

Step 3a: How can the forecasted loadings and deliveries be used to predict the required trucking capacity?

Step 3a

Step 1

Forecasting the loadings and deliveries based on *historical* data

Step 2

Adjusting the forecast of step 1 by utilizing *advance demand information*

Step 3

Translate the adjusted forecast of step 2 into:

a. A prediction for the required **trucking** capacity

The historical trucking capacity is estimated based on actuals and a number of theoretical assumptions

Estimation of historical trucking capacity

1	Estimation of the historical trucking capacity	Assumptions	Actuals
		• Pickup: 45 min • Drop: 45 min • Clean: 60 min • Speed truck: 60 km/h	• Loading action • Delivery action • Location and sequence of actions

2

$$\delta_T(\tau) = \beta_0 + \beta_1 * Lo(\tau) + \beta_2 * De(\tau) + \beta_3 * Lo_{D(\tau)} + \beta_4 * De_{D(\tau)} + \beta_5 * \delta(\tau - 14) + \beta_6 * \delta(\tau - 28) + \sum_{k=1}^{8} \beta_{6+k} x_k(\tau) + \varepsilon_T(\tau)$$

$\delta_T(\tau)$	the forecasted trucking capacity in hours for period τ as of time T	$x_2(\tau)$	1 if $D(\tau)$ is a Tuesday, 0 otherwise
$Lo(\tau)$	the number of loadings during period τ	$x_3(\tau)$	1 if $D(\tau)$ is a Wednesday, 0 otherwise
$De(\tau)$	the number of deliveries during period τ	$x_4(\tau)$	1 if $D(\tau)$ is a Thursday, 0 otherwise
$Lo_{D(\tau)}$	the number of loadings during $D(\tau)$, but not in period τ	$x_5(\tau)$	1 if $D(\tau)$ is a Friday, 0 otherwise
$De_{D(\tau)}$	the number of deliveries during $D(\tau)$, but not in period τ	$x_6(\tau)$	1 if $D(\tau)$ is a Saturday, 0 otherwise
$\delta(\tau - 14)$	the actual trucking capacity in hours in period $\tau - 14$ (i.e. one week ago)	$x_7(\tau)$	1 if $D(\tau)$ is a holiday, 0 otherwise
$\delta(\tau - 28)$	the actual trucking capacity in hours in period $\tau - 28$ (i.e. two weeks ago)	$x_8(\tau)$	1 if period τ falls within AM, 0 otherwise
$x_1(\tau)$	1 if $D(\tau)$ is a Monday, 0 otherwise	$\varepsilon_T(\tau)$	error term

A multiple linear regression model was developed to predict the required trucking capacity

Multiple linear regression model

1

Estimation of the historical trucking capacity	Assumptions	Actuals
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Multiple linear regression model

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	Assumptions	Actuals
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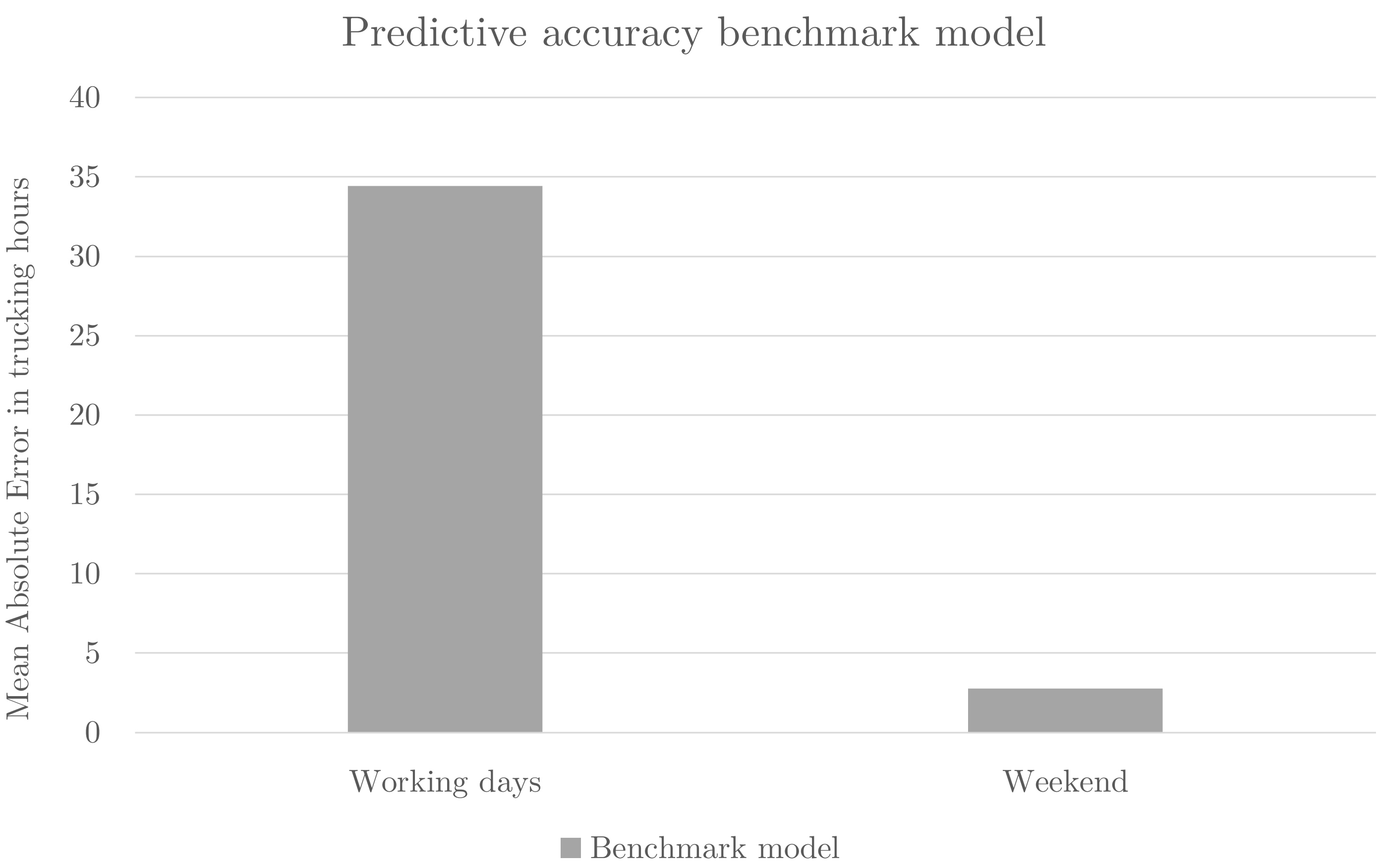
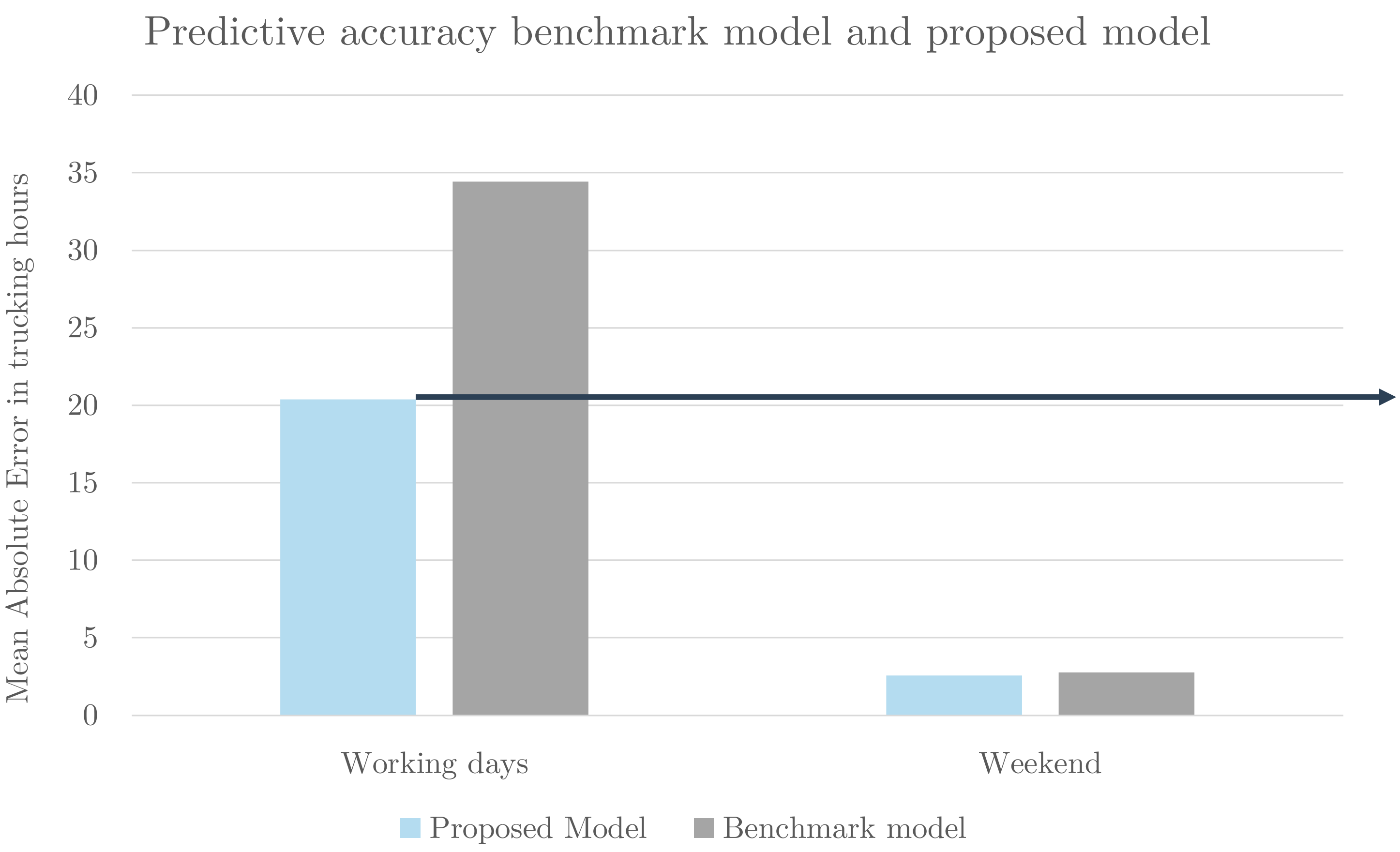
The proposed forecasting model is compared against a benchmark model that is currently used at H&S

Accuracy proposed forecasting methodology BFN region



The proposed forecasting model is 41% more accurate than the current model in the BFN region

Accuracy proposed forecasting methodology BFN region



Improvement of 41% in accuracy during working days

Step 3b: How can the forecasted loadings be converted to the required tank container capacity?

Step 3b

Step 1

Forecasting the loadings and deliveries based on *historical* data

Step 2

Adjusting the forecast of step 1 by utilizing *advance demand information*

Step 3

Translate the adjusted forecast of step 2 into:
b. A prediction for the required **tank container** capacity

Recall that the output of the Bayesian algorithm is a forecast of the expected number of loadings (and deliveries)

Recap Bayesian of step 1 and 2

Historical data forecast

- Artificial Neural Network
- Dynamic Harmonic Regression
- Simple Mean Method

Bayesian algorithm

Output

The forecasted number of **loadings** (and deliveries) in a certain region in a given period

Every (forecasted) loading represents the need for exactly one tank container

Idea tank container forecast

Historical data forecast

- Artificial Neural Network
- Dynamic Harmonic Regression
- Simple Mean Method

Bayesian algorithm

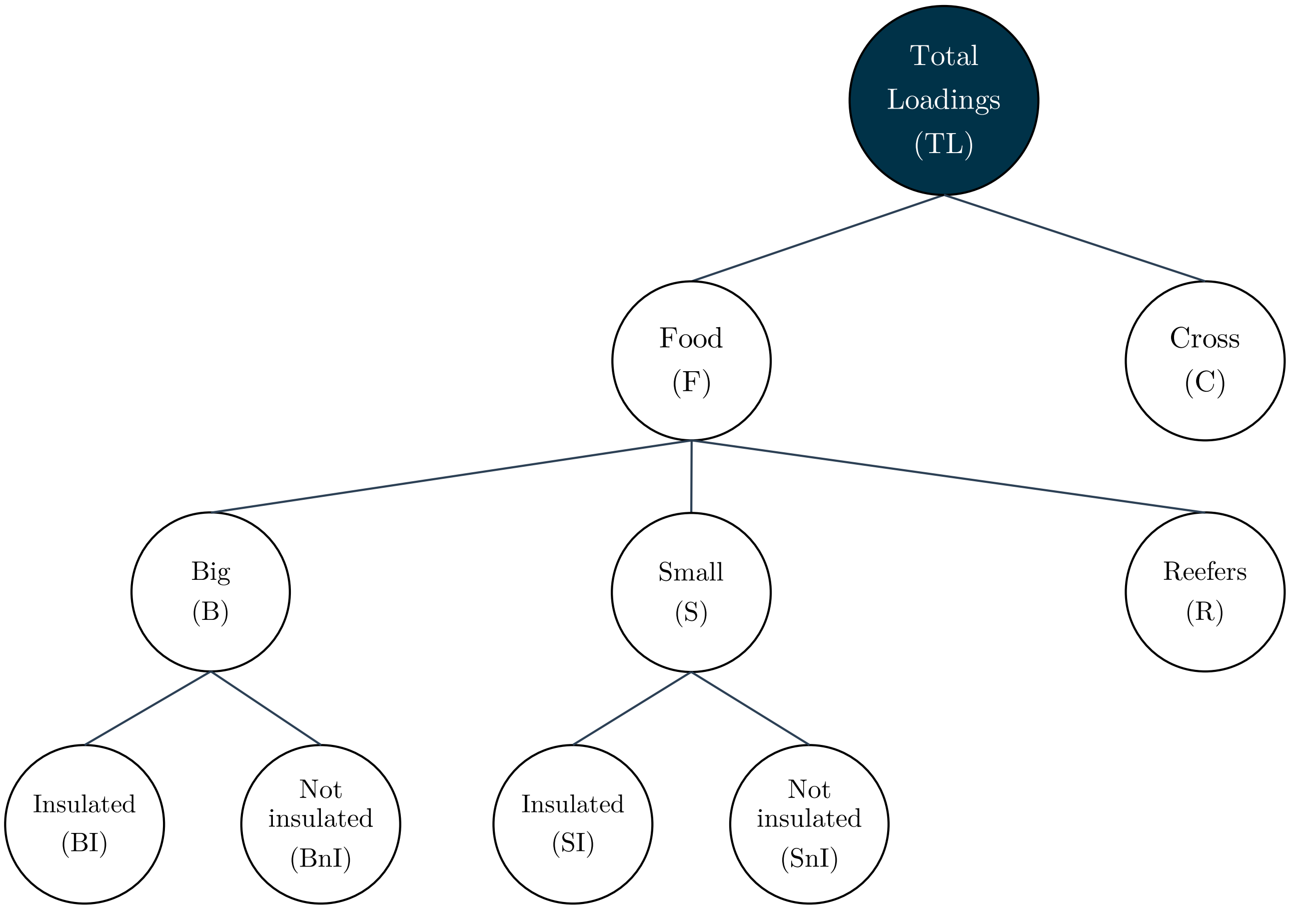
Output

The forecasted number of **loadings** (and deliveries) in a certain region in a given period

Assumption: every (forecasted) loading in a certain region represents the need for exactly 1 tank container

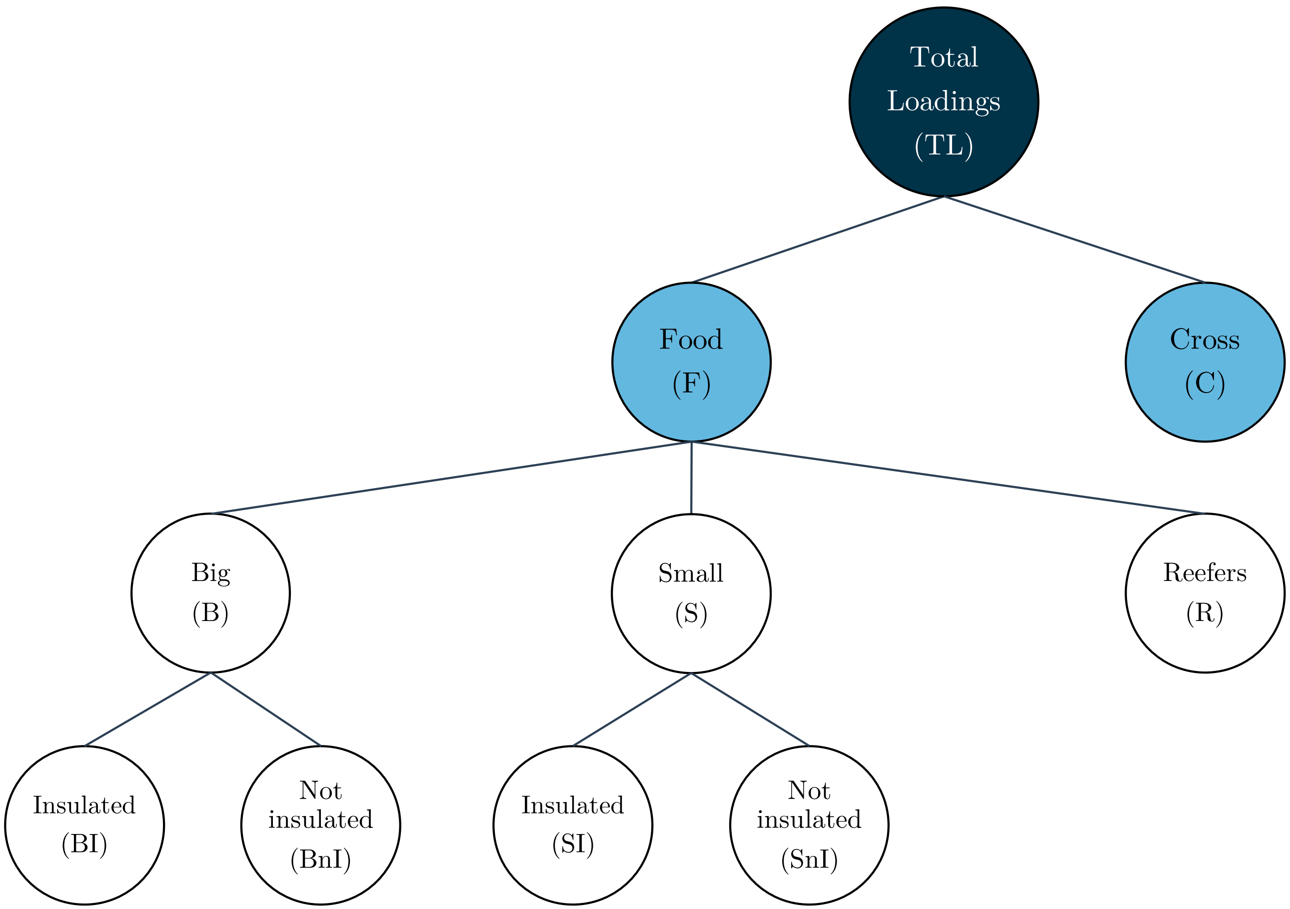
The total number of loadings can be disaggregated by type of tank container

Hierarchical time series tank container types H&S



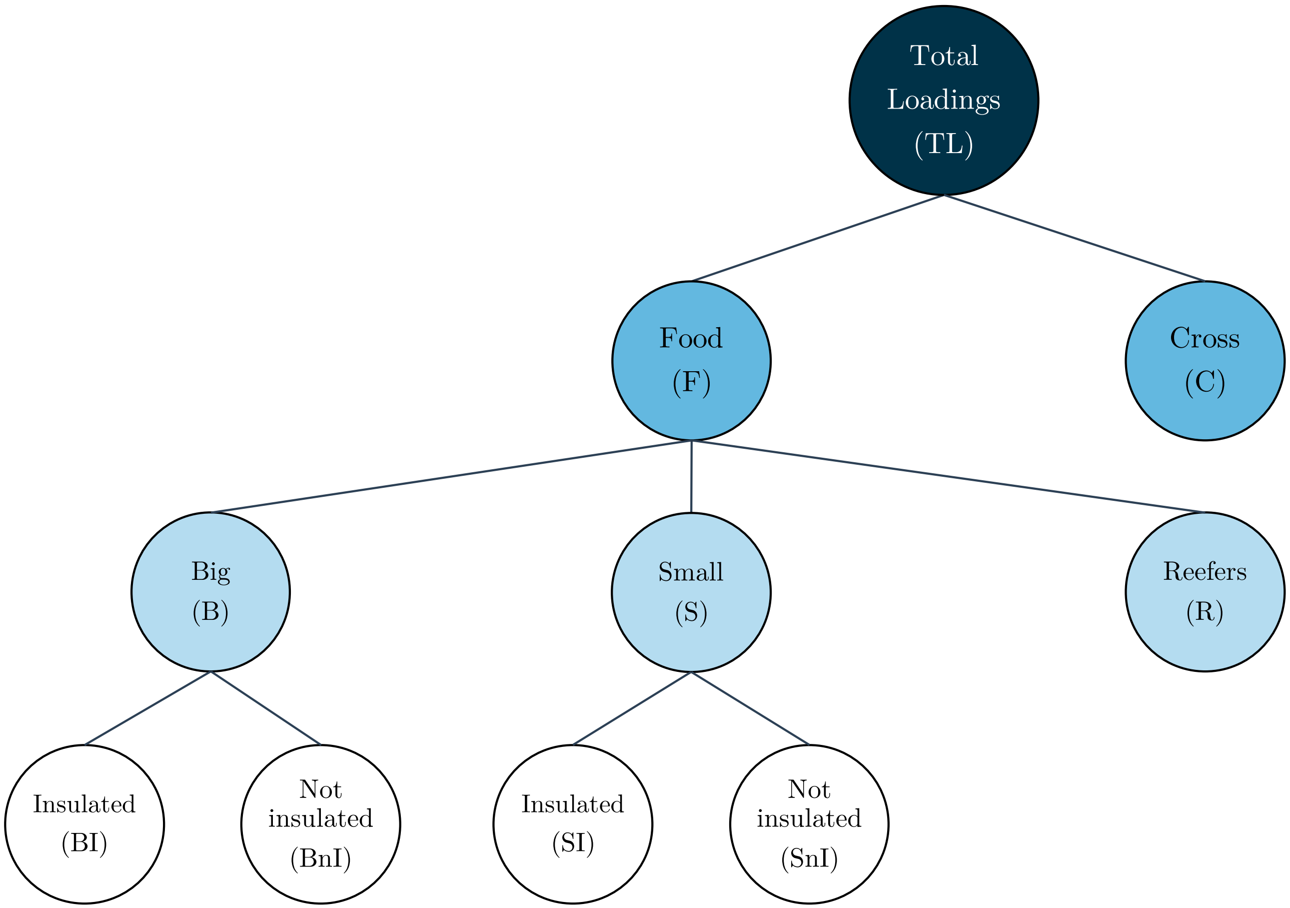
The total number of loadings can be disaggregated by type of tank container

Hierarchical time series tank container types H&S



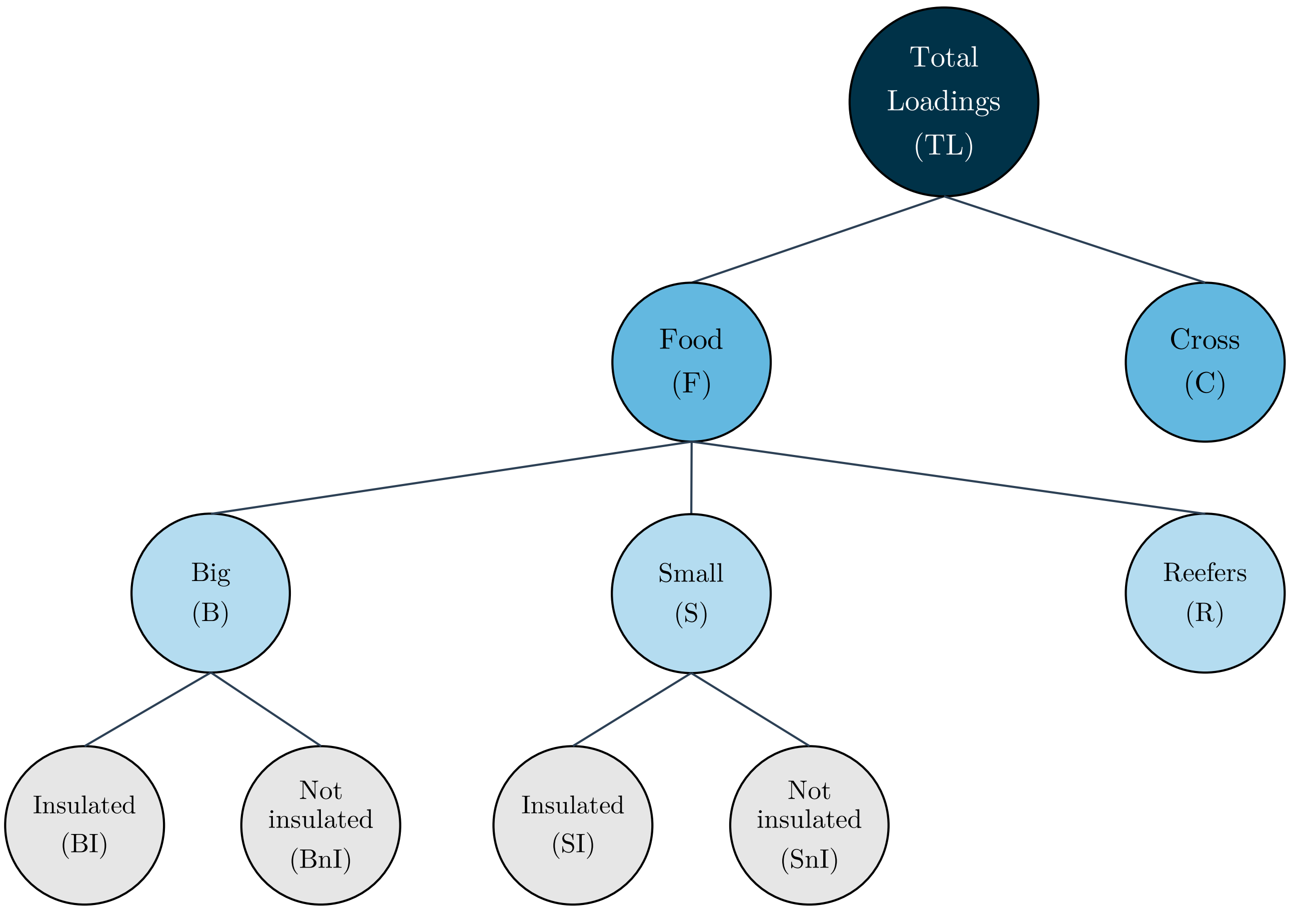
The total number of loadings can be disaggregated by type of tank container

Hierarchical time series tank container types H&S



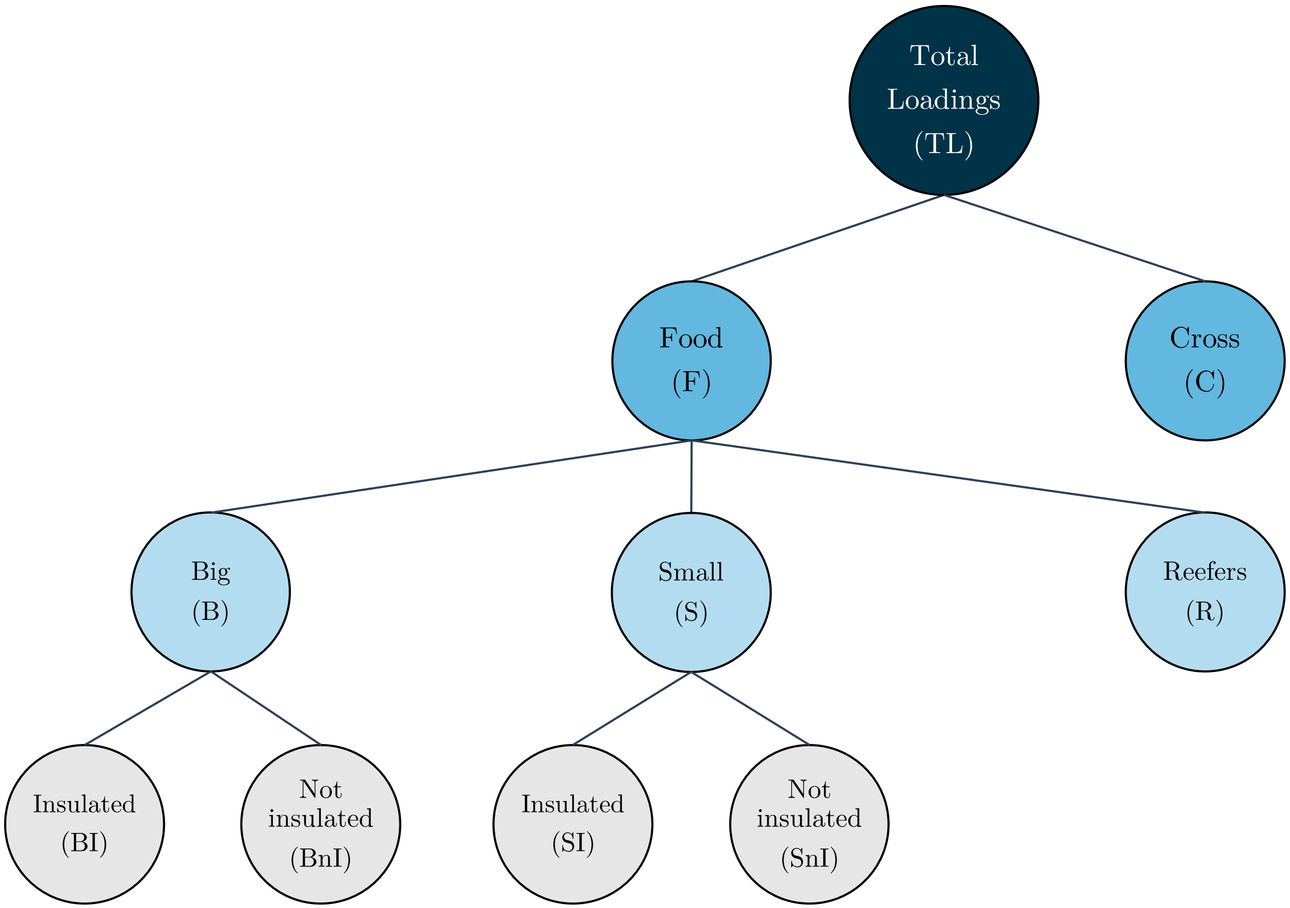
The total number of loadings can be disaggregated by type of tank container

Hierarchical time series tank container types H&S



How can a forecast be obtained for every type of tank container?

Tank container forecast



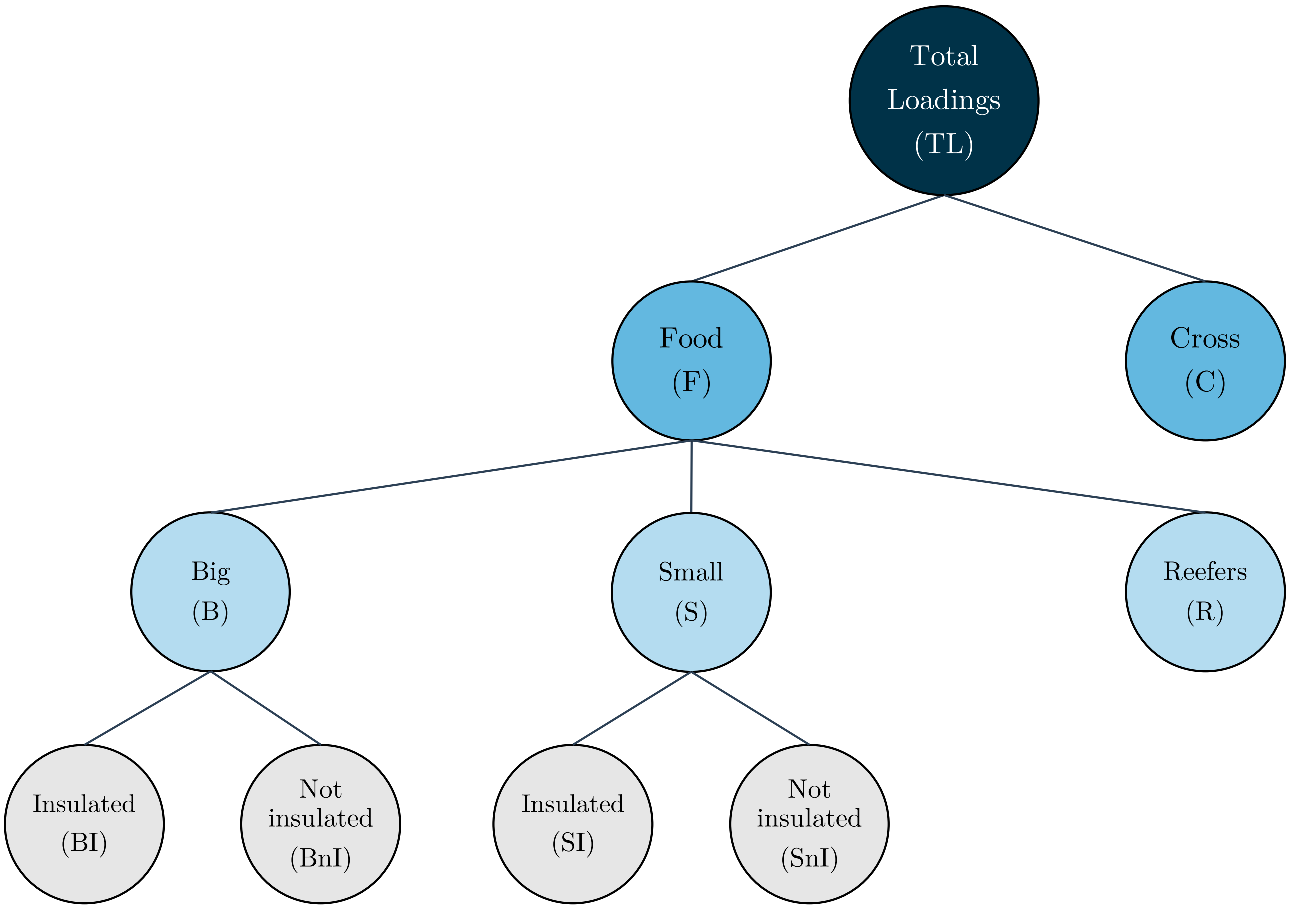
Tank container forecast

Output Bayesian technique

1. Proportions for the container types are forecasted independently
2. The aggregated forecast is disaggregated down the hierarchy based on the forecasted proportions

The next question to answer is how the total number of loadings should be disaggregated to obtain a forecast per tank container type

Tank container forecast



Tank container forecast

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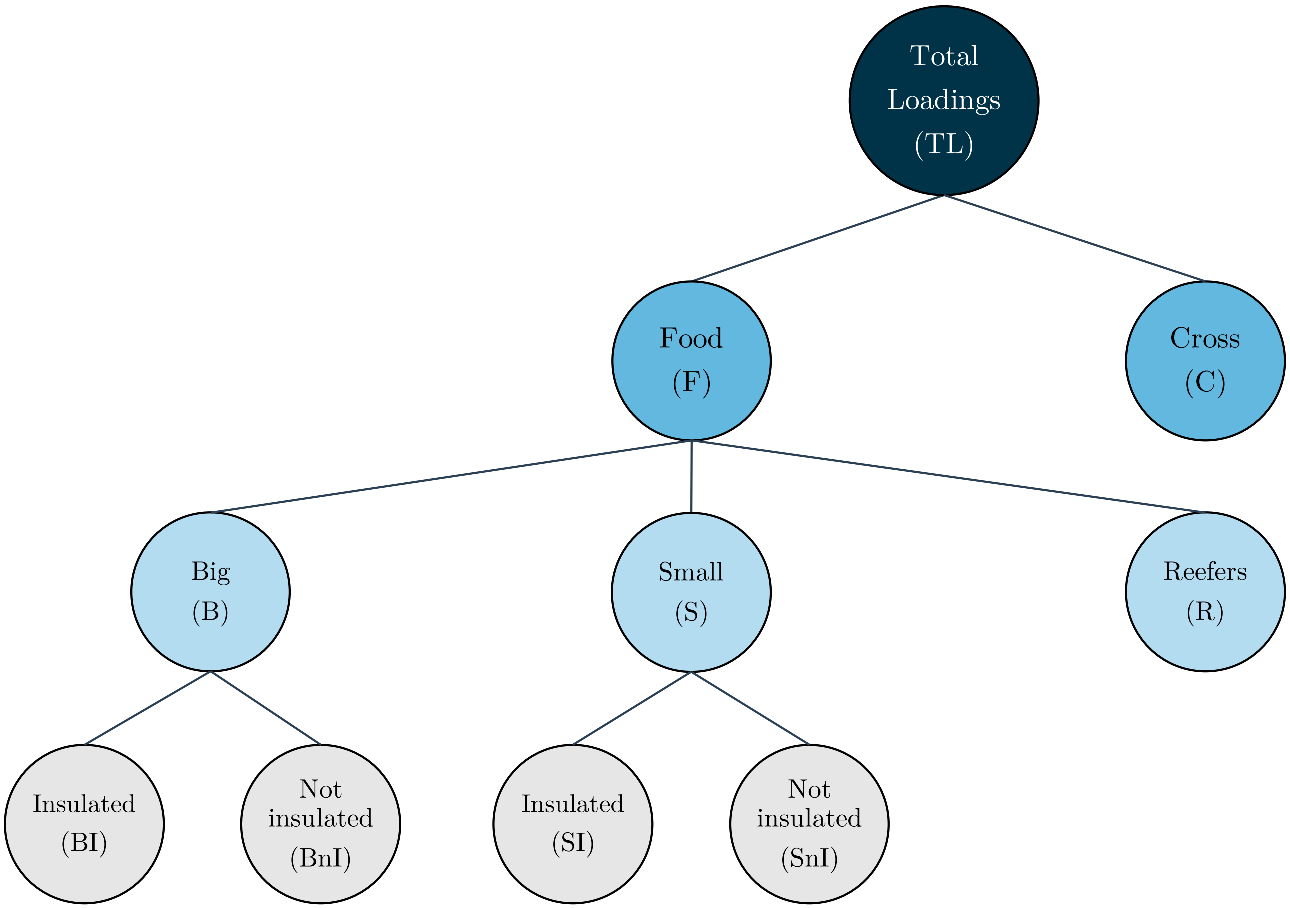
Tank container forecast

Tank container forecast



Output Bayesian technique

1. Proportions for the container types are forecasted independently
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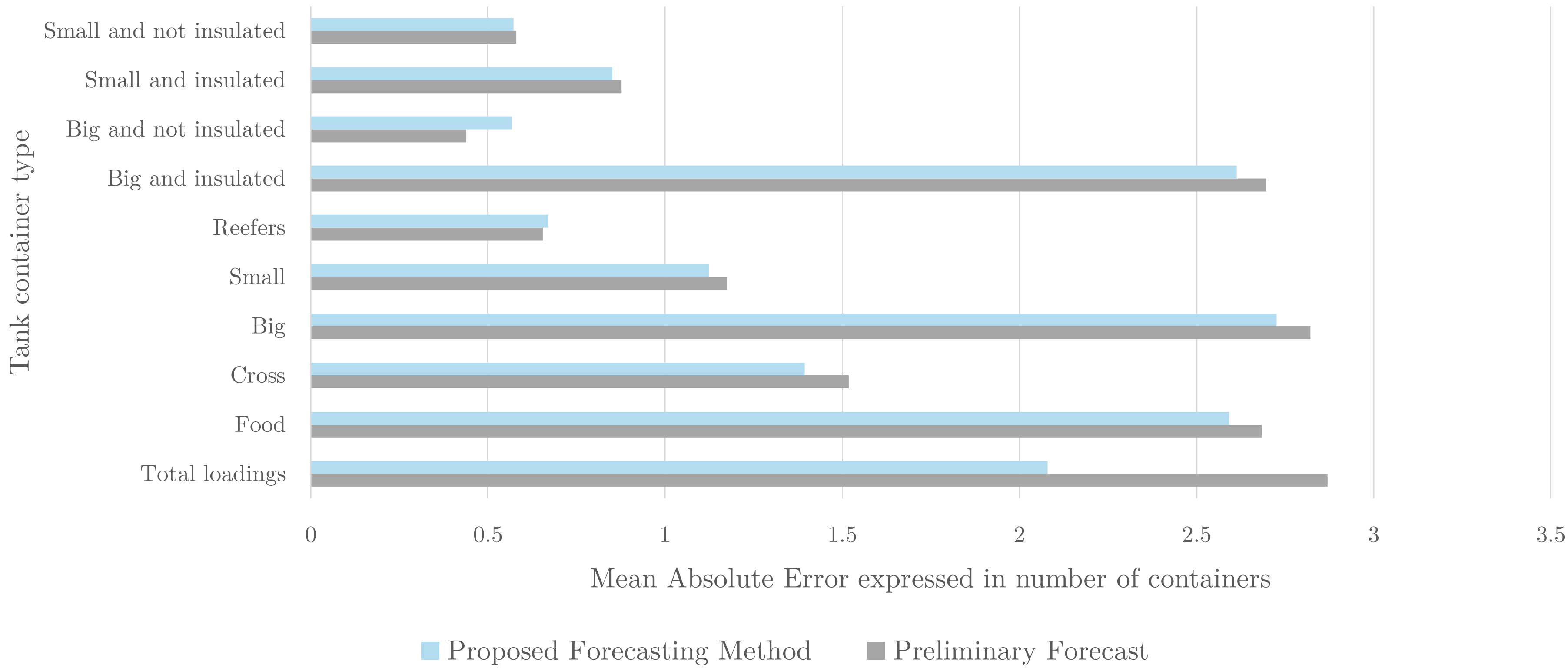
Predictive accuracy tank container forecast in the Rotterdam planning region



- Mean Absolute Error differs per type of tank container
- For most aggregation levels it outperforms the preliminary forecast, albeit not by much

Introduction and problem description

Proposed forecasting methodology

Completing the circle: benefits & implementation

Discussion

Account managers might use the forecast to create a more balanced workload which might in turn lead to a reduction in trucking costs

Who will use the forecast?	Which decisions will the forecast support?	What will be the benefits?
Account managers	Proactively (re)plan orders to **smooth workload** throughout the day and week	• Decrease in the number of trucks needed → reduction in costs • 5% improvement in balance between AM & PM results in approximately €750,000
TCP and MMP planners	• **Book charters** earlier in the process • Assist Guido and Samara to make more **efficient repositioning decisions** of empty tanks (yearly costs > €11,000,000)	• Lower charter costs and increased quality • Enhanced performance towards clients • **Reduction in empty tank container repositioning costs** • Reduces risk
Commercial managers	Proactively look for work for periods in which the demand is expected to be low (i.e. **commercial focus on filling gaps**)	• Workload more equally divided • Increased utilization of own trucks
Purchasing managers	Book charters earlier in the process (i.e. **purchasing decisions of charters**)	• Lower charter costs and increased quality • Enhanced performance towards clients

TCP and MMP planners might use the forecast to book charters at an earlier stage and make more efficient tank container repositioning decisions

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Purchasing managers	Book charters earlier in the process (i.e. **purchasing decisions of charters**)	• Lower charter costs and increased quality • Enhanced performance towards clients

In addition to TCP planners, purchasing managers might also use the forecast to book charters at an earlier stage

Who will use the forecast?	Which decisions will the forecast support?	What will be the benefits?
Account managers	Proactively (re)plan orders to **smooth workload** throughout the day and week	• Decrease in the number of trucks needed → reduction in costs • 5% improvement in balance between AM & PM results in approximately €750,000
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The forecasting methodology proposed by this research is now being implemented at H&S (and Den Hartogh)

Implementation project

Stakeholders implementation project

H&S GROUP

DEN HARTOGH

CQM Consultants in Quantitative Methods

inforit

Timeline implementation project

1. Orientation and data gathering
2. Testing wider applicability of the models
3. Fine-tuning models and extension to all planning regions
4. Integration in software

Introduction and problem description

Proposed forecasting methodology

Completing the circle: benefits & implementation

Discussion

Forecasting the required tank container and trucking capacity for an intermodal logistics service provider

27/08/2019

Rijk van der Meulen, MSc student Operations Management & Logistics

TU/E School of Industrial Engineering

H&S GROUP

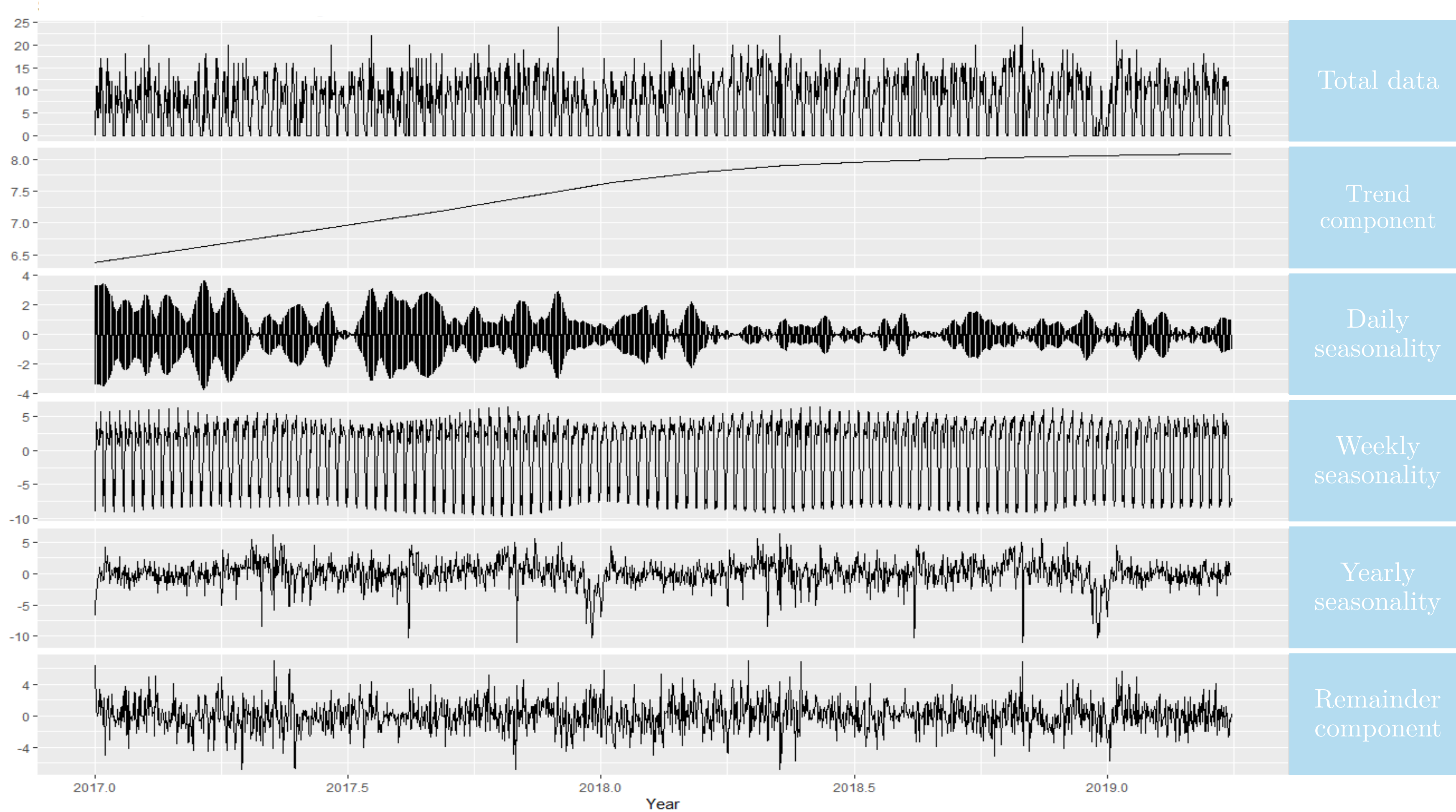
TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

APPENDIX A

Forecasting accuracy models based on historical data

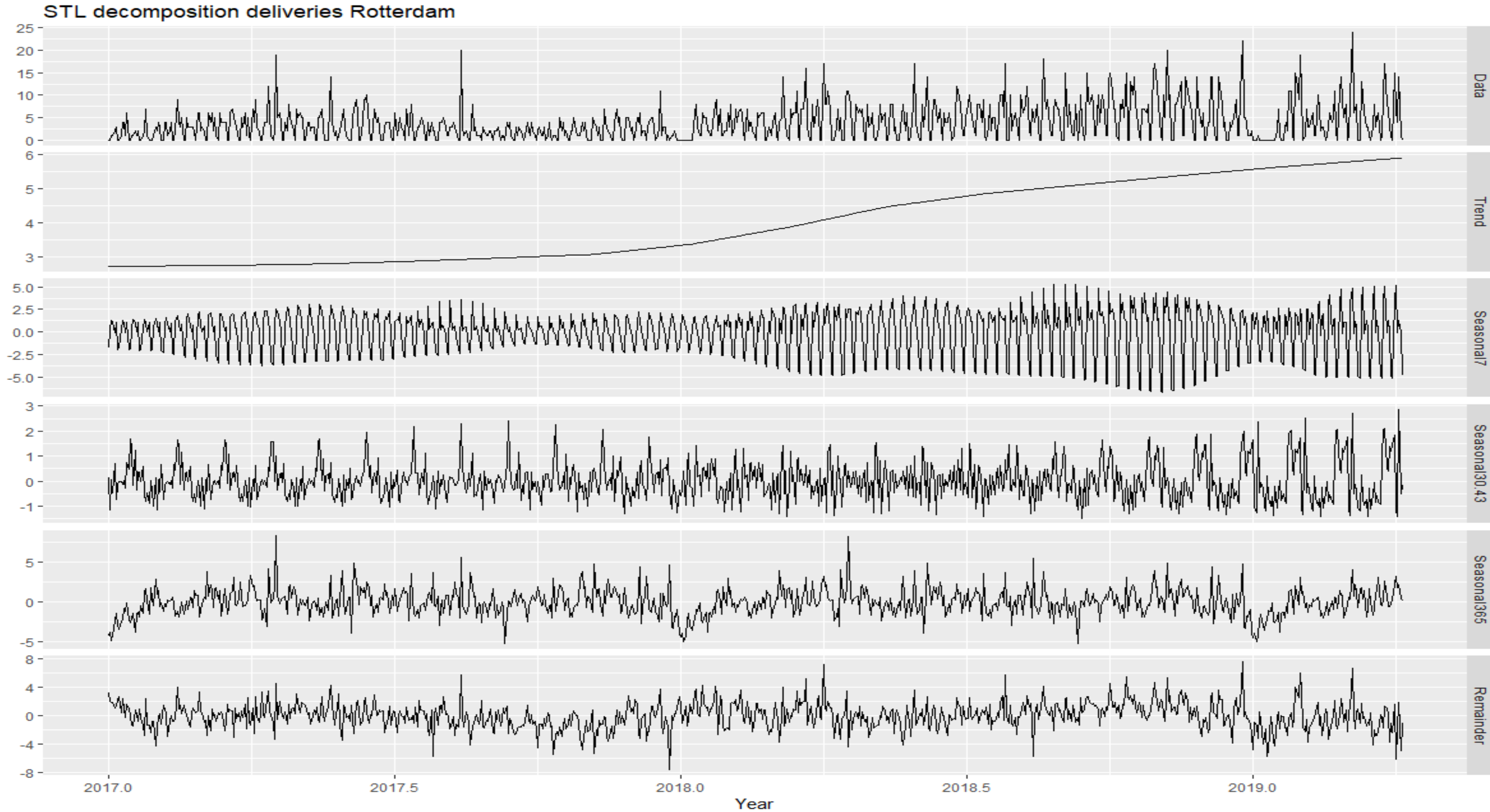
The various seasonal components were analysed in each series using time series decomposition

STL decomposition BFN loadings series



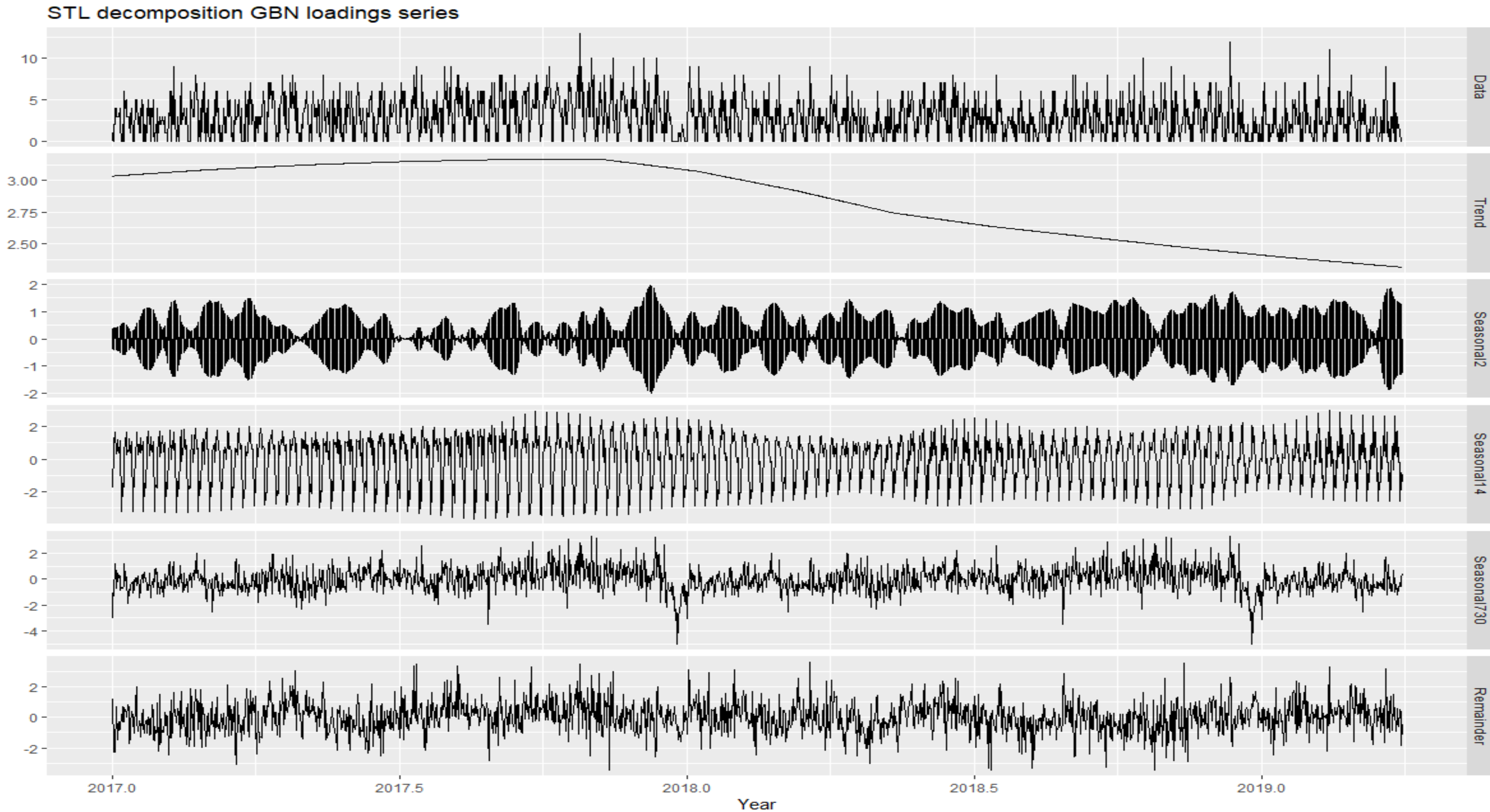
Seasonal Trend Decomposition deliveries Rotterdam

STL decomposition using Loess



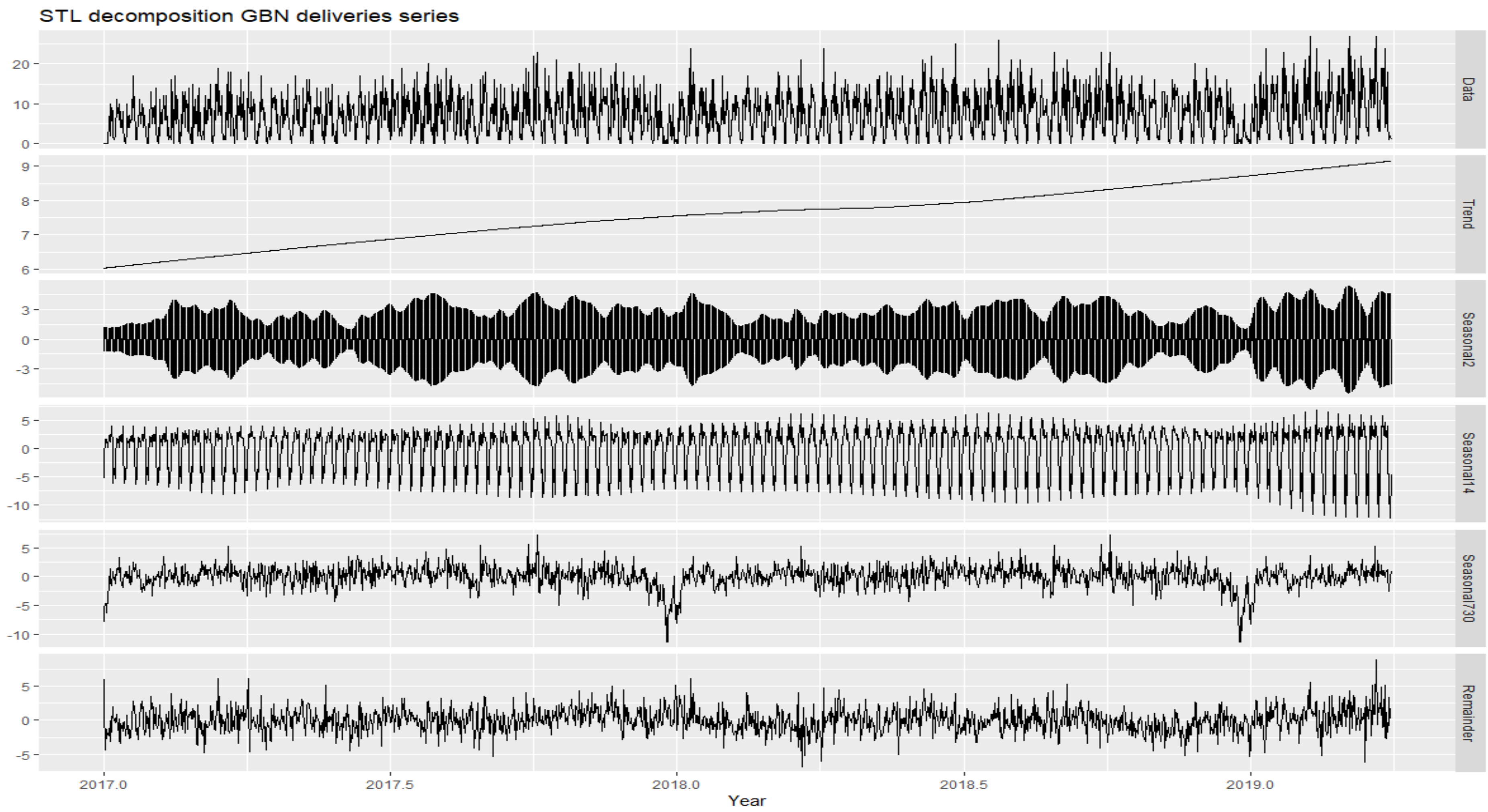
Seasonal Trend Decomposition loadings GBN

STL decomposition using Loess



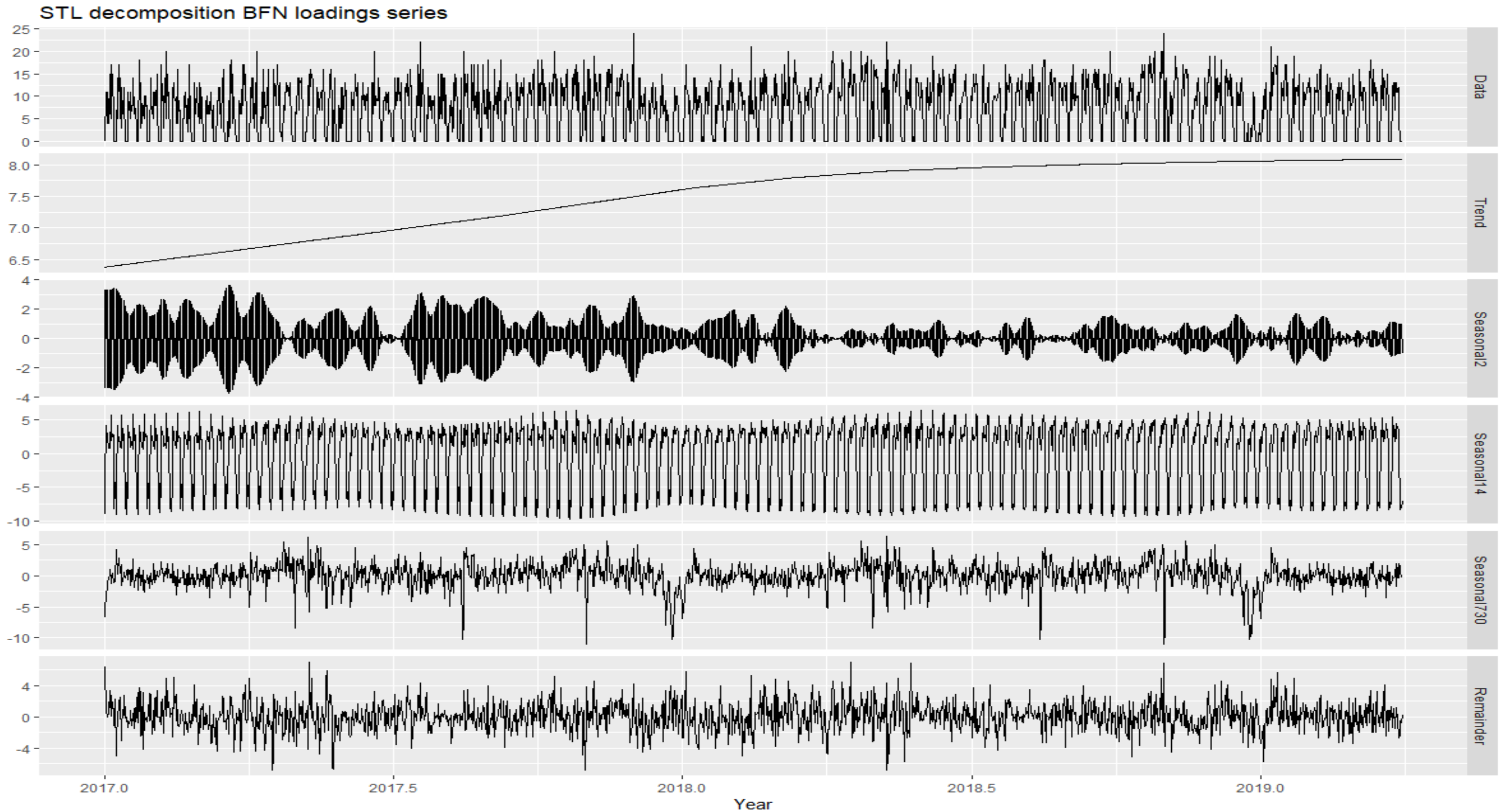
Seasonal Trend Decomposition deliveries GBN

STL decomposition using Loess



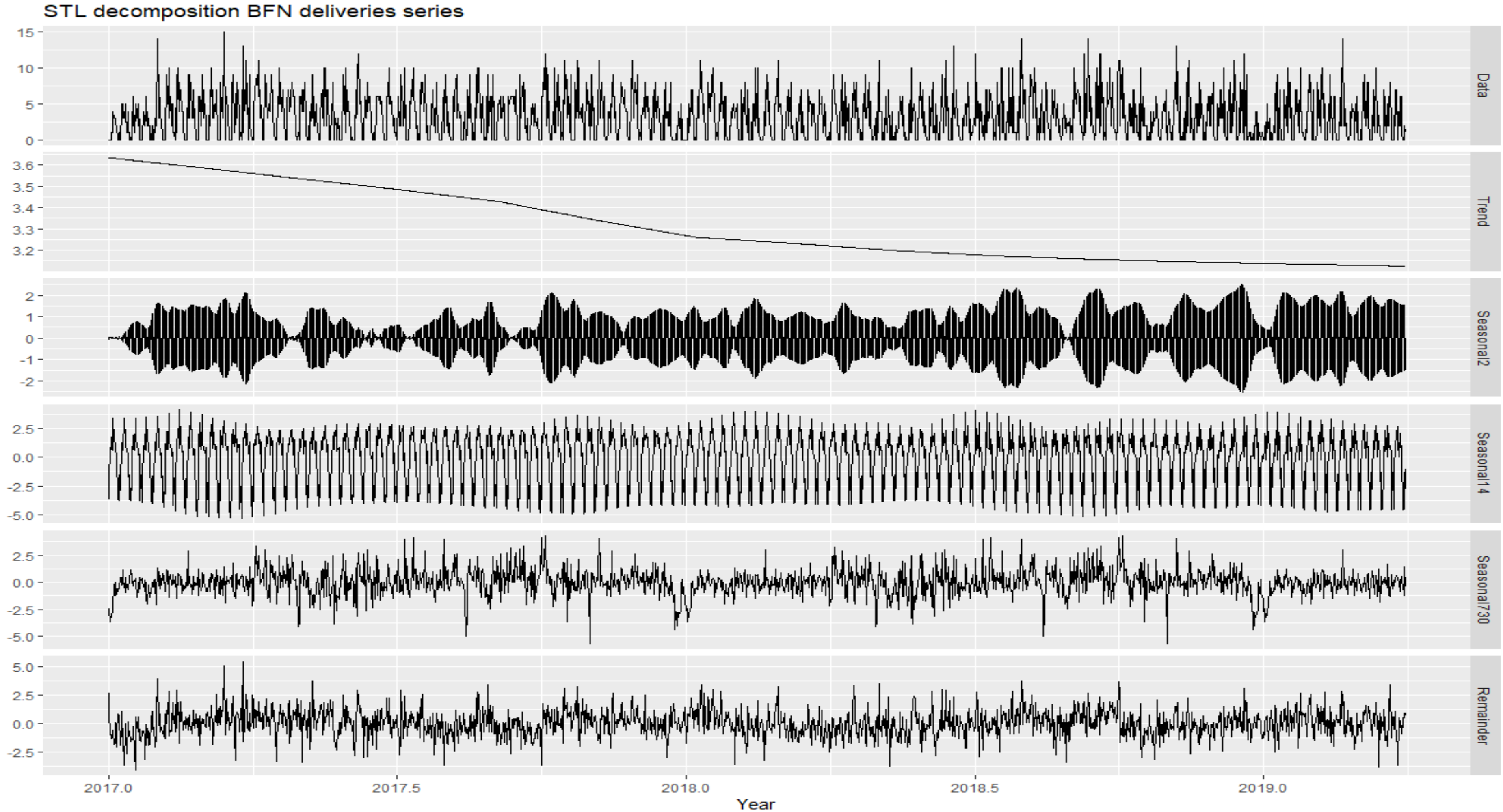
Seasonal Trend Decomposition loadings BFN

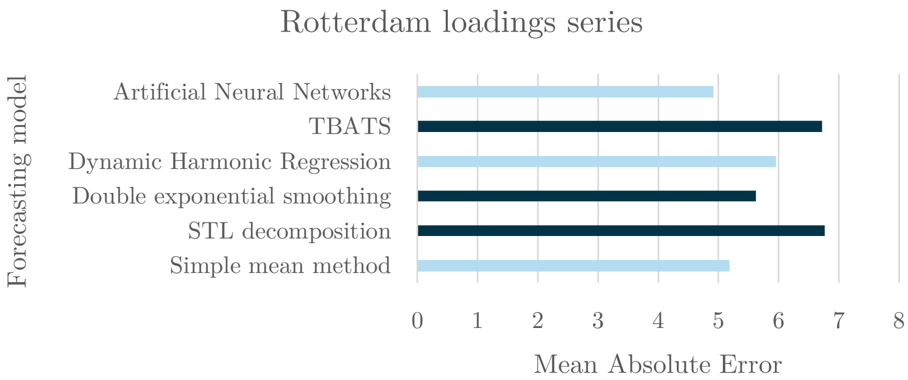
STL decomposition using Loess

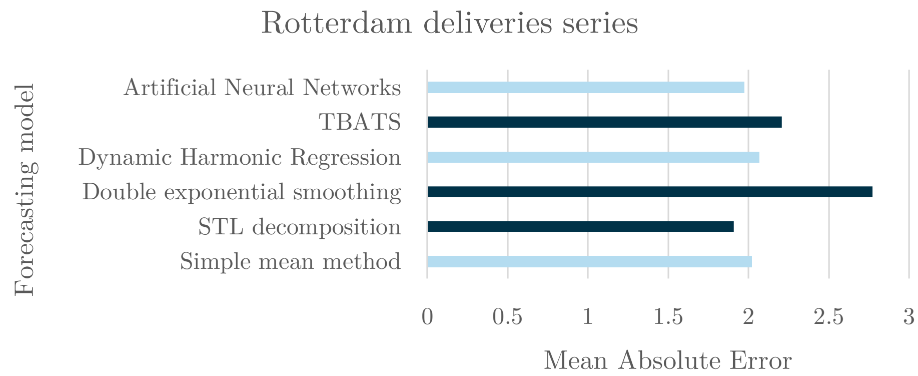


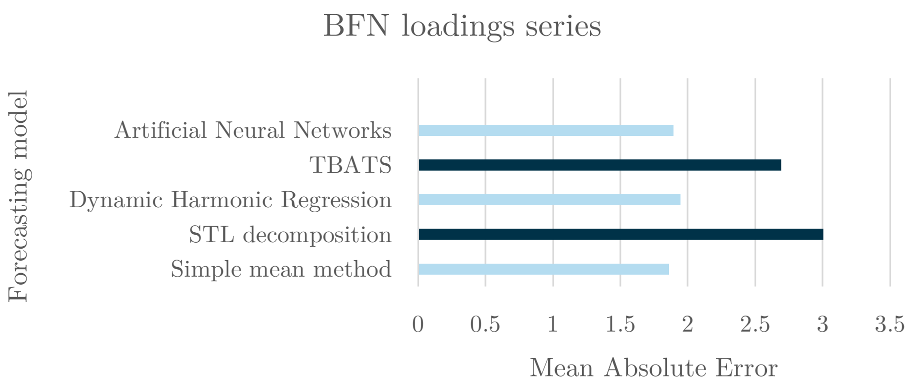
Seasonal Trend Decomposition deliveries BFN

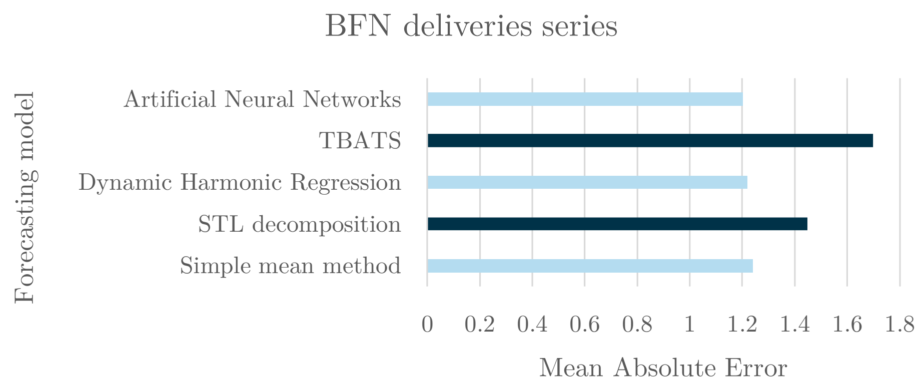
STL decomposition using Loess

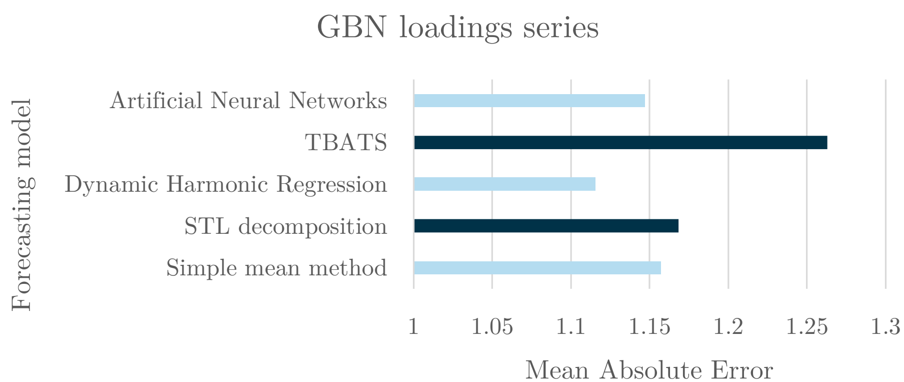


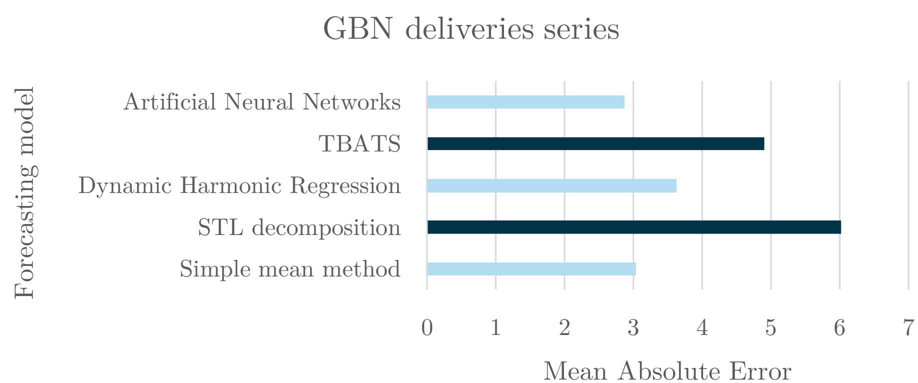

Rotterdam loadings series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
Double exponential smoothing
STL decomposition
Simple mean method
0 1 2 3 4 5 6 7 8
Mean Absolute Error


Rotterdam deliveries series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
Double exponential smoothing
STL decomposition
Simple mean method
0 0.5 1 1.5 2 2.5 3
Mean Absolute Error


BFN loadings series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
STL decomposition
Simple mean method
0 0.5 1 1.5 2 2.5 3 3.5
Mean Absolute Error


BFN deliveries series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
STL decomposition
Simple mean method
0 0.2 0.4 0.6 0.8 1 1.2 1.4 1.6 1.8
Mean Absolute Error


GBN loadings series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
STL decomposition
Simple mean method
1 1.05 1.1 1.15 1.2 1.25 1.3
Mean Absolute Error


GBN deliveries series
Forecasting model
Artificial Neural Networks
TBATS
Dynamic Harmonic Regression
STL decomposition
Simple mean method
0 1 2 3 4 5 6 7
Mean Absolute Error

APPENDIX B

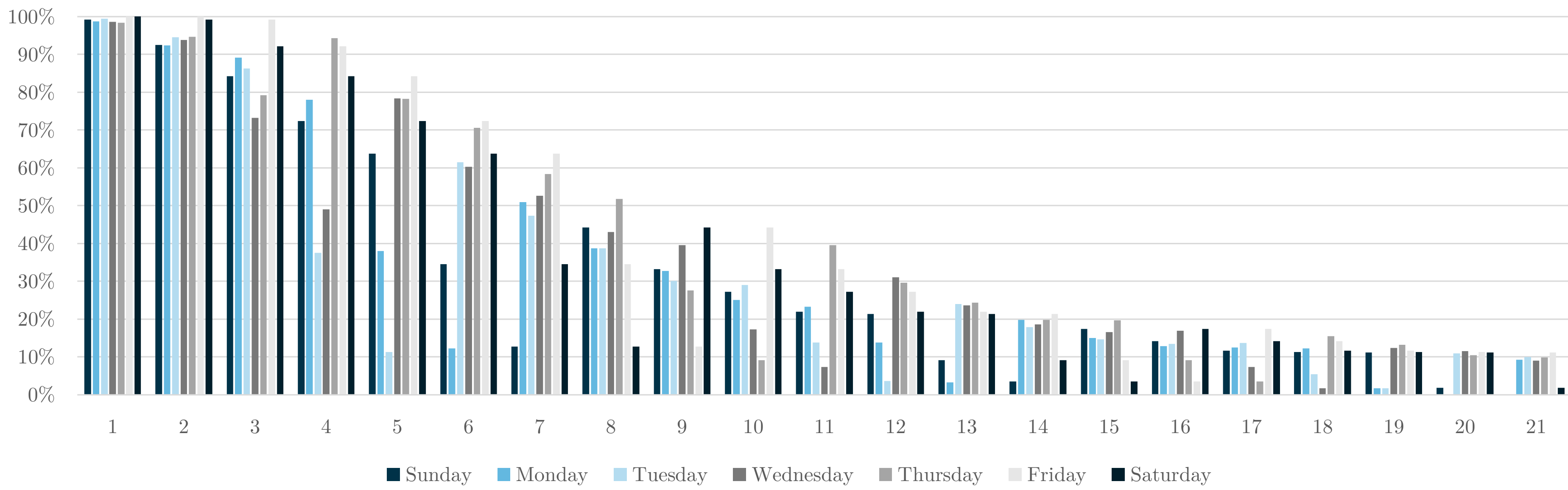
Utilizing the advance demand information

How long in advance are orders (i.e. loadings and deliveries) known?

Analysis order flow H&S

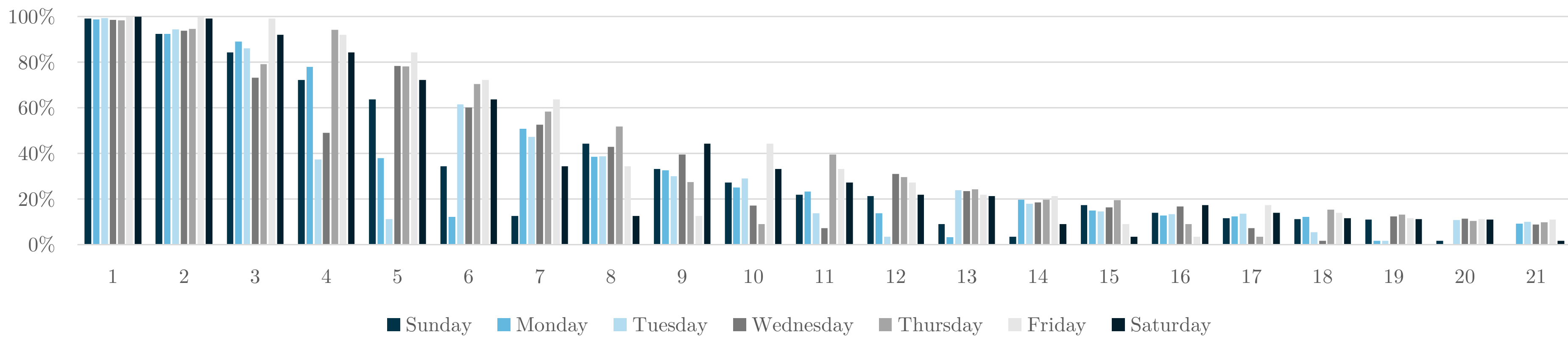
- Depends on day of the week
- Varies per planning region
- Deliveries are known longer in advance than loadings (obviously)

- Note: estimated based on how long orders are placed in advance: this doesn't say anything regarding how often orders are changed after they have initially been placed! →
  - Changes due to planners' initiative: no problem since this doesn't represent customers demand?
  - Changes due to customers' initiative: more problematic as this does represent customers demand?

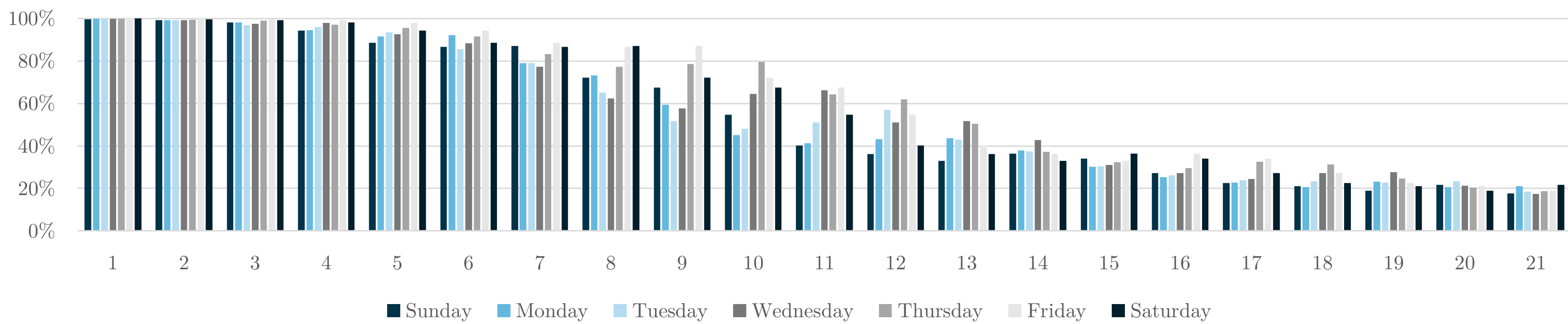


How long in advance are loadings and deliveries known in the Rotterdam planning region?

Loadings

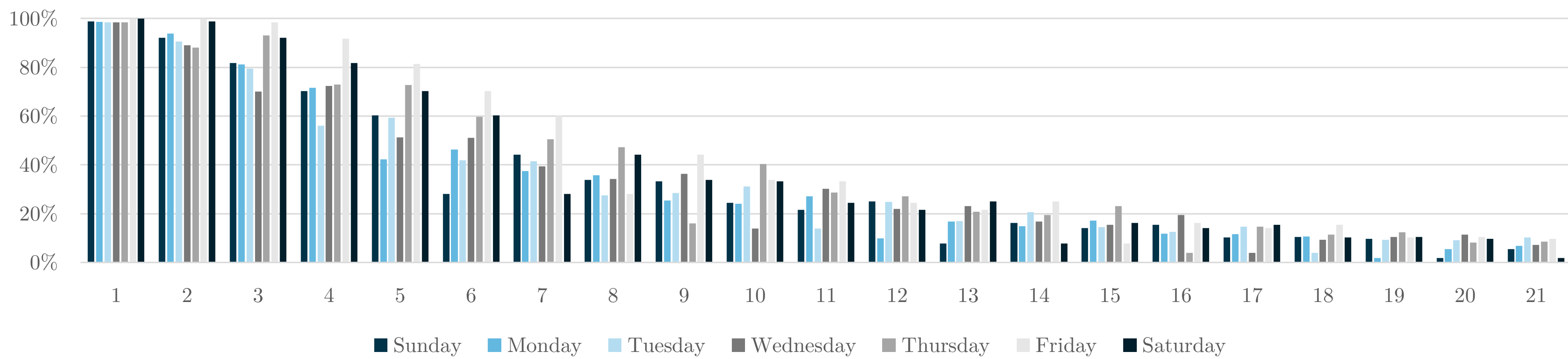


Deliveries

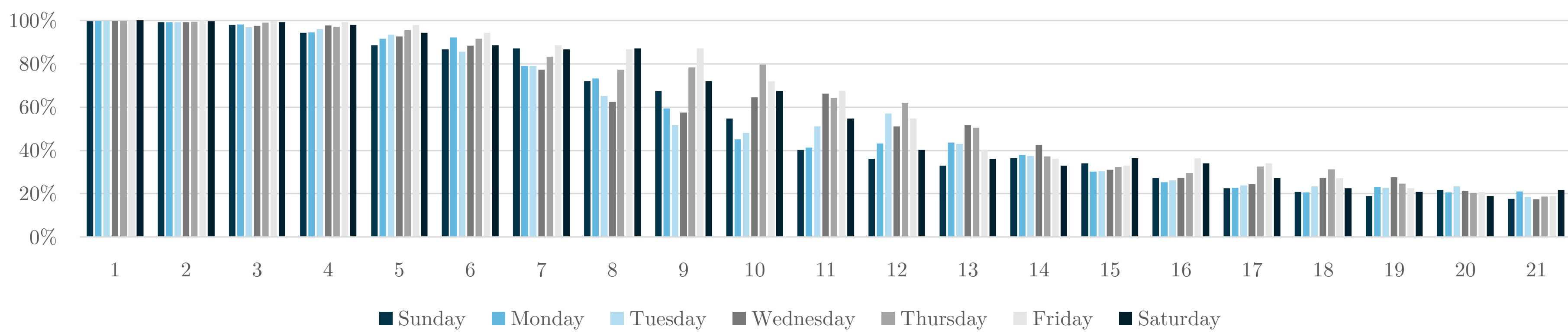


How long in advance are loadings and deliveries known in the GBN planning region?

Loadings

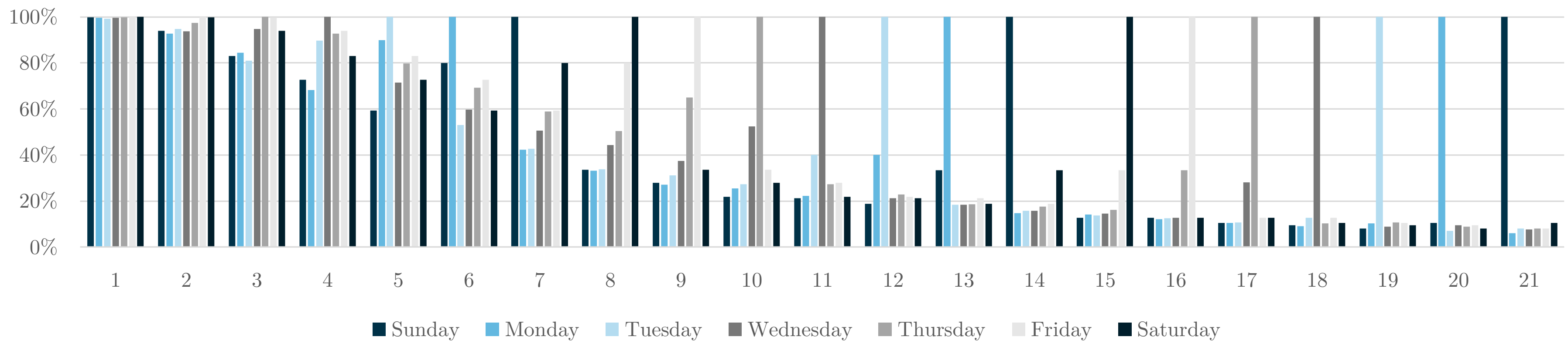


Deliveries

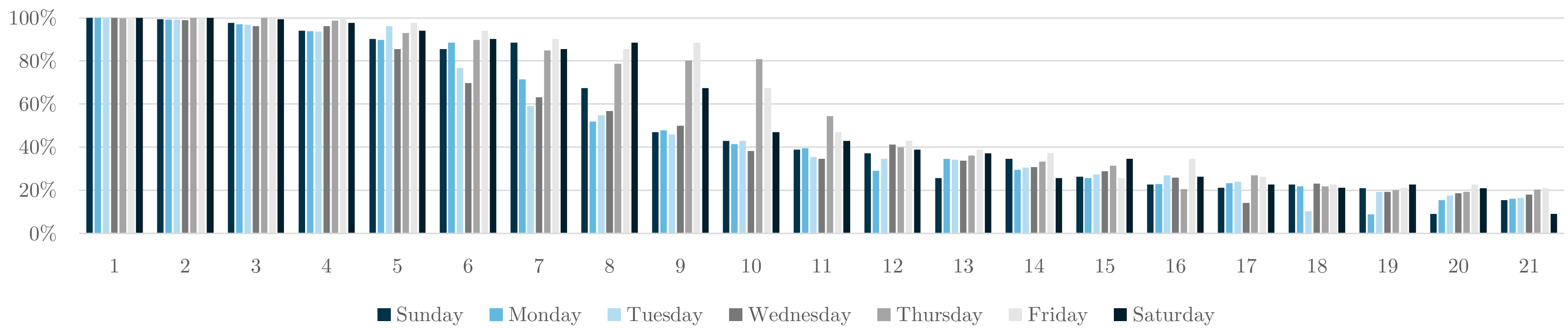


How long in advance are loadings and deliveries known in the BFN planning region?

Loadings



Deliveries



NOTE: The strange peaks in the first figure can be explained by the fact that there are (almost) no loadings at the BFN region on Sundays. The result of this is that if τ days in the future is a Sunday, all loadings are already in the system

Example Bayesian adjustment with $n_{a\tau} = 2$, Initial forecast = 4 & Theta = 0.6

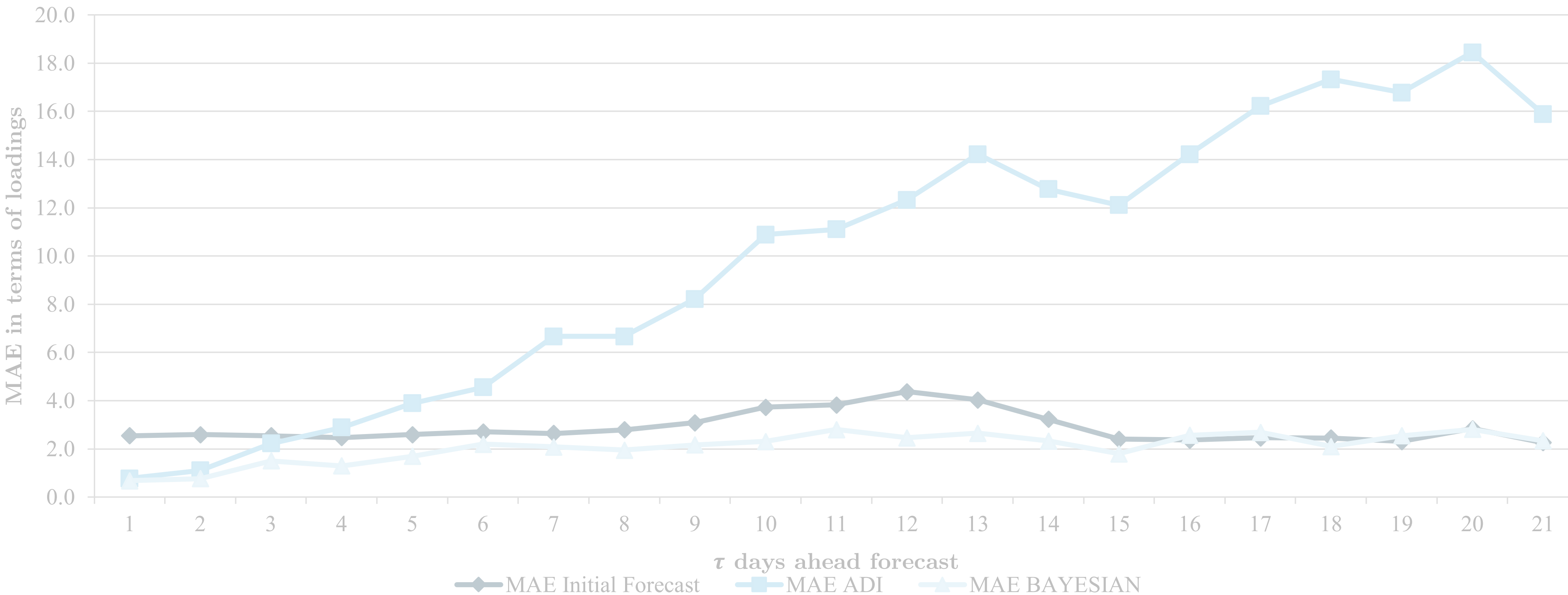
n_j	$P\langle n_j\rangle$	$P\langle n_{a\tau} \mid n_j\rangle$	$P\langle n_{a\tau} \mid n_j\rangle * P\langle n_j\rangle$	$P\langle n_j \mid n_{a\tau}\rangle$	$n_j P\langle n_j \mid n_{a\tau}\rangle$
0	-	-	-	-	-
1	-	-	-	-	-
2	0.146525	0.36	0.052749	0.201897	0.403793
3	0.195367	0.432	0.084398	0.323034	0.969103
4	0.195367	0.3456	0.067519	0.258428	1.03371
5	0.156293	0.2304	0.03601	0.137828	0.68914
6	0.104196	0.13824	0.014404	0.055131	0.330787
7	0.05954	0.077414	0.004609	0.017642	0.123494
8	0.02977	0.041288	0.001229	0.004705	0.037636
9	0.013231	0.021234	0.000281	0.001075	0.009678
10	0.005292	0.010617	5.62E-05	0.000215	0.002151
11	0.001925	0.00519	9.99E-06	3.82E-05	0.000421
12	0.000642	0.002491	1.6E-06	6.12E-06	7.34E-05
13	0.000197	0.001178	2.32E-07	8.9E-07	1.16E-05
14	5.64E-05	0.00055	3.1E-08	1.19E-07	1.66E-06
15	1.5E-05	0.000254	3.81E-09	1.46E-08	2.19E-07
16	3.76E-06	0.000116	4.36E-10	1.67E-09	2.67E-08
17	8.85E-07	5.26E-05	4.65E-11	1.78E-10	3.03E-09
18	1.97E-07	2.37E-05	4.65E-12	1.78E-11	3.2E-10
19	4.14E-08	1.06E-05	4.38E-13	1.68E-12	3.18E-11
20	8.28E-09	4.7E-06	3.89E-14	1.49E-13	2.98E-12
			$\sum_j P\langle n_{a\tau} \mid n_j\rangle * P\langle n_j\rangle = 0.261$		$\sum_j n_j P\langle n_j \mid n_{a\tau}\rangle = 3{,}6$

Note that in this example the Poisson probability distribution is used

Accuracy of the Bayesian adjustment for the Rotterdam planning region: 21 days ahead (average over τ)

Accuracy Bayesian technique Rotterdam

Accuracy averaged over τ	
Method	**Mean Absolute Error**
Initial forecast	2.87
Only using advance demand information	9.97
Bayesian adjustment	2.08



Accuracy of the Bayesian adjustment for the Rotterdam planning region: 21 days ahead

Accuracy Bayesian technique Rotterdam

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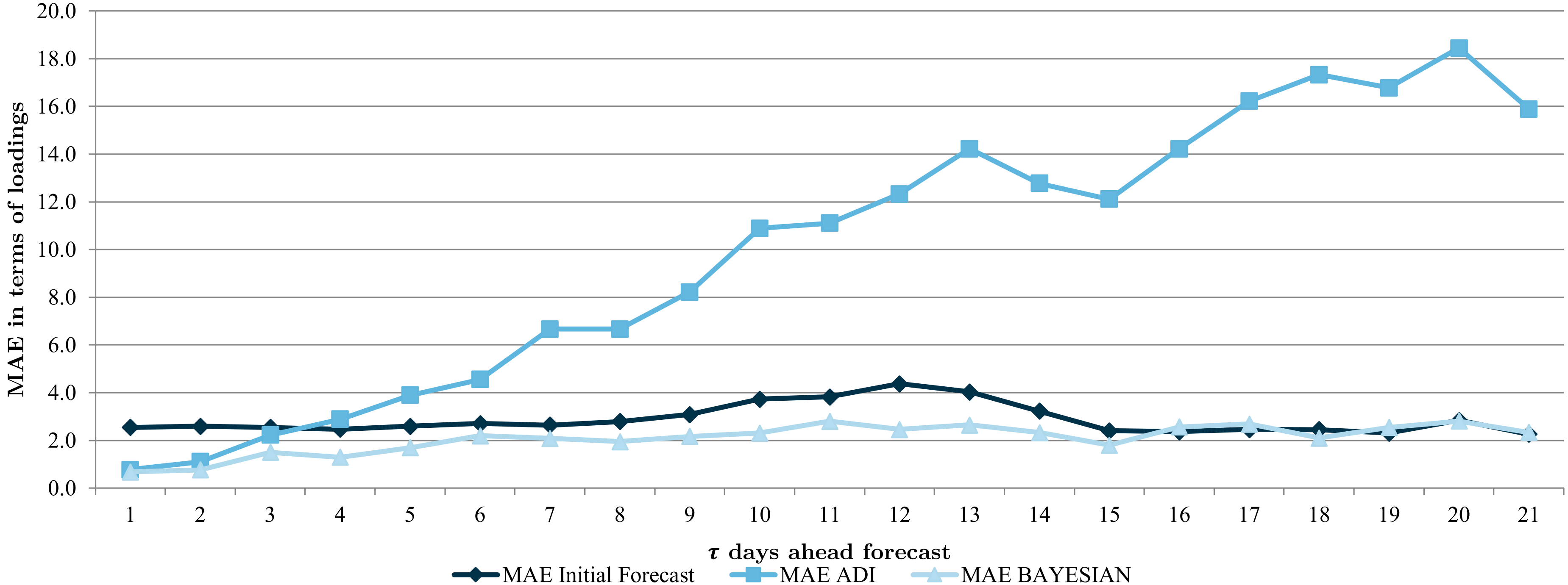
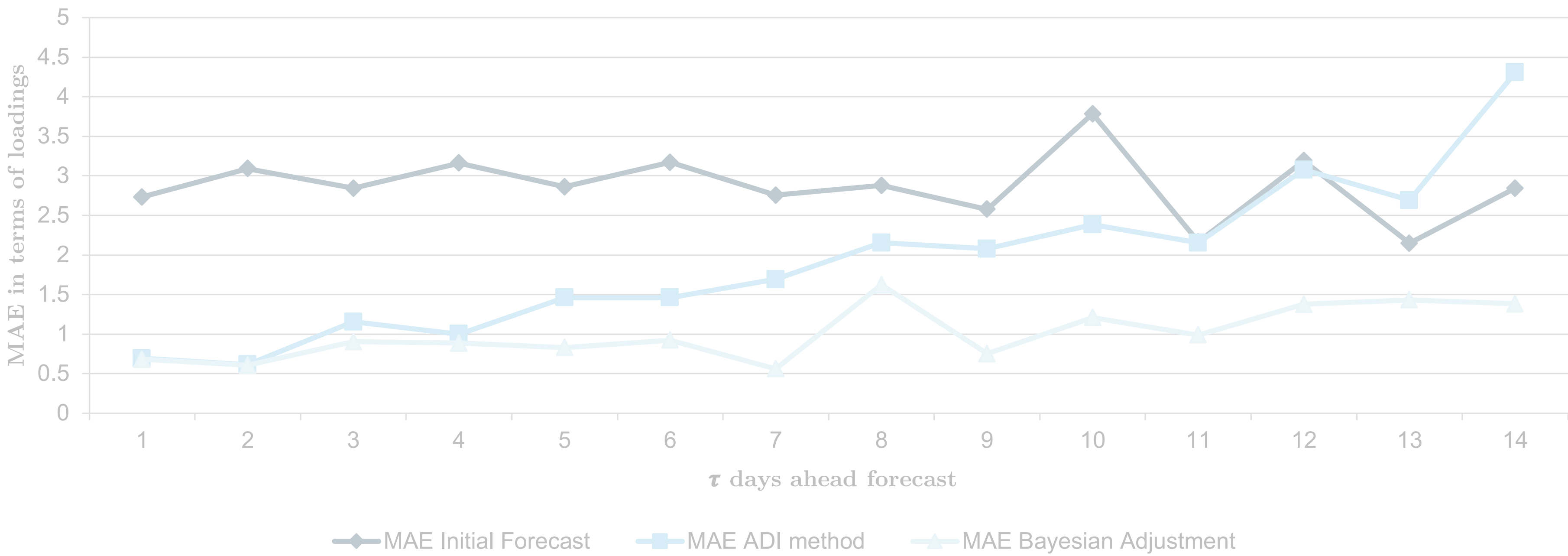


Accuracy of the Bayesian adjustment for the Belgium / France planning region: 21 days ahead (average over τ)

Accuracy Bayesian technique Belgium and Northern France

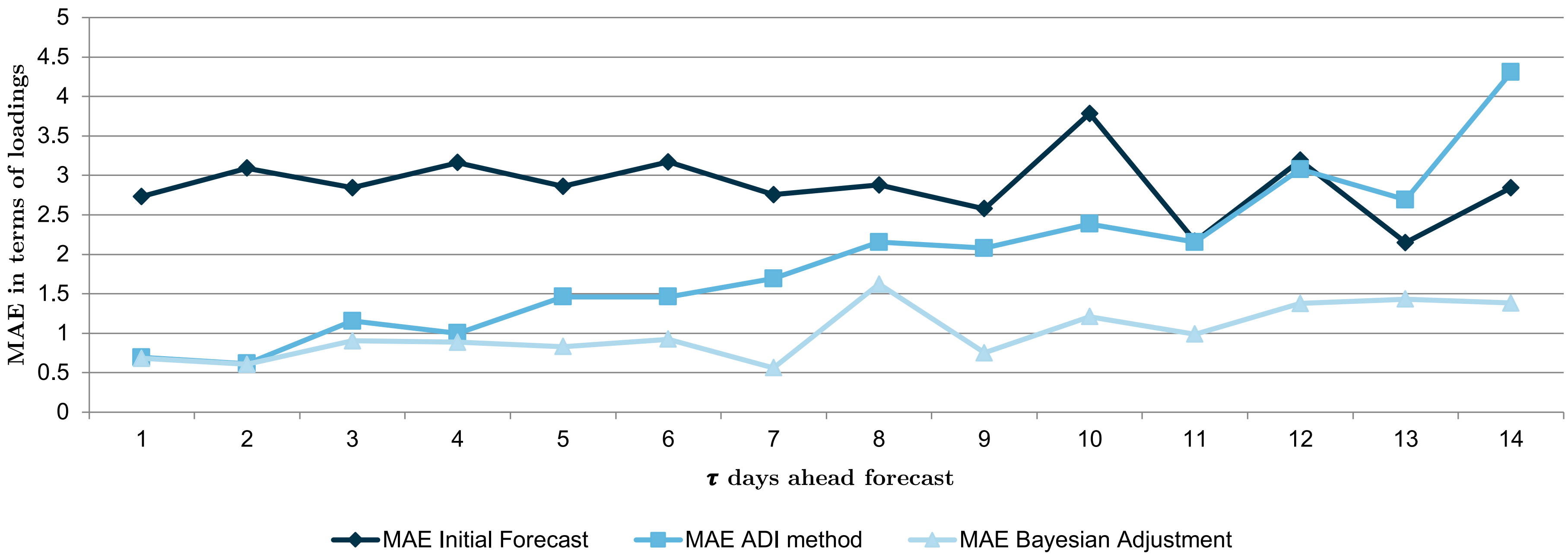
Accuracy averaged over τ	
Method	**Mean Absolute Error**
Initial forecast	2.87
Only using advance demand information	1.92
Bayesian adjustment	1.01



Accuracy of the Bayesian adjustment for the Belgium / France planning region: 21 days ahead

Accuracy Bayesian technique Belgium and Northern France

Accuracy averaged over τ	
Method	**Mean Absolute Error**
Initial forecast	2.87
Only using advance demand information	1.92
Bayesian adjustment	1.01



Using the Advance Demand Information

Method 2: The Combined Forecast

Combined Forecast

α [Initial forecast from historical data] $+ (1-\alpha)$ [Forecast from inflator algorithm: $\dfrac{n_{a\tau}}{\theta_\tau}$]

The inflator algorithm utilizes advance demand information in a very easy and intuitive manner, but its variability increases if we forecast longer ahead

Inflator algorithm

Inflator algorithm

Notation

$$Forecast = \frac{n_{a\tau}}{\theta_\tau}$$

Example

- 18 loadings in the system for 5 days in advance (i.e. $n_{a\tau} = 18$)
- Probability that a loading for 5 days in the future is already known at present is 50% (i.e. $\theta_5 = 50\%$)

Inflator algorithm forecast: $^{18}/_{50\%} = 36$ loadings

(dis)advantages

\+ Very easy and intuitive way to use the advance demand information

– Variability increases and accuracy decreases if we derive a forecast for longer in the future

The inflator algorithm utilizes advance demand information in a very easy and intuitive manner, but its variability increases if we forecast longer ahead

Inflator algorithm

Inflator algorithm

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Inflator algorithm forecast: ${}^{18}/_{50\%} = 36$ loadings

(dis)advantages

+ Very easy and intuitive way to use the advance demand information → for this reason used in practice

− Variability increases and accuracy decreases if we derive a forecast for longer in the future

The combined forecast can be considered as an alternative to the more complex Bayesian adjustment

Combined Forecast

Combined Forecast

Initial forecast based on historical data:

e.g. the Simple mean method!

Inflator algorithm:

$$\frac{n_{a\tau}}{\theta_\tau}$$

The combined forecast can be considered as an alternative to the more complex Bayesian adjustment

Combined Forecast

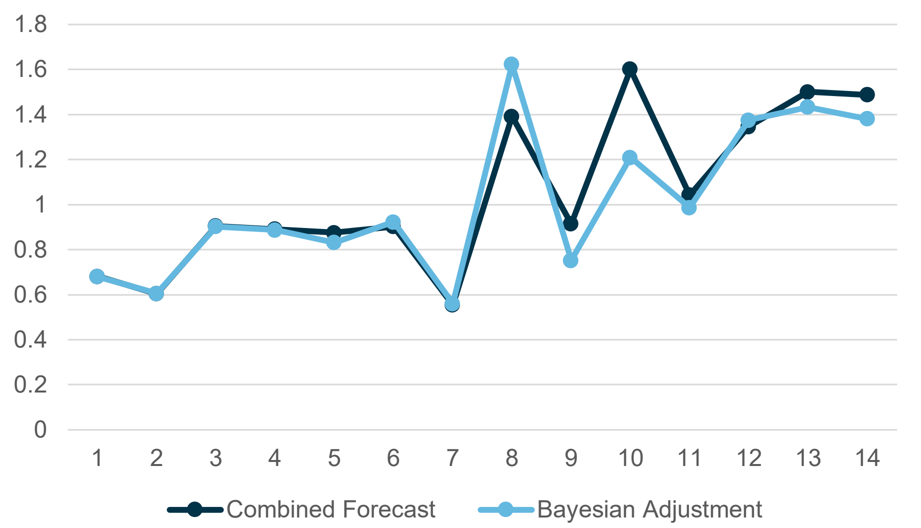
α [Initial forecast from historical data] $+(1-\alpha)$ [Forecast from inflator algorithm]

- The Combined Forecast utilizes both the initial forecast and the inflator algorithm
- The values of α should increase for larger values of τ

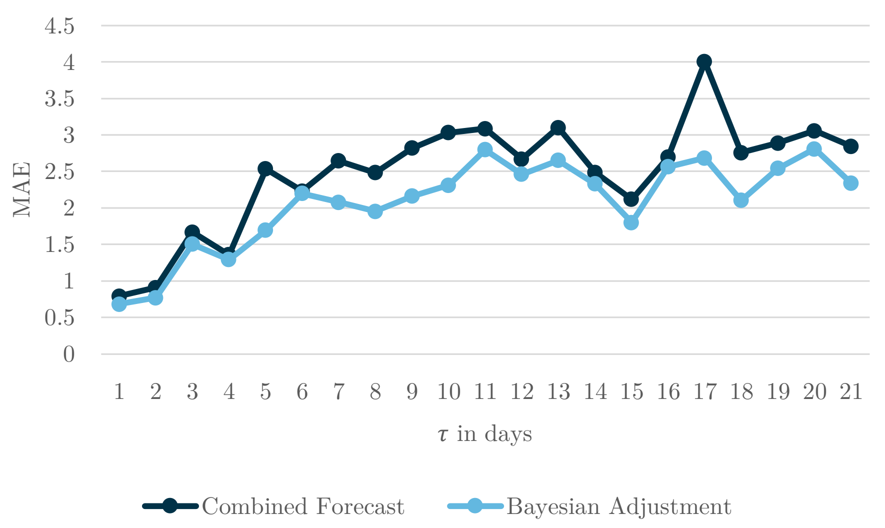
Accuracy of the Combined Forecast as a function of tau

Method	MAE Belgium and North France loadings	MAE Rotterdam loadings
Initial Forecast	2.87	2.87
Bayesian Algorithm	1.01	2.08
Combined Forecast	1.05	2.50

BFN planning region

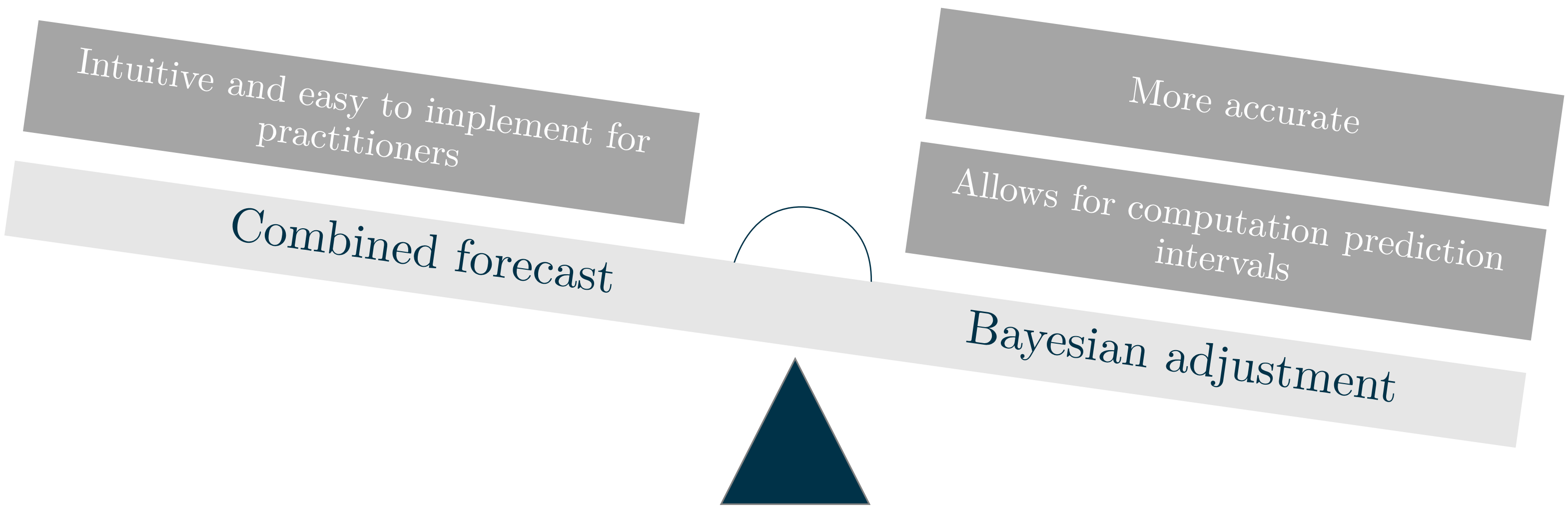


Rotterdam planning region



Although more complex, the Bayesian adjustment might still be preferable over the combined forecast

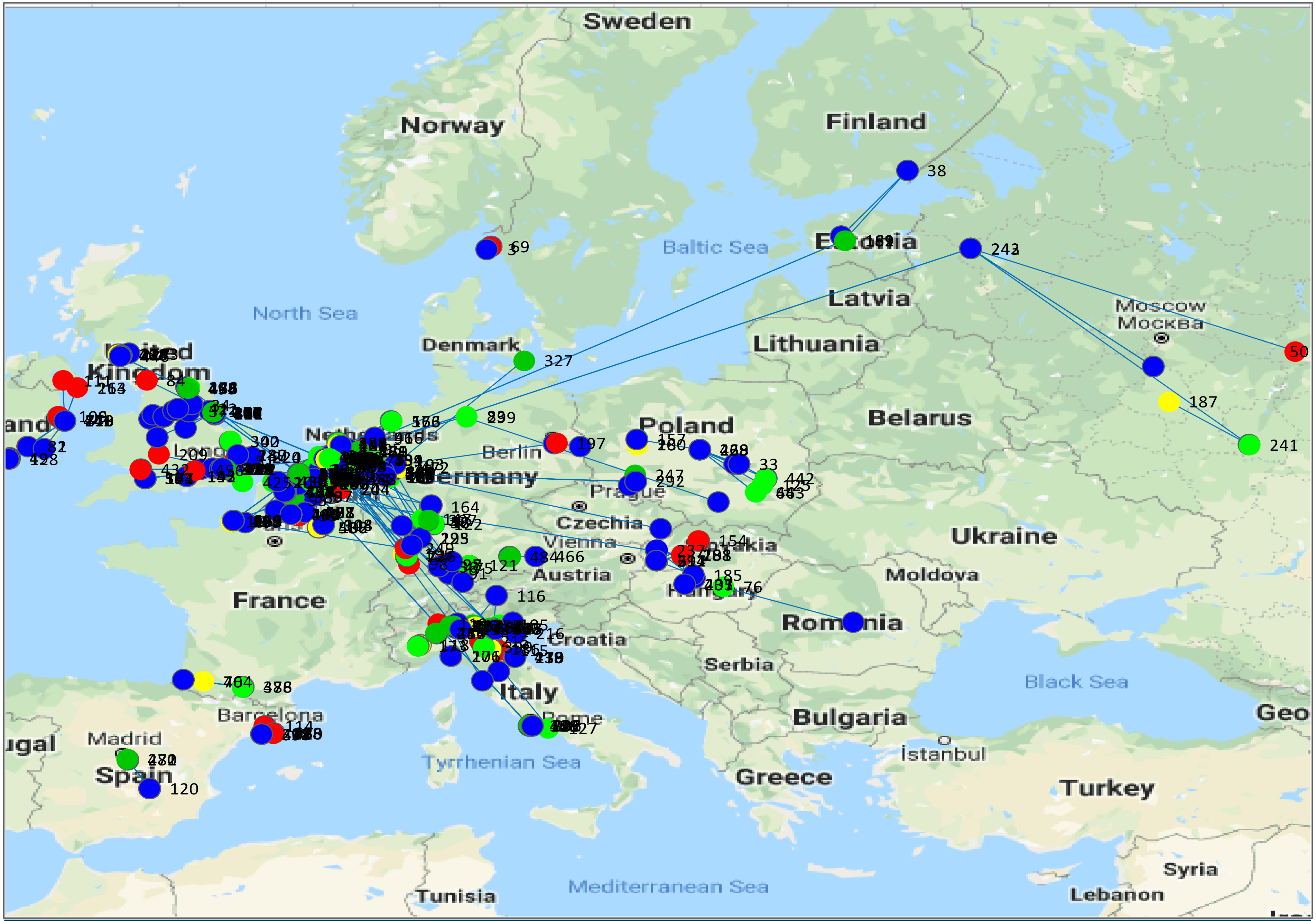
Combined forecast vs. Bayesian adjustment



Currently, the Bayesian model is being implemented by CQM

APPENDIX C

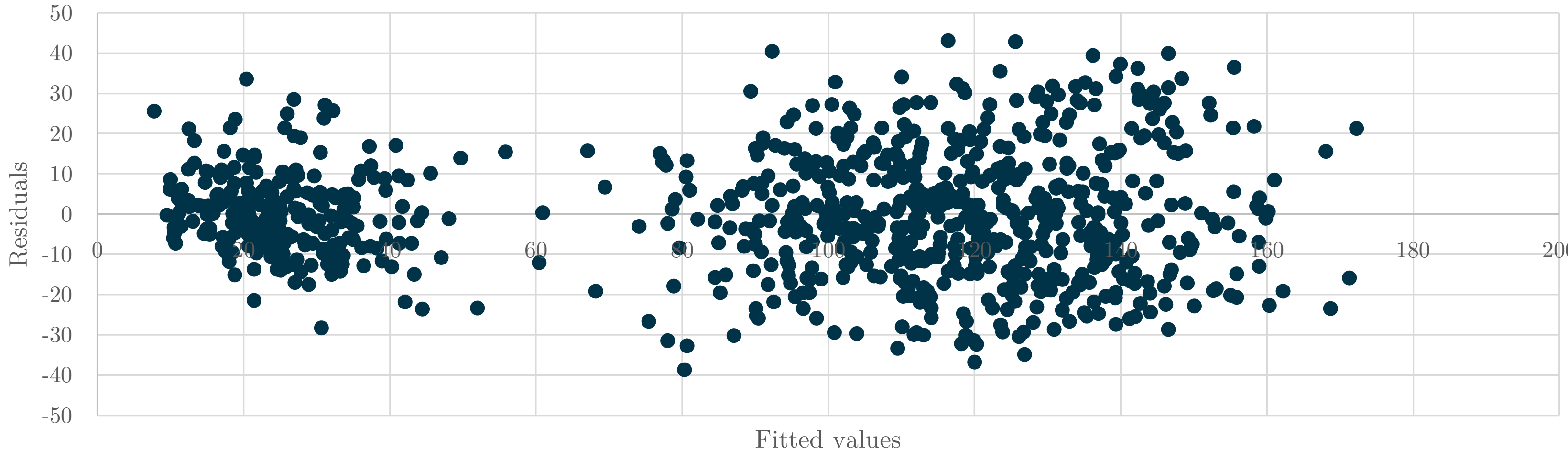
Trucking capacity



All trucking actions 24/07/0219

A Box Cox transformation was used to resolve the heteroscedasticity of the residuals

Box Cox transformation



Box Cox transformation

$$w_t = \begin{cases} \ln(\delta_t) & if\ \lambda = 0; \\ \dfrac{\delta_t^{\lambda} - 1}{\lambda} & otherwise. \end{cases}$$

Reverse Box Cox transformation

$$\delta_t = \begin{cases} \exp(w_t) & if\ \lambda = 0; \\ (\lambda w_t + 1)^{\frac{1}{\lambda}} & otherwise. \end{cases}$$

Output multiple linear regression models GBN and BFN planning regions

Parameters multiple linear regression

BFN region	Corresponding explanatory variable	Coefficient	Standard error	p-value	GBN region	Coefficient	Standard error	p-value
β_0	Intercept	-0.345	0.185	0.063	β_0	9.158	1.514	**$<$ 0,0001**
β_1	$Lo(\tau)$	0.358	0.021	**$<$ 0,0001**	β_1	0.822	0.252	**0.001**
β_2	$De(\tau)$	0.280	0.032	**$<$ 0,0001**	β_2	2.197	0.124	**$<$ 0,0001**
β_3	$Lo_{D(\tau)}$	0.116	0.021	**$<$ 0,0001**	β_3	1.415	0.250	**$<$ 0,0001**
β_4	$De_{D(\tau)}$	0.186	0.032	**$<$ 0,0001**	β_4	2.220	0.127	**$<$ 0,0001**
β_5	$\delta(\tau - 14)$	0.007	0.002	**0.003**	β_5	0.094	0.019	**$<$ 0,0001**
β_6	$\delta(\tau - 28)$	0.004	0.002	0.113	β_6	0.088	0.019	**$<$ 0,0001**
β_7	$x_1(\tau)$	10.416	0.512	**$<$ 0,0001**	β_7	14.242	3.027	**$<$ 0,0001**
β_8	$x_2(\tau)$	10.532	0.555	**$<$ 0,0001**	β_8	5.070	3.172	0.110
β_9	$x_3(\tau)$	9.956	0.531	**$<$ 0,0001**	β_9	5.512	3.253	0.091
β_{10}	$x_4(\tau)$	9.989	0.559	**$<$ 0,0001**	β_{10}	8.235	3.091	**0.008**
β_{11}	$x_5(\tau)$	9.659	0.520	**$<$ 0,0001**	β_{11}	6.546	2.695	**0.015**
β_{12}	$x_6(\tau)$	3.924	0.235	**$<$ 0,0001**	β_{12}	-0.154	1.505	0.919
β_{13}	$x_7(\tau)$	-7.254	0.641	**$<$ 0,0001**	β_{13}	-6.230	3.409	**0.048**
β_{14}	$x_8(\tau)$	-0.636	0.164	**$<$ 0,0001**	β_{14}	-6.730	1.389	**$<$ 0,0001**

NOTE: after running this multiple linear regression model, one should still perform a reverse Box Cox transformation to obtain the forecast in the original data

APPENDIX D

Tank container capacity

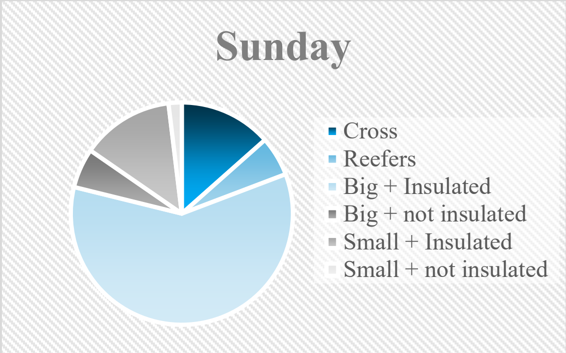
In consultation with the MMP department, six tank container types were defined

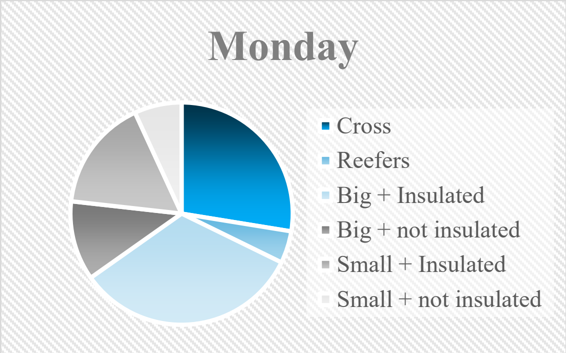
Description of tank container fleet H&S

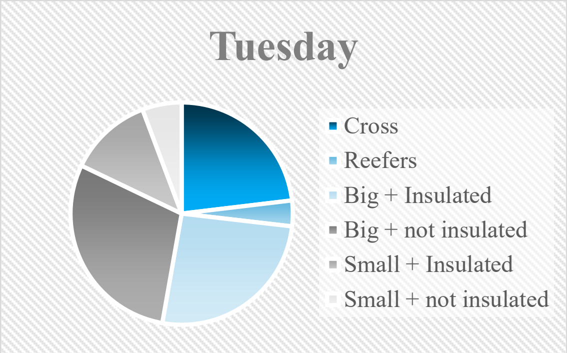
Tank container types

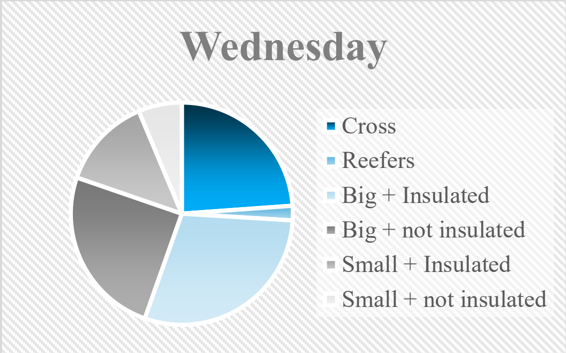
Cross	*Used for non-food products*
Reefers	*Glycol heating mechanism*
Big & Insulated	*> 30,000 ltr + insulated*
Big & not insulated	*> 30,000 ltr + not insulated*
Small & insulated	*< 30,000 ltr + insulated*
Small & not insulated	*< 30,000 ltr + not insulated*

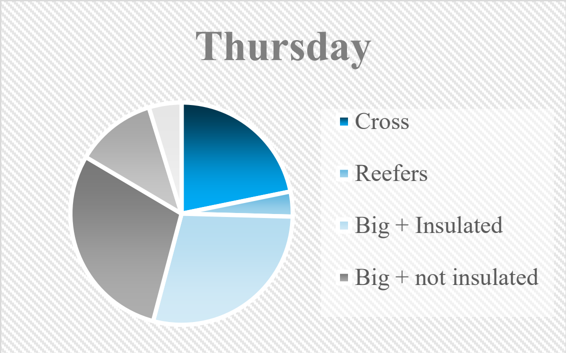
Day of the weak seasonality tank container use in the Rotterdam planning region

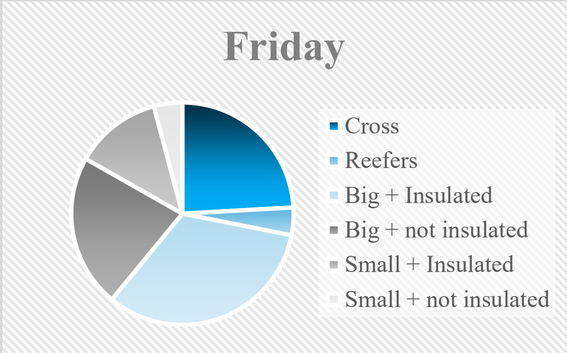


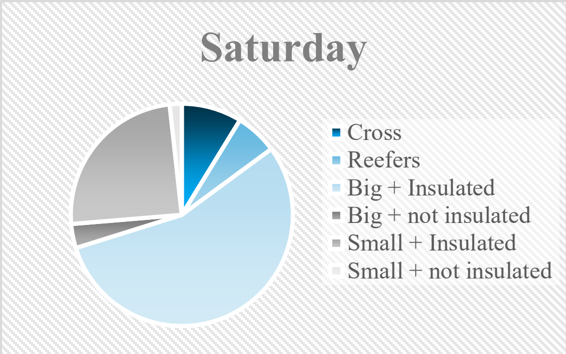




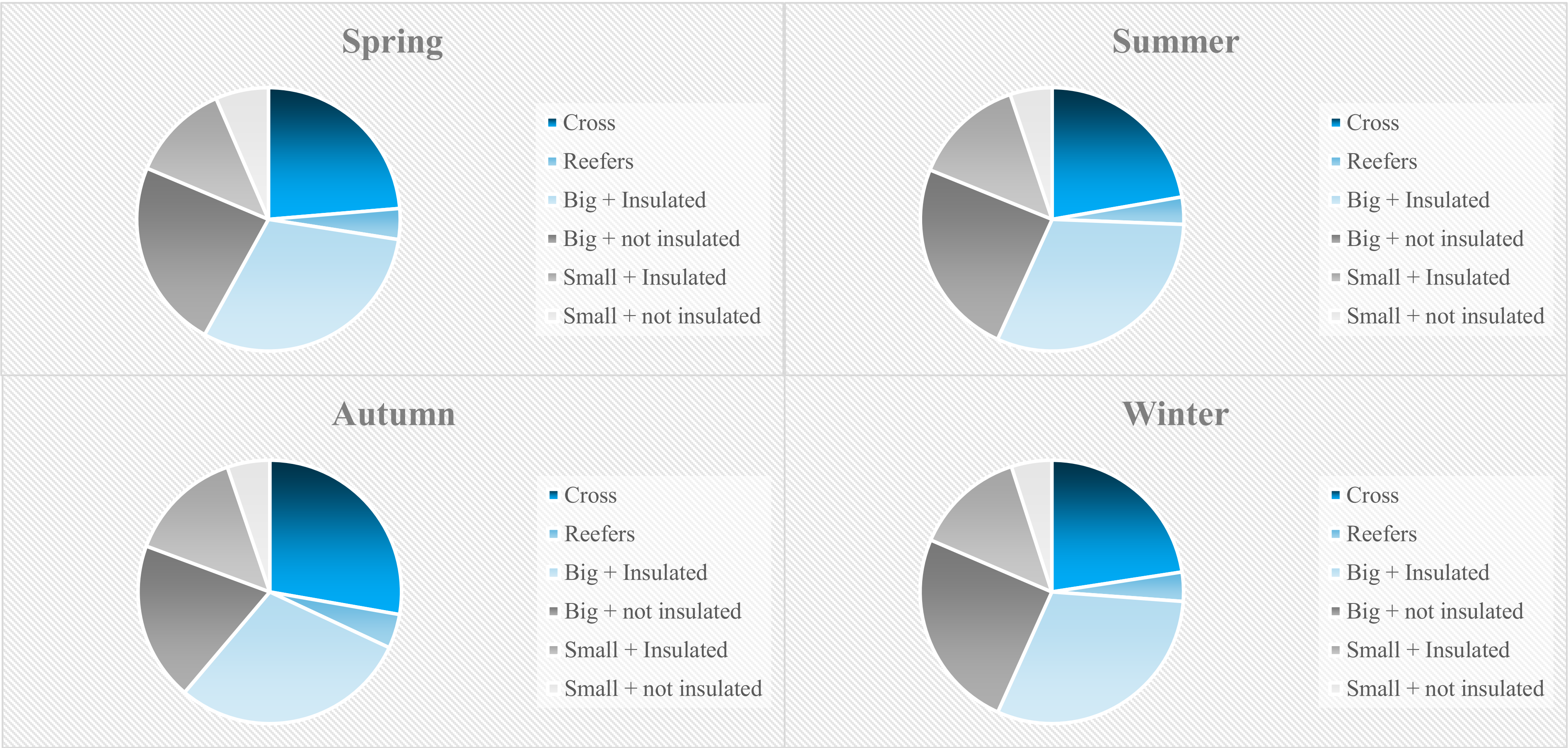






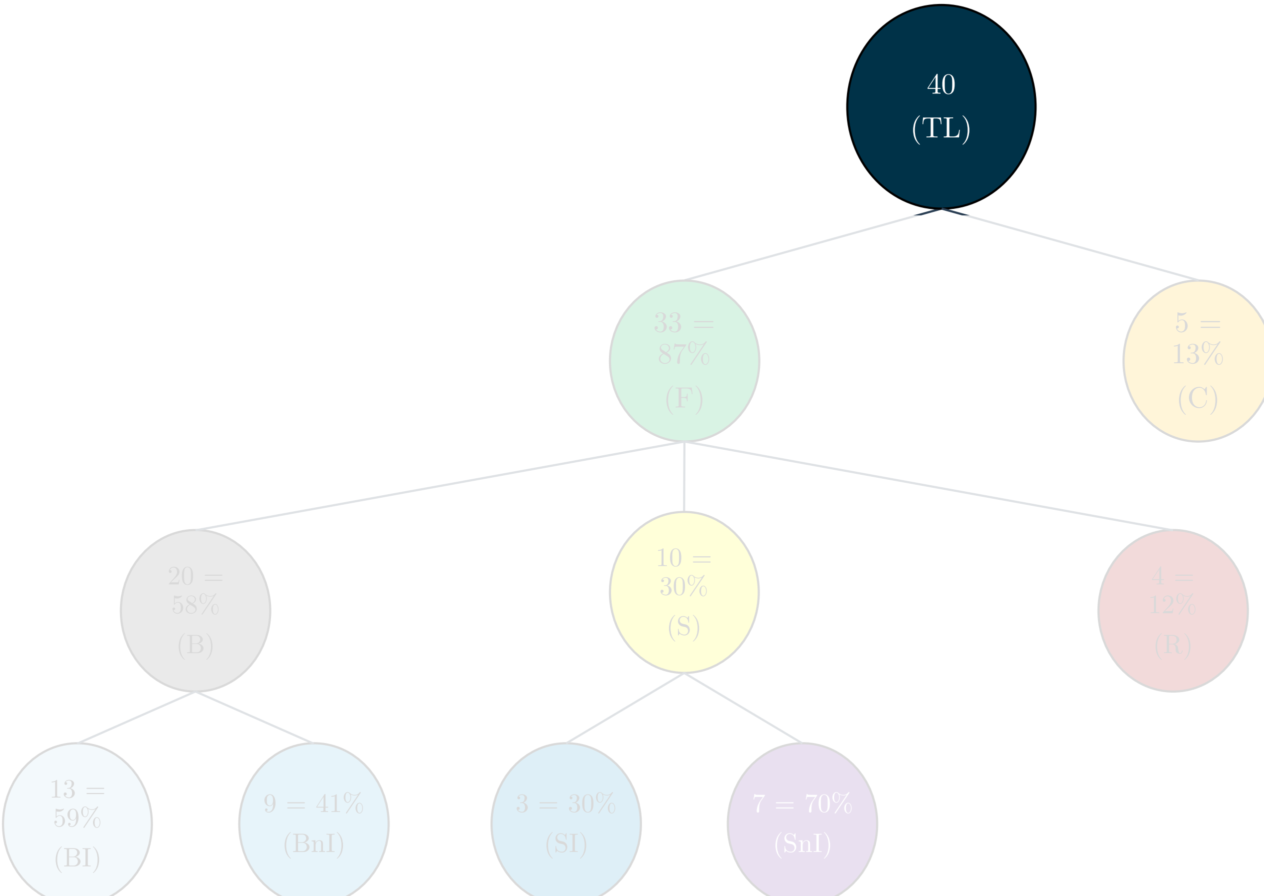


Meteorological seasonality tank container use in the Rotterdam planning region

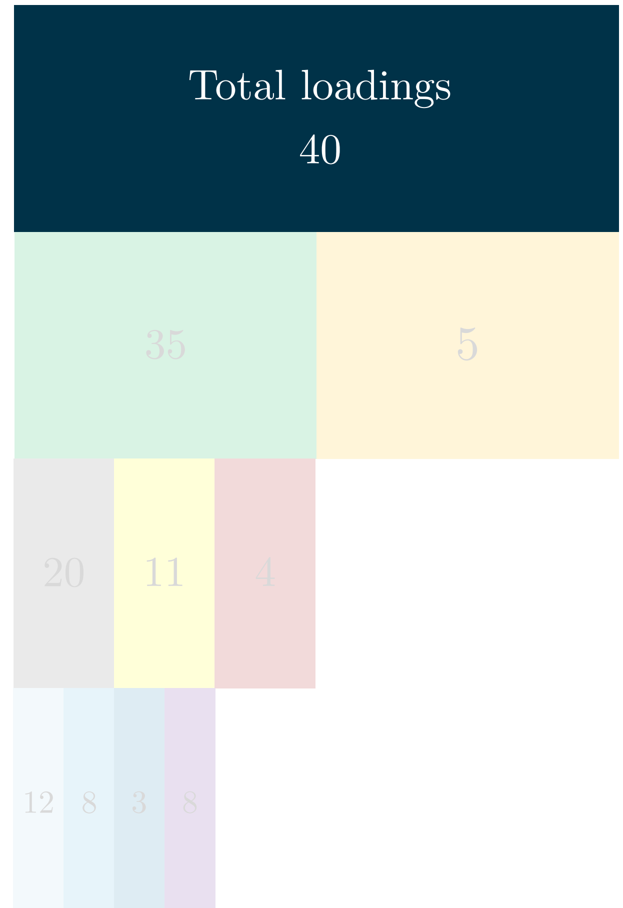


Example: (1) predict the expected number of loadings → derived from the Bayesian technique

Forecast proportions for tank containers

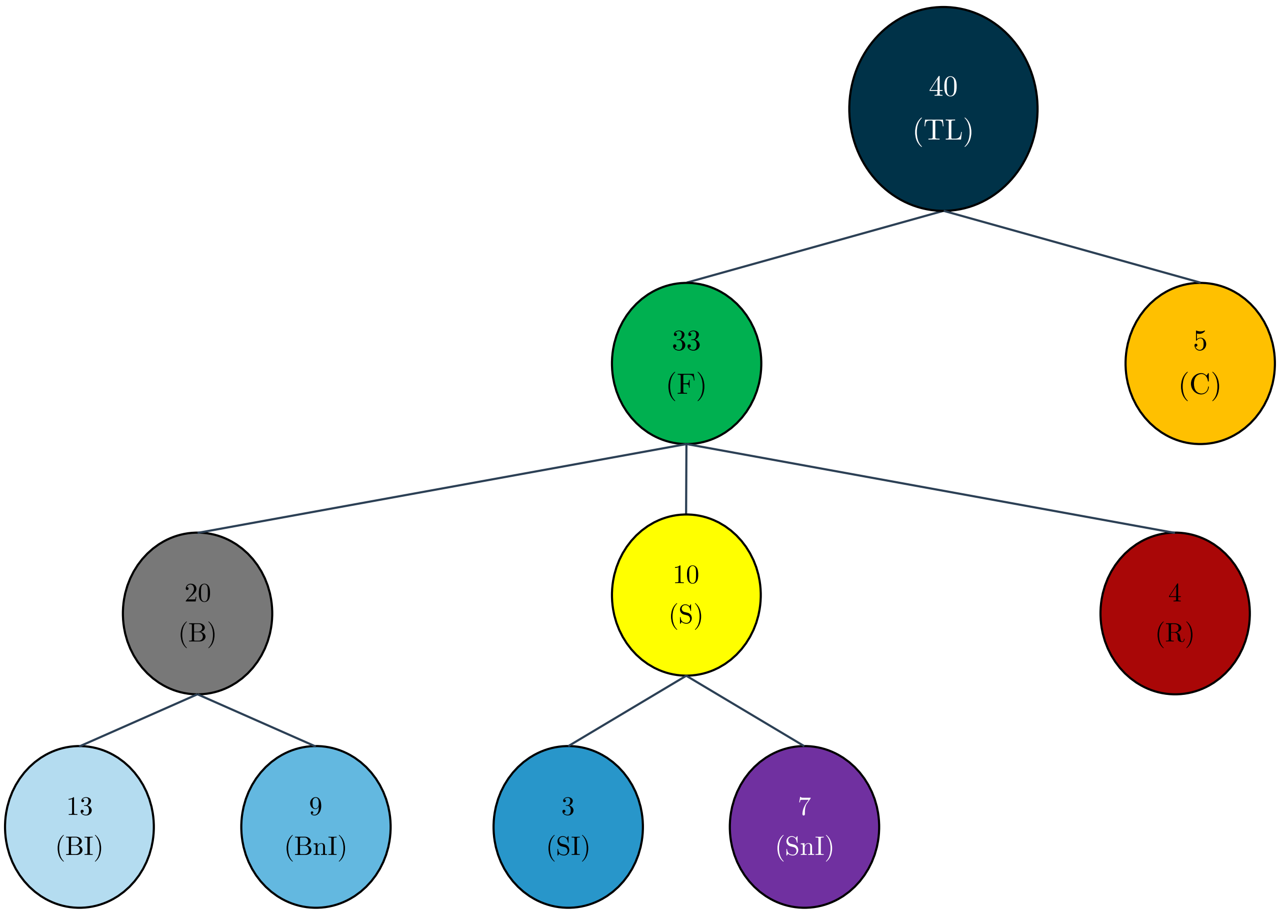


Final tank container forecast

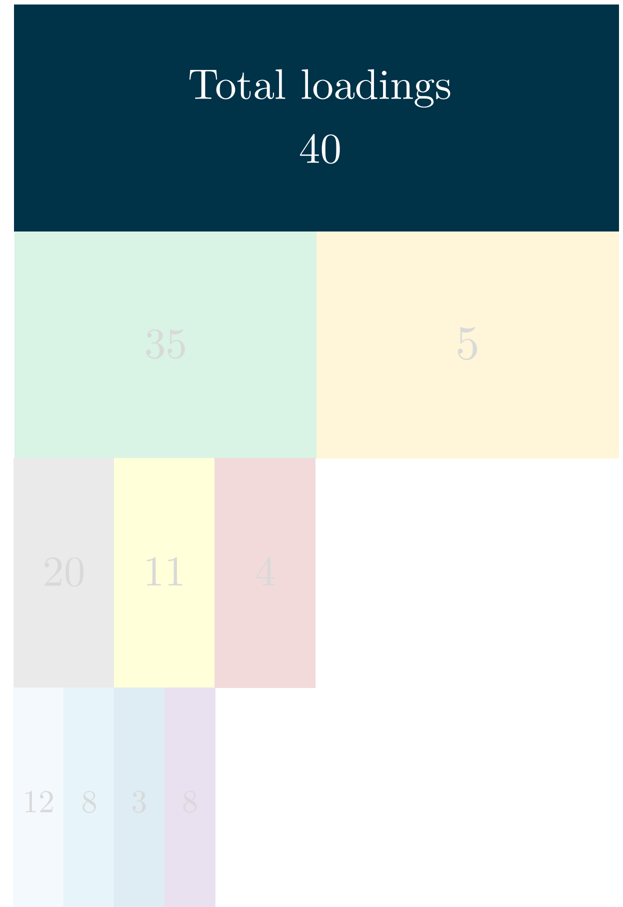


Example: (2) Derive a forecast per container type (i.e. per aggregation level) and compute the forecasted proportions

Forecast proportions for tank containers

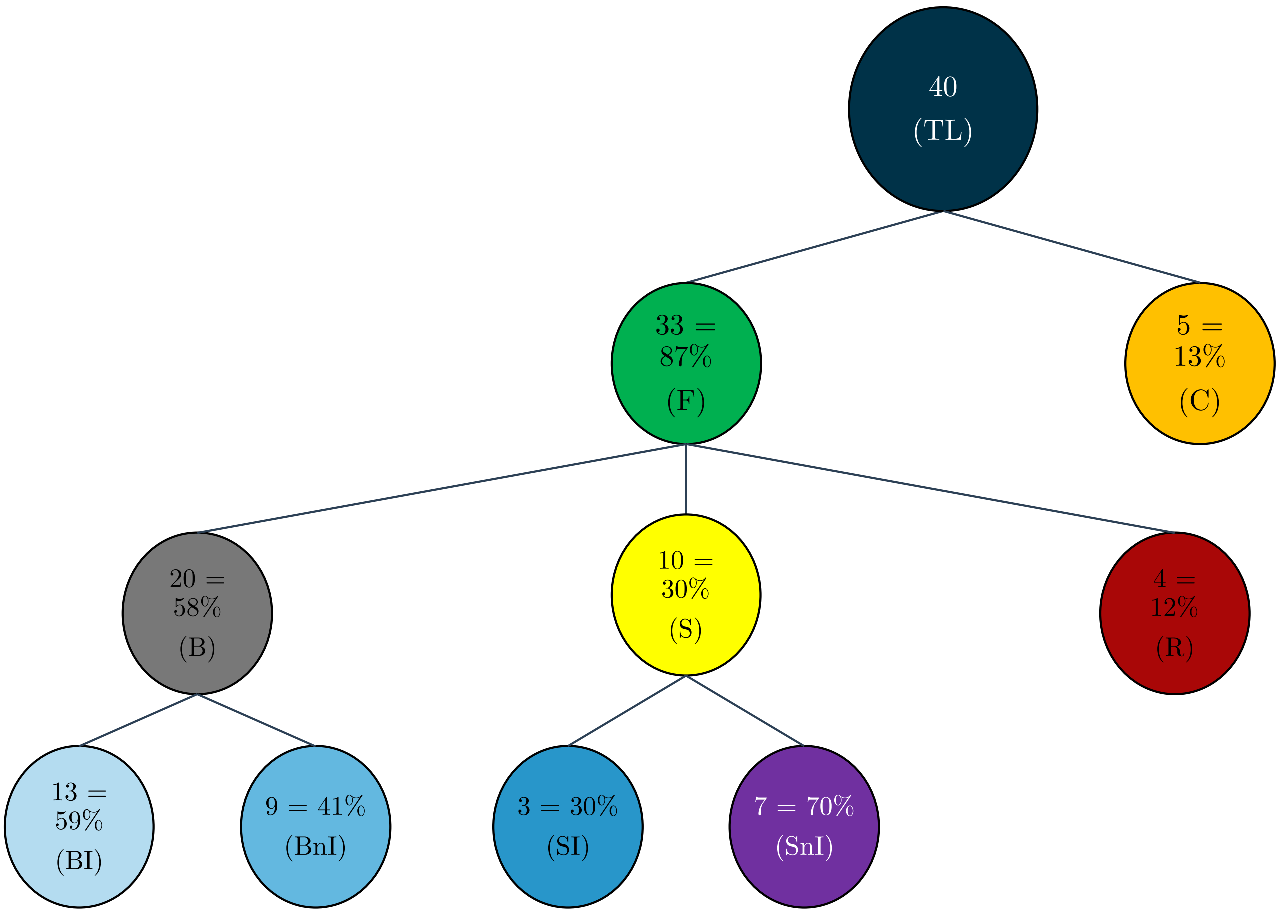


Final tank container forecast

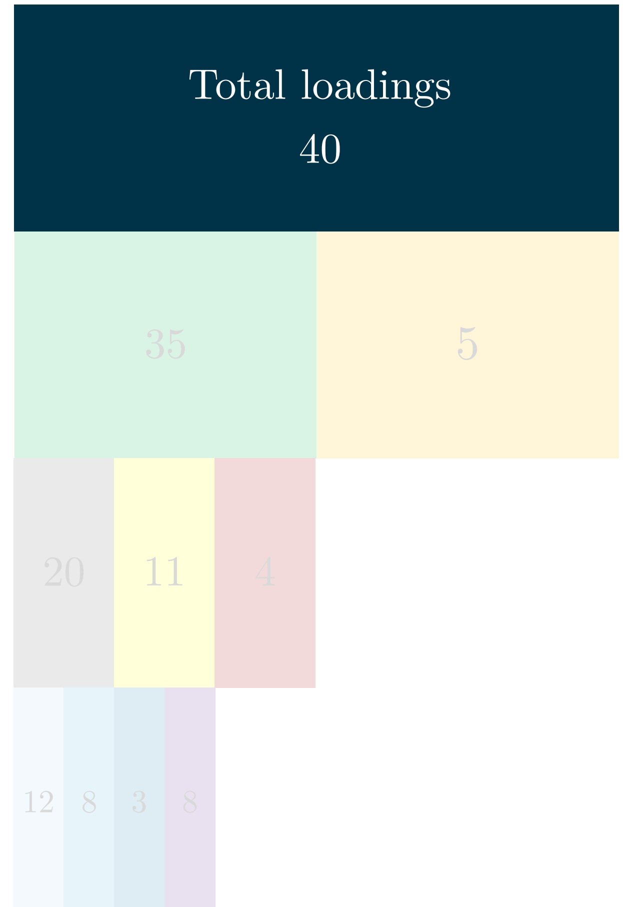


Example: (2) Derive a forecast per container type (i.e. per aggregation level) and compute the forecasted proportions

Forecast proportions for tank containers

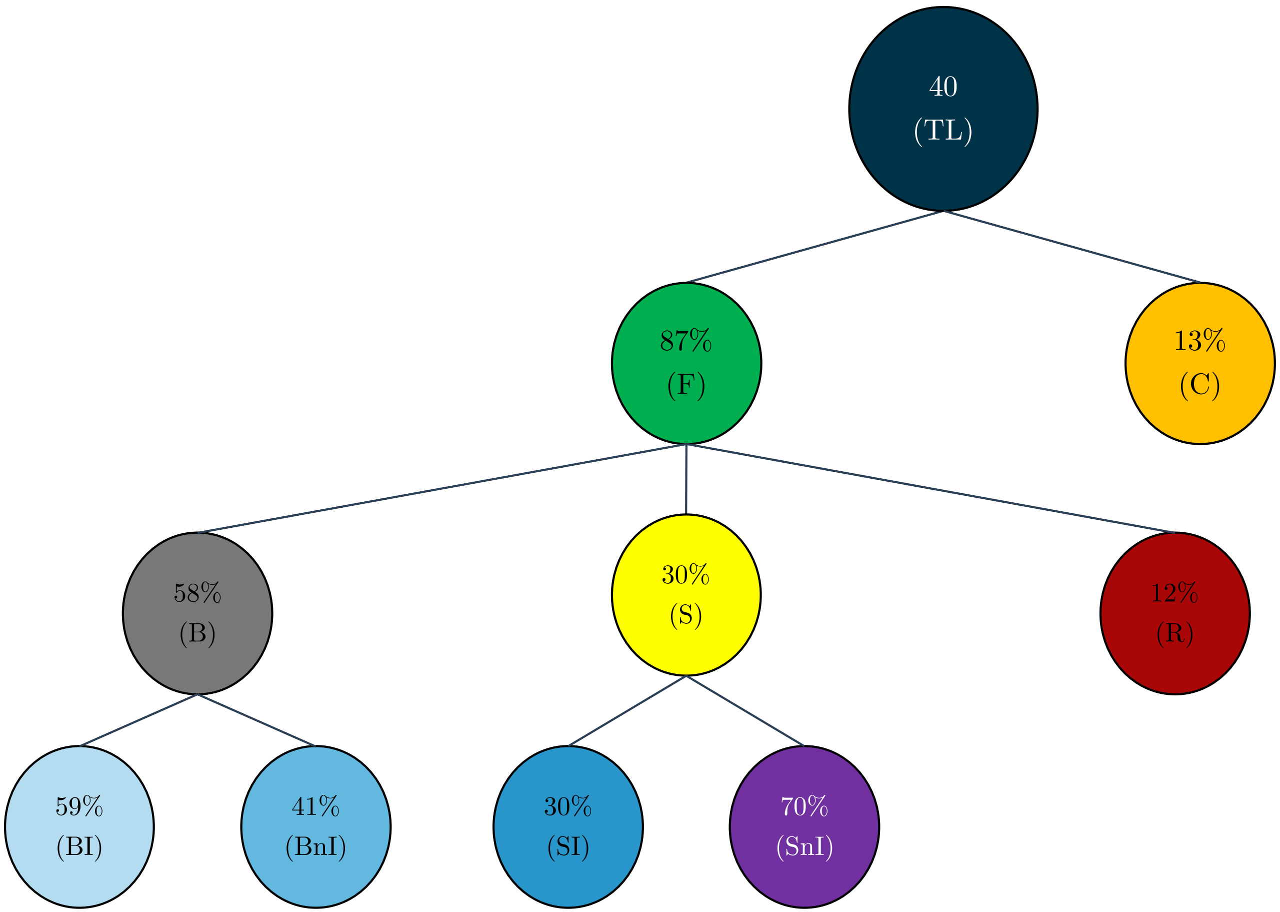


Final tank container forecast

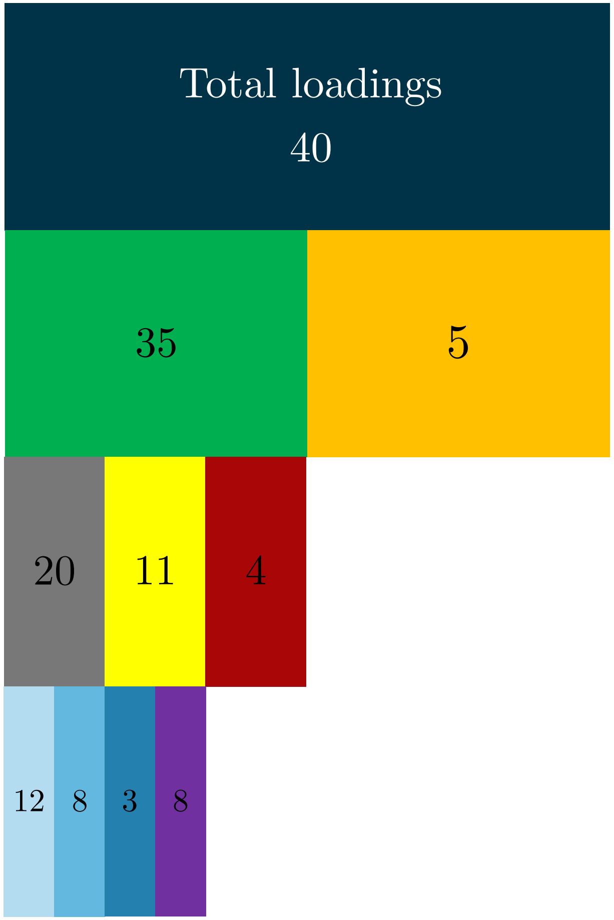


Example: (3) Disaggregate the forecast of the total number of loadings down the hierarchy based on the forecasted proportions

Forecast proportions for tank containers



Final tank container forecast



APPENDIX E

General

Challenge 1: proactive truck planning (i.e. drayage operations)

Operational challenges H&S

Current truck planning

- Occurs relatively ad hoc
- Charters booked at the very last moment → costly
- No smoothing of workload

Truck planning in an *ideal* world

- Truck planning should occur in a more **proactive** fashion:
- Book charters longer in advance
- Actively balancing workload

What is needed to move to this *ideal* world?

Insight in the expected number of orders and the corresponding **trucking** capacity for a future time period

Current container repositioning

- Network imbalance → need to reposition empty containers
- Currently, repo decisions are made based on qualitative experience

Container repo in an *ideal* world

- Use the experience of the two planners but not rely on it exclusively
- Having a statistical model on which to base repositioning decisions

What is needed to move to this *ideal* world?

Insight in the expected number of orders and the corresponding **tank container** capacity for a future time period

Challenge 2: efficient empty tank container repositioning

Operational challenges H&S

Current truck planning

- Occurs relatively ad hoc
- Charters booked at the very last moment → costly
- No smoothing of workload

Truck planning in an *ideal* world

- Truck planning should occur in a more **proactive** fashion:
- Book charters longer in advance
- Smooth workload

What is needed to move to this *ideal* world?

- Insight in the expected number of orders and the corresponding **trucking** capacity for a future time period

Current container repositioning

- Network imbalance → need to reposition empty containers
- Currently, repo decisions are made based on qualitative experience

Container repo in an *ideal* world

- Use the experience of the two planners but not rely on it exclusively
- Having a statistical model on which to base repositioning decisions

What is needed to move to this *ideal* world?

- Insight in the expected number of orders and the corresponding **tank container** capacity for a future time period

In order to demarcate the scope of this research, three planning regions were selected to focus on

Project deliverables and scope of the research

Trucking capacity

Focus regions:
- Belgium & northern part of France (**BFN**)
- Northern part of Great Britain (**GBN**)

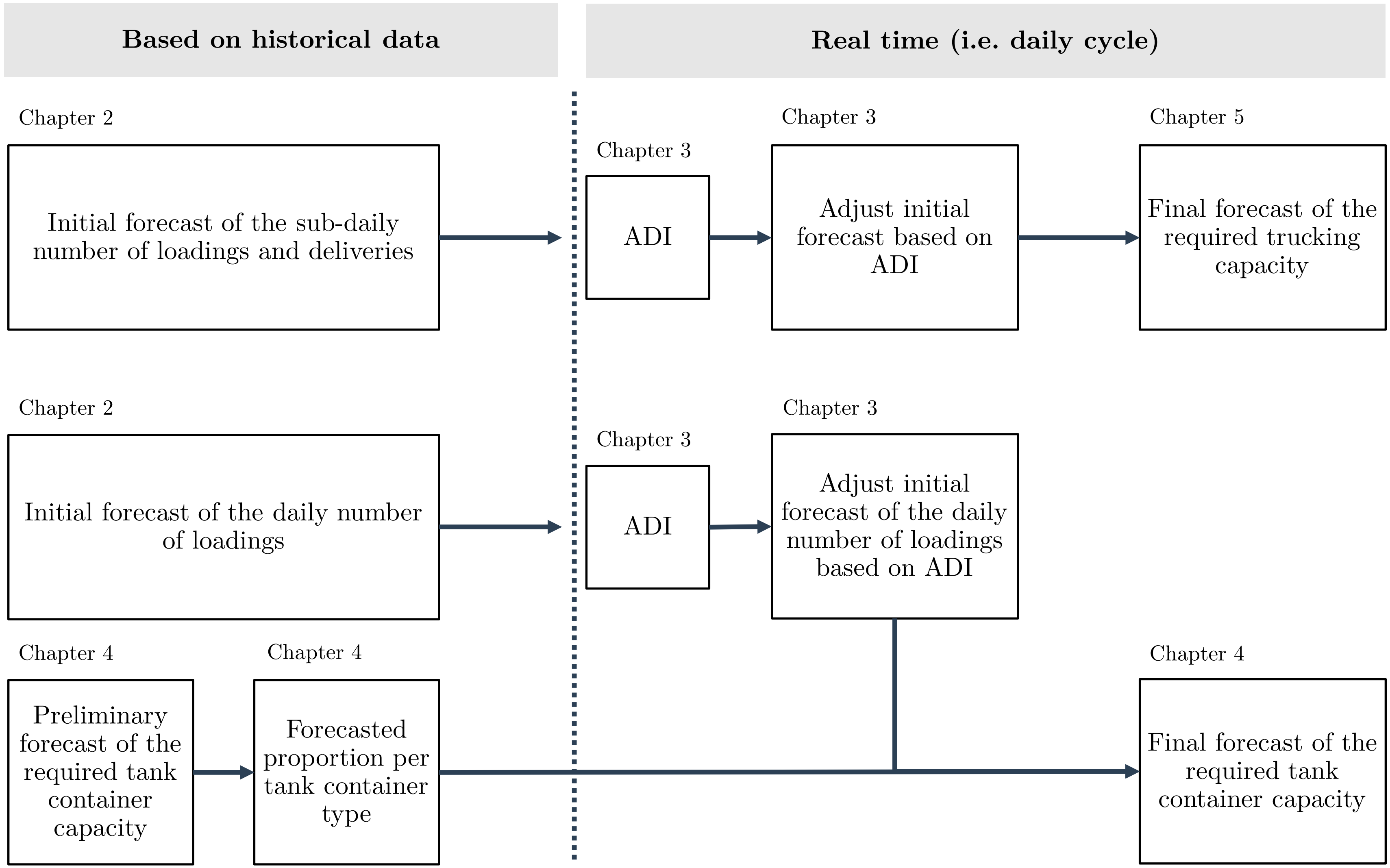
Forecast:
sub-daily (AM / PM) number of loadings and deliveries forecasted **1 week ahead**

Tank container capacity

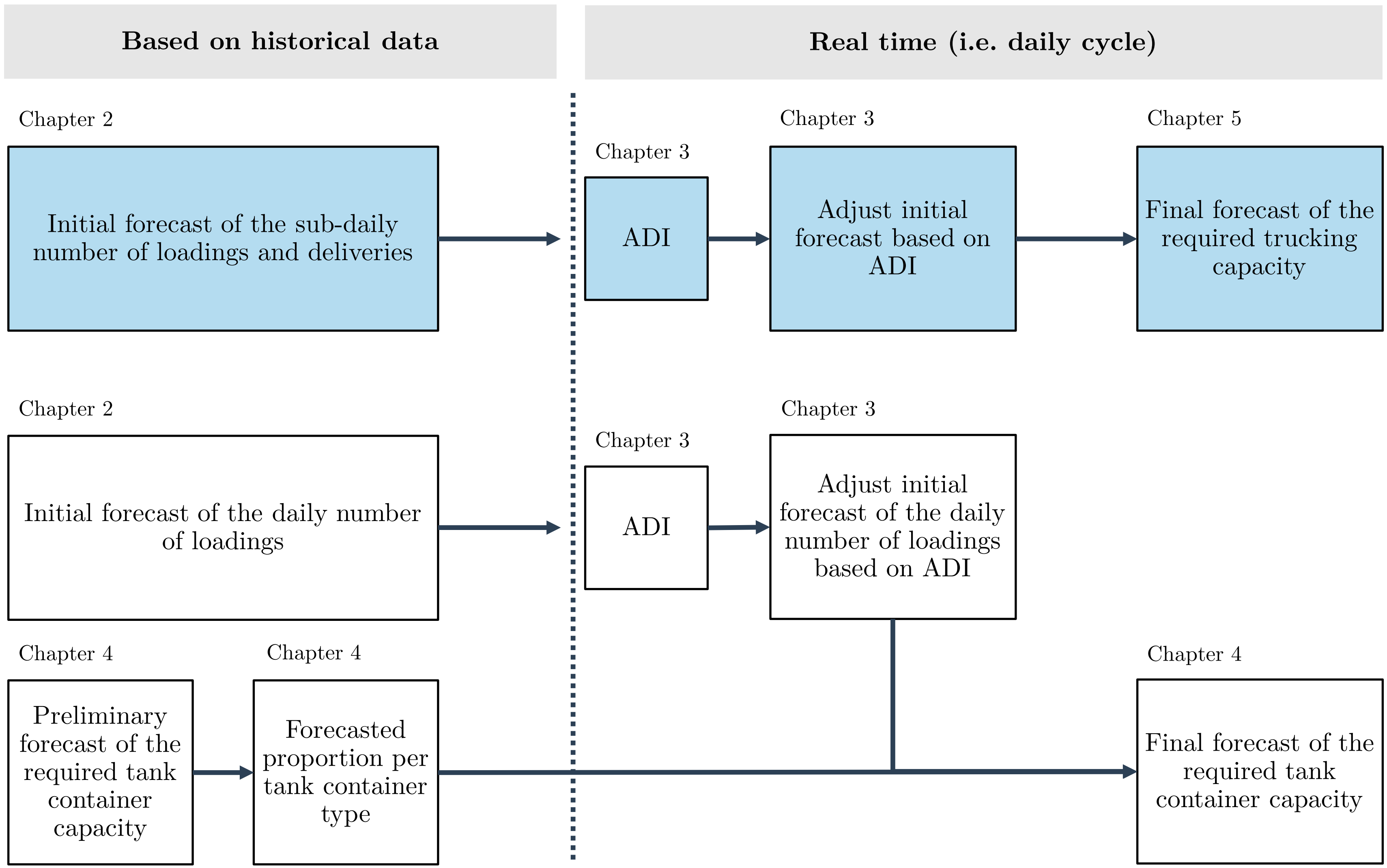
Focus region:
- Rotterdam

Forecast:
daily number of loadings and deliveries forecasted **3 weeks ahead**

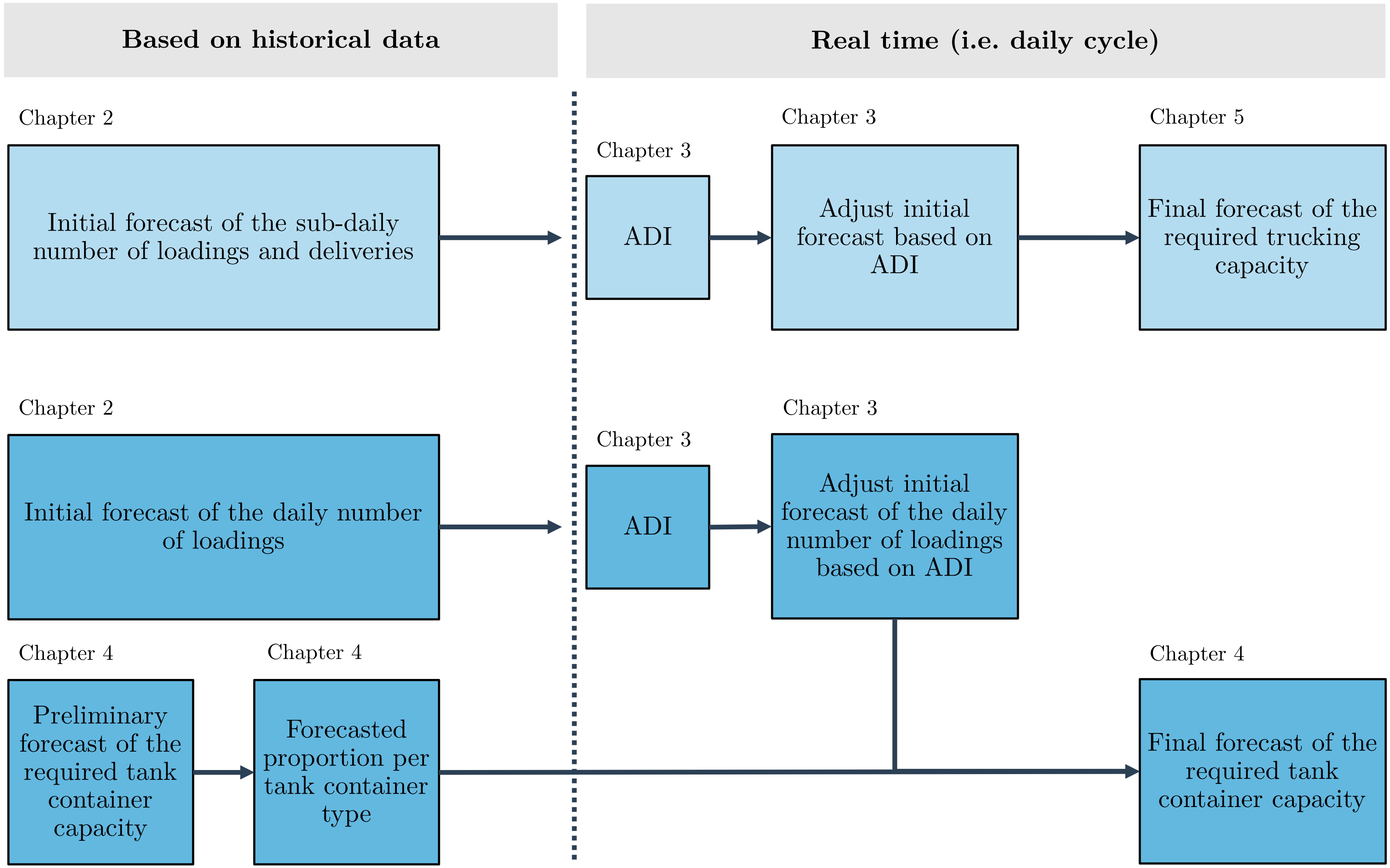
Summary of the proposed forecasting methodology for predicting the number of orders and corresponding capacity requirements



Summary of the proposed forecasting methodology for predicting the number of orders and corresponding capacity requirements



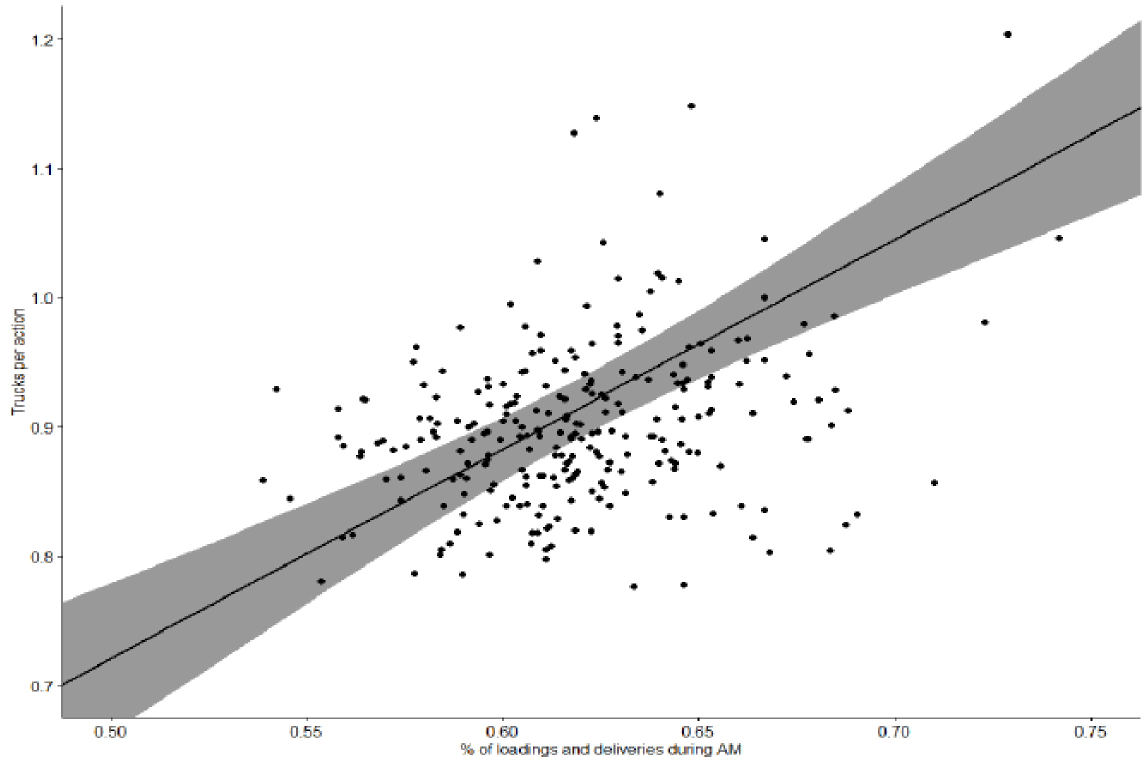
Summary of the proposed forecasting methodology for predicting the number of orders and corresponding capacity requirements



There seems to be a correlation between the imbalance between AM & PM and the number of trucks per action on a given day

Correlation between (im)balance and number of trucks per action

$$\frac{Number\ of\ trucks\ used}{(Loadings + Deliveries)}$$



$\%\ of\ loadings\ during\ AM$

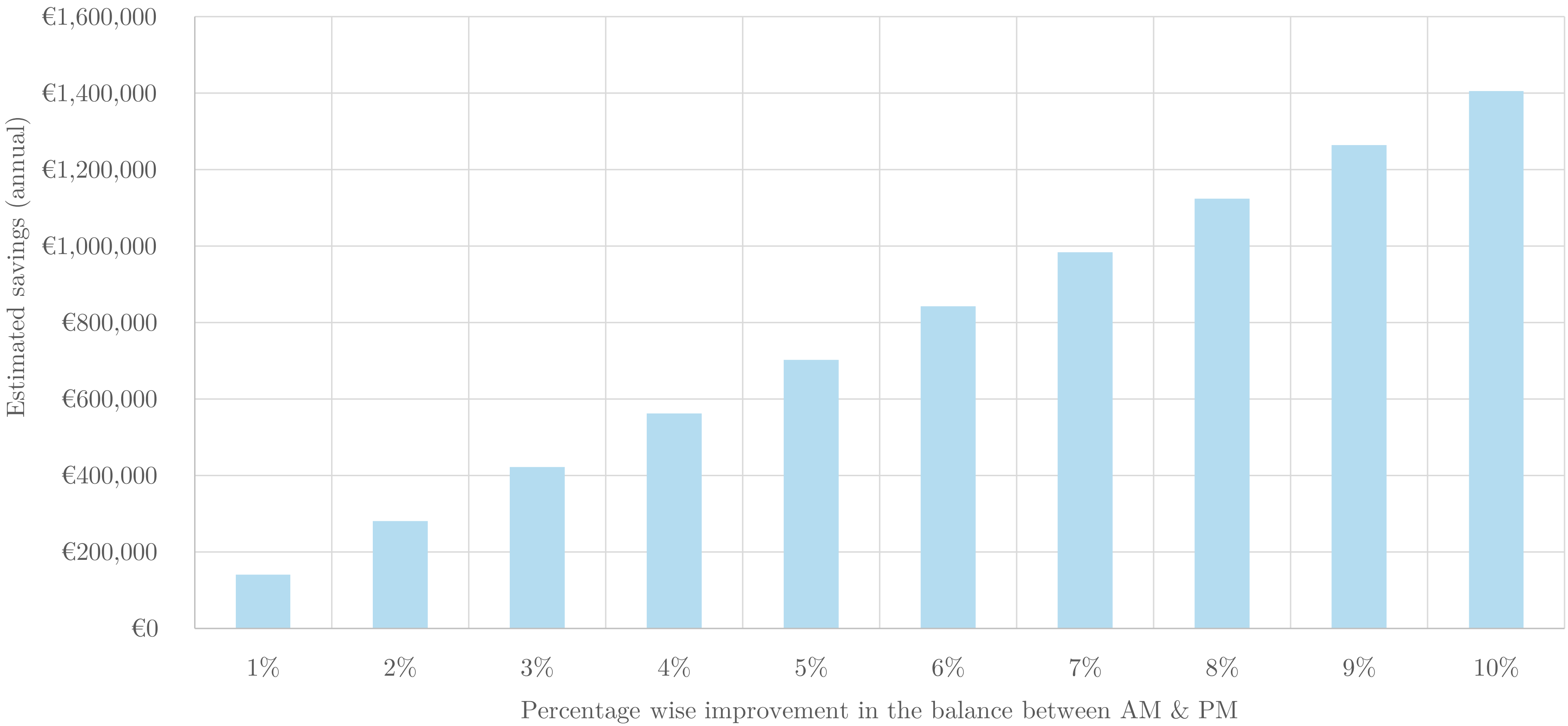
A guesstimate was conducted to estimate the potential savings that might be expected if the balance between AM & PM would be improved

1	Assume that by employing the forecasting methodology, H&S could enhance the balance of the workload between AM and PM by **1%**	1%
2	Estimate the savings in the number of trucks per action	0.016
3	It is known how many actions are performed per year	60,000
4	Multiply (2) by (3) to estimate the number of trucks "saved" per year	972
5	The total number of trucks that are used per year is known	56,000
6	Express (5) as a percentage decrease	2%
7	The total trucking cost per year is known	€ 27,000000
8	Make an assumption regarding which part of the total trucking cost depends on the number of trucks used	30%
9	The annual savings can now be estimated by multiplying (6) by (7) by(8)	€ 140,549

TU/e H&S GROUP

By balancing the workload throughout the day it is expected that H&S can save a substantial amount of trucking costs

Estimated savings for various scenario's



More balanced workload → less trucks per action → savings in trucking cost

% improvement in balance throughout the day	Savings in number of trucks per action	Number of actions per year	Savings in trucks per year	Total number of trucks used per year	% decrease in number of trucks used per year	Total costs associated with trucking operations	% of trucking costs dependent on number of trucks	Total estimated savings from improvement of balance
1%	0.016	60,000	972	56,000	-2%	€ 27,000,000	30%	€ 140,549
2%	0.032	60,000	1,943	56,000	-3%	€ 27,000,000	30%	€ 281,099
3%	0.049	60,000	2,915	56,000	-5%	€ 27,000,000	30%	€ 421,648
4%	0.065	60,000	3,887	56,000	-7%	€ 27,000,000	30%	€ 562,198
5%	0.081	60,000	4,859	56,000	-9%	€ 27,000,000	30%	€ 702,747
6%	0.097	60,000	5,830	56,000	-10%	€ 27,000,000	30%	€ 843,297
7%	0.113	60,000	6,802	56,000	-12%	€ 27,000,000	30%	€ 983,846
8%	0.130	60,000	7,774	56,000	-14%	€ 27,000,000	30%	€ 1,124,396
9%	0.146	60,000	8,745	56,000	-16%	€ 27,000,000	30%	€ 1,264,945
10%	0.162	60,000	9,717	56,000	-17%	€ 27,000,000	30%	€ 1,405,495

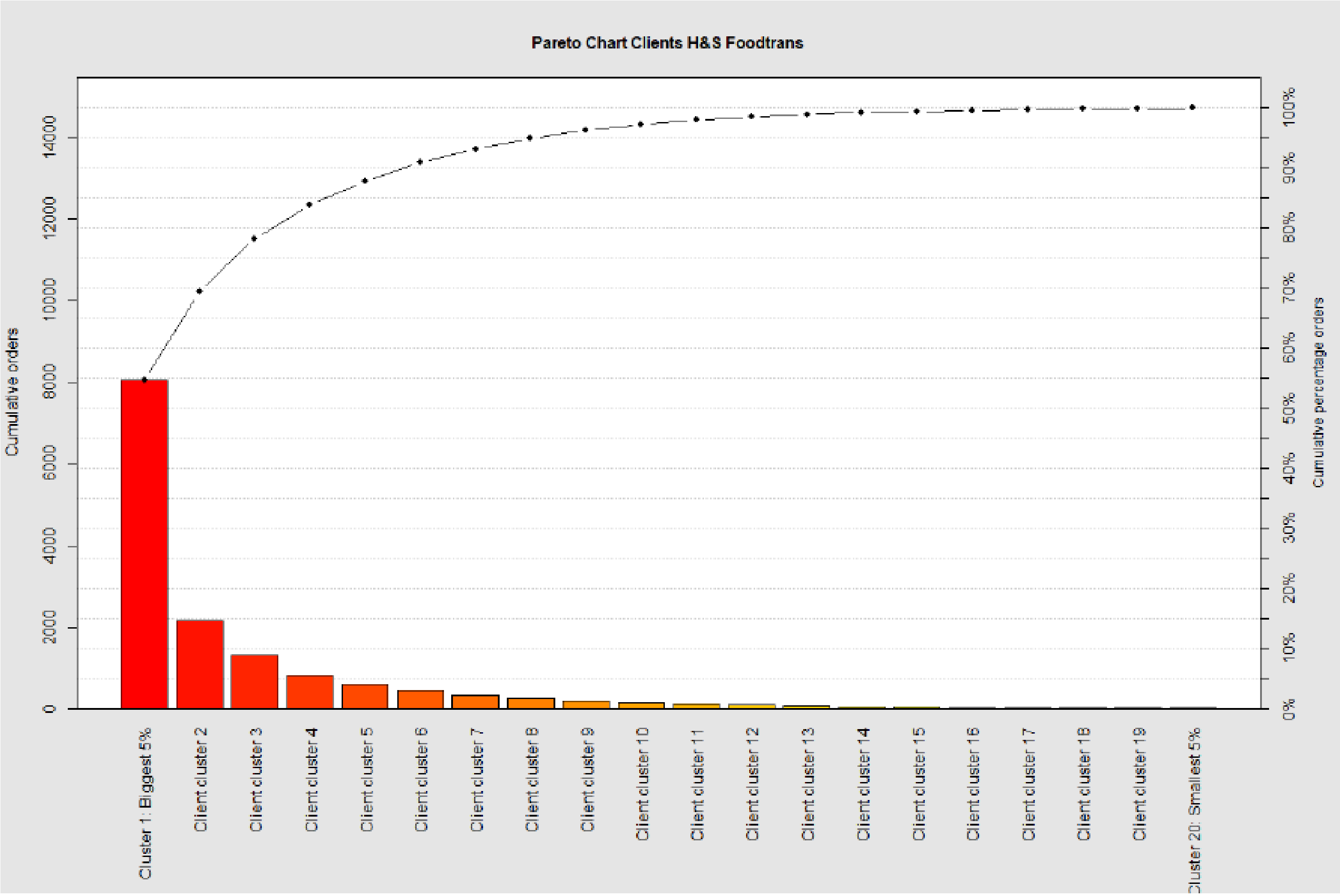
At this moment, the proposed forecasting methodology propsoed by this research is being implemented at H&S

Timeline project

	Orientation and data gathering	Testing wider applicability of the model	Finetuning model and extension to all regions	Implementation INFORIT
Activities	• The proposed forecasting methodology is explained to CQM • 2 meetings with CQM and Den Hartogh in order to get a clear idea about the project • Data gathering	• CQM is going to implement the proposed forecasting methodology • The promising results of this study are replicated on larger test set	• If necessary the proposed forecasting model is fine-tuned and improved	• Implement the final forecasting model and integrate it in the current planning software

Goal	• Define project scope and deliverables
	• Decide on what data is needed from INFORIT
		• The overall quality of the proposed forecasting methodology is assessed:
		  • Does it work for all regions?
		  • Does it work for Den Hartogh?
			• To deliver a final forecasting model that can be implemented by INFORIT	• Integrate the forecasting model in Transfusion

The 5% largest clients account for 55% of all orders of H&S Foodtrans



H&S Foodtrans is a logistics service provider engaged in intermodal transportation of liquid foodstuff