Federatie Textielbeheer Nederland

Online services, E-commerce & smart logistics: wat levert het op?

Laundry Experience Event 2019 – Clova, Wommelgem, Belgie

Federatie Textielbeheer Nederland

(Relatively) new markets for e-commerce & smart logistics

1. Elderly care

2. SME sector

3. Construction

4. Modern consumers

5. Additional logistic services

‘small order sizes’ | ‘flexible service level’ | automated administration & logistics

For example by combining logistical flows

Groceries & laundry

Laundry & ….

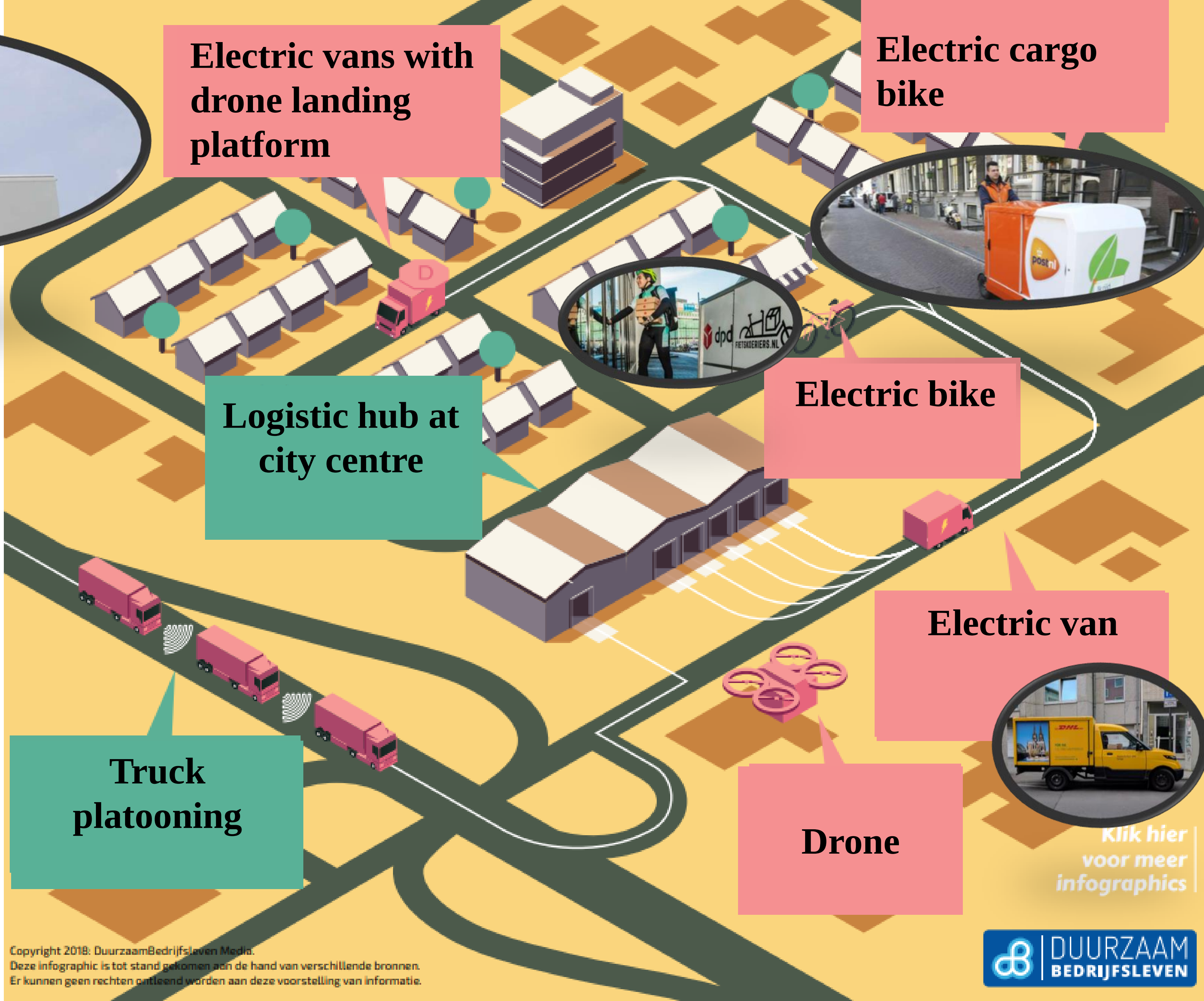
Outsourcing laundry + complementary products

Benefits:

Spread cost of logistics: 1 address, 2 services

Stronger connection to your customer – better competitive position

Sustainable (last mile) logistics now and in the future



Federatie Textielbeheer Nederland

Federatie Textielbeheer Nederland

UK-based Oxwash partners with Deliveroo to go green!

Logistics: densification of routes is essential for new market segments

BIZ & TECH // BUSINESS

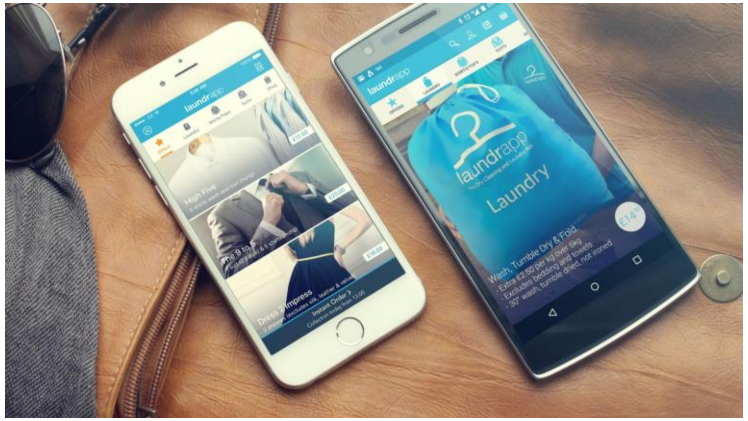
Mulberrys buys Laundry Locker, becomes California's largest clothing cleaner

Roland Li | Oct. 12, 2018 | Updated: Oct. 12, 2018 5 a.m.

Tad Jenkins (left), CEO of newly acquired Laundry Locker, and Mulberrys CEO Dan Miller, are outside the Mulberrys Marina store. Mulberrys now is the largest clothing cleaning company in California.
Photo: Brian Feulner / Special to The Chronicle

Zipjet & Laundrapp in Merger Talks; JIVR Overfunds

by Hugh Williams on 4th Apr 2019 in News



laundrapp

ZipJet

*"…agreement is **aimed at creating critical mass** in the two companies combined London operations"*

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

13/09/2019

Ir. Rijk van der Meulen, MSc Graduate in Operations Management & Logistics

TU/E School of Industrial Engineering

DATA 2 MOVE

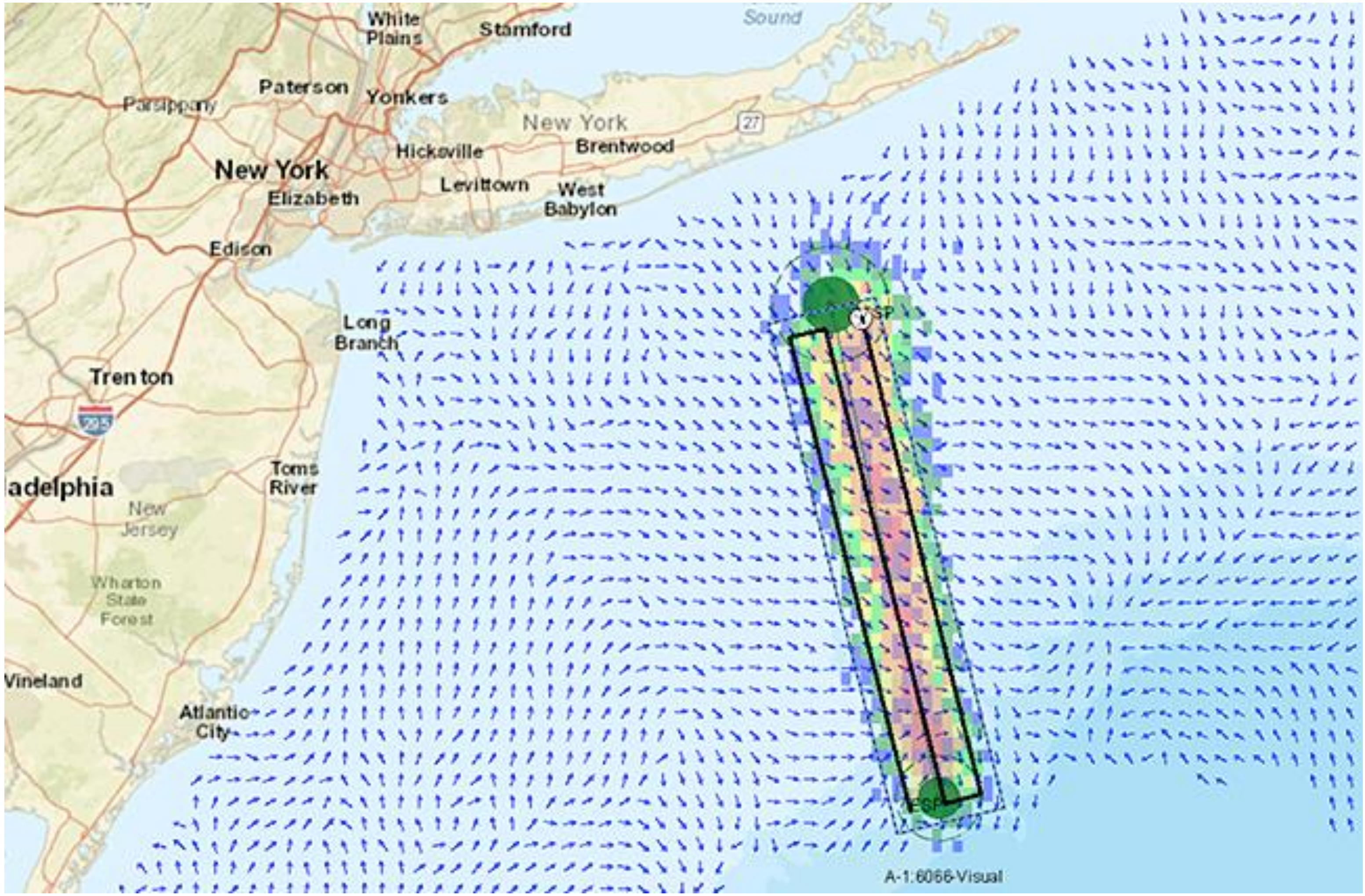
H&S GROUP

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

A Speck in the Sea – The New York Times

Bayesian Search for Missing People

Finding a Needle in a Haystack




DATA 2
MOVE
LEADING COMMUNITY FOR LOGISTICS, SCM AND BIG DATA

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

Step 1

Forecasting the loadings and deliveries based on *historical* data

Step 2

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

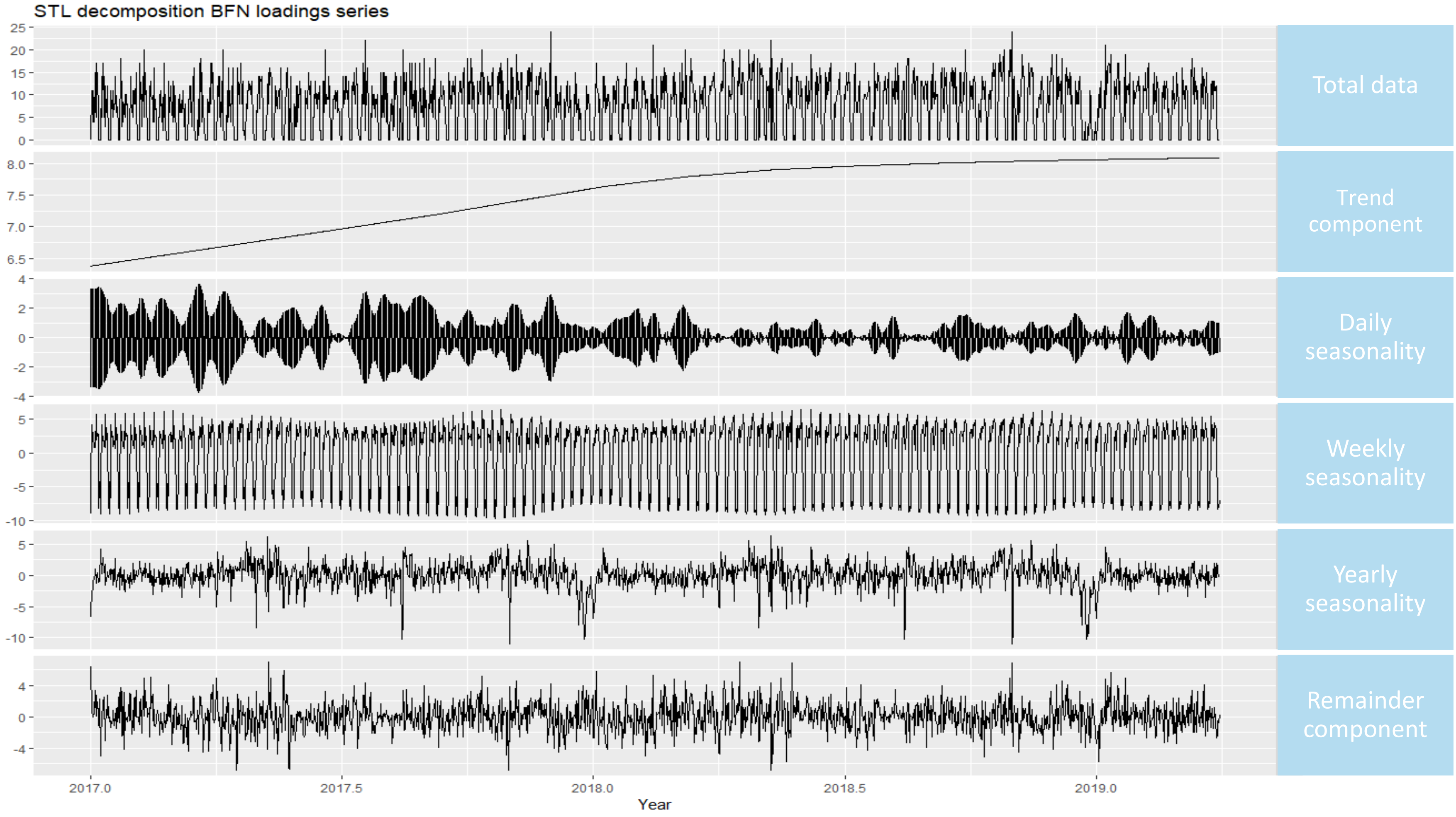
Step 3

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

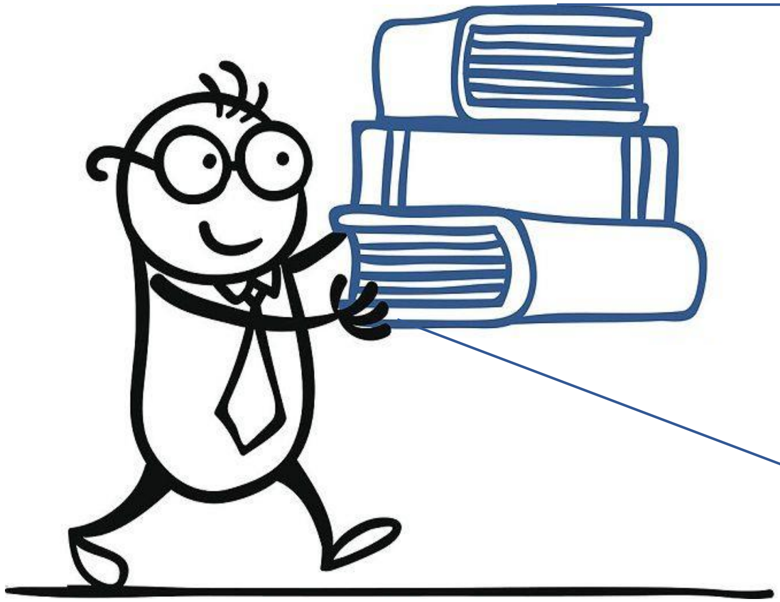
The data exhibits multiple seasonal patterns

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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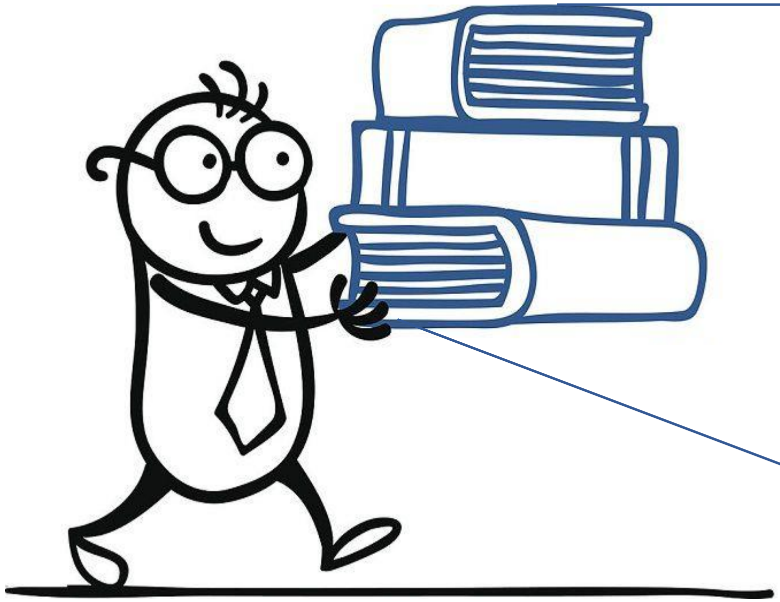

- STL decomposition
- Double exponential smoothing
- Dynamic harmonic regression
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- Artificial neural network
- Simple mean method

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

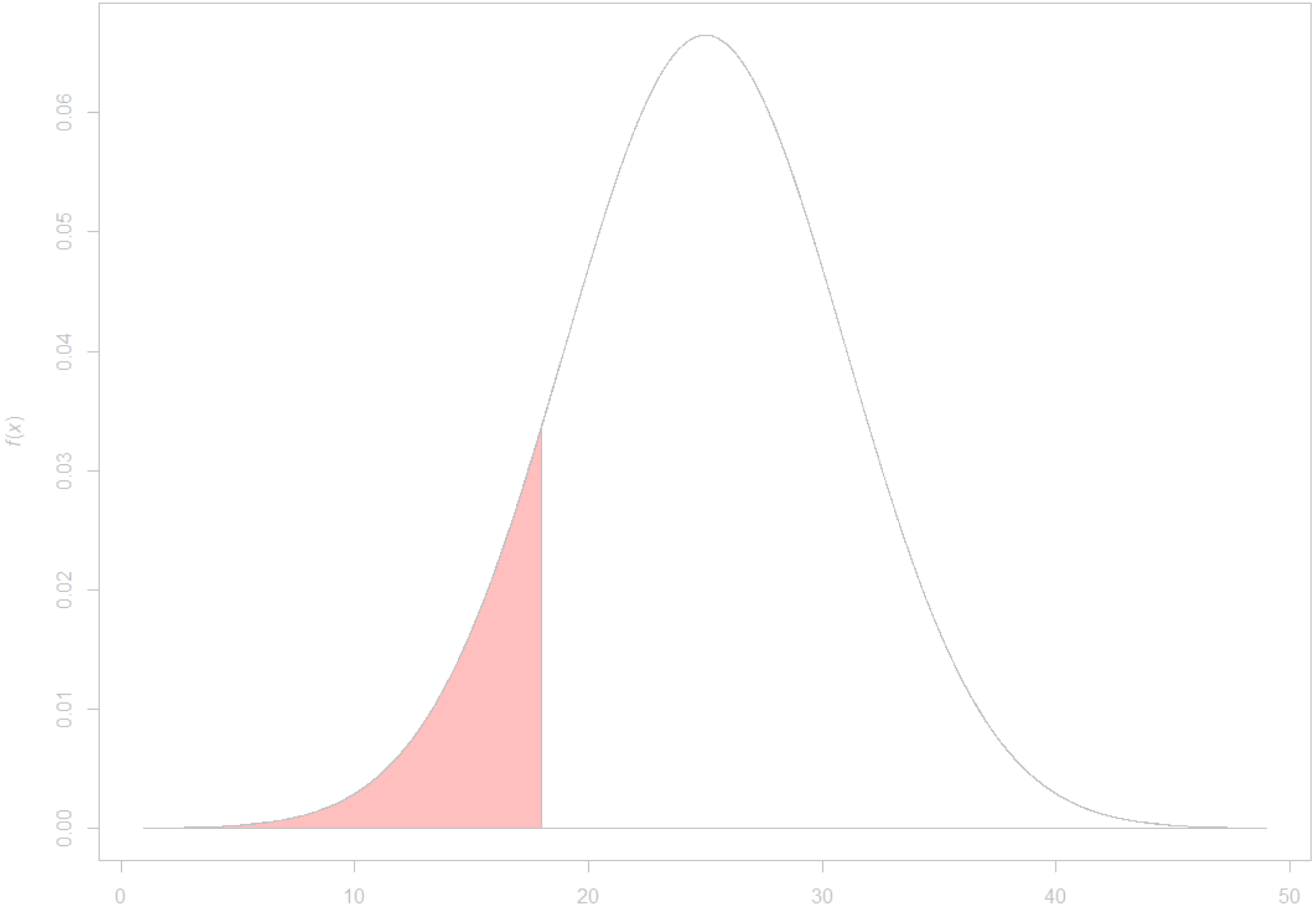
Bayesian Adjustment

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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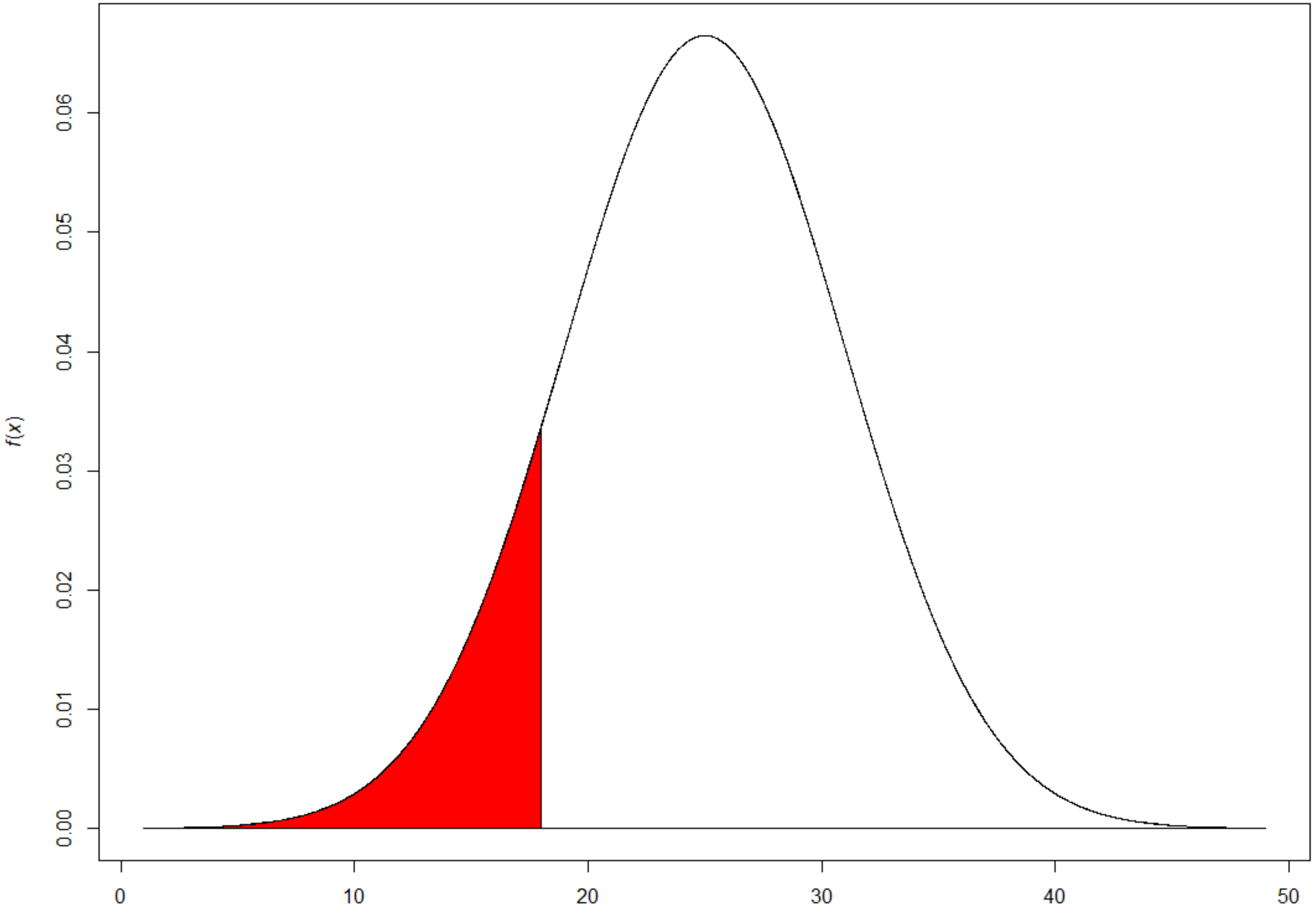

The Bayesian technique significantly improves the initial forecast

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

		Assumptions	Actuals
1	Estimation of the historical trucking capacity	• 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
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A multiple linear regression model was developed to predict the required trucking capacity

Multiple linear regression model

1

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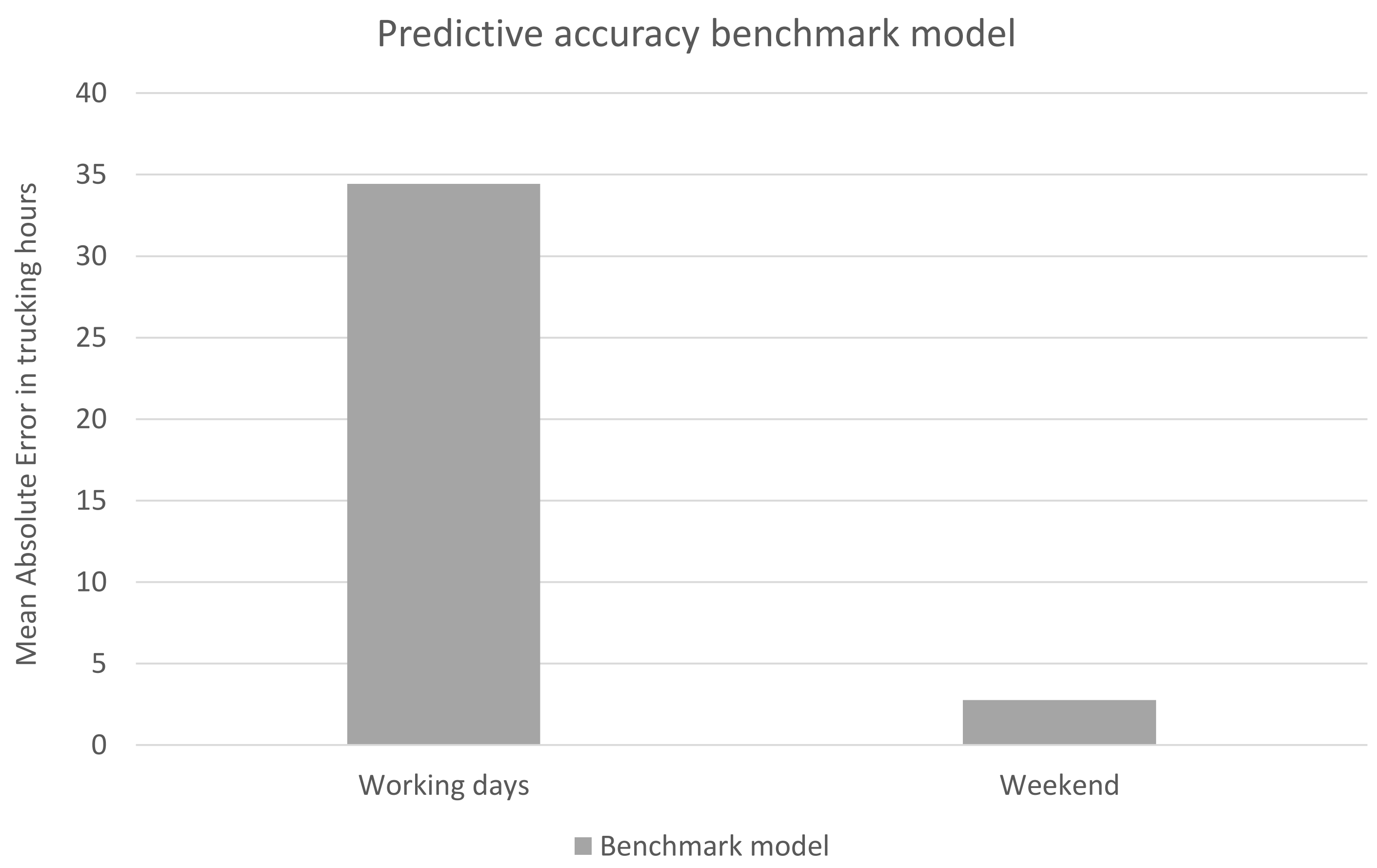
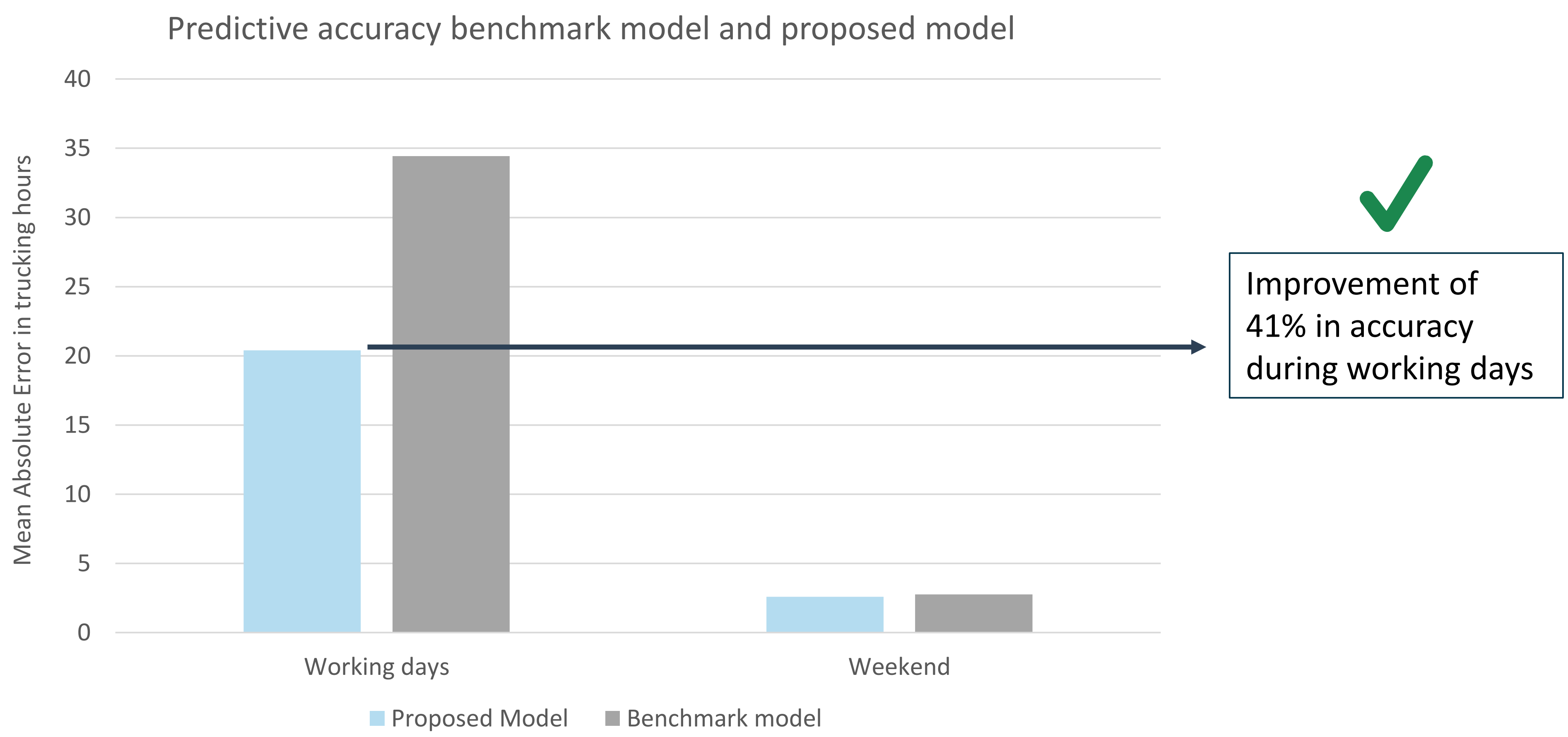
The proposed forecasting model is compared against a benchmark model that is currently used at H&S

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



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

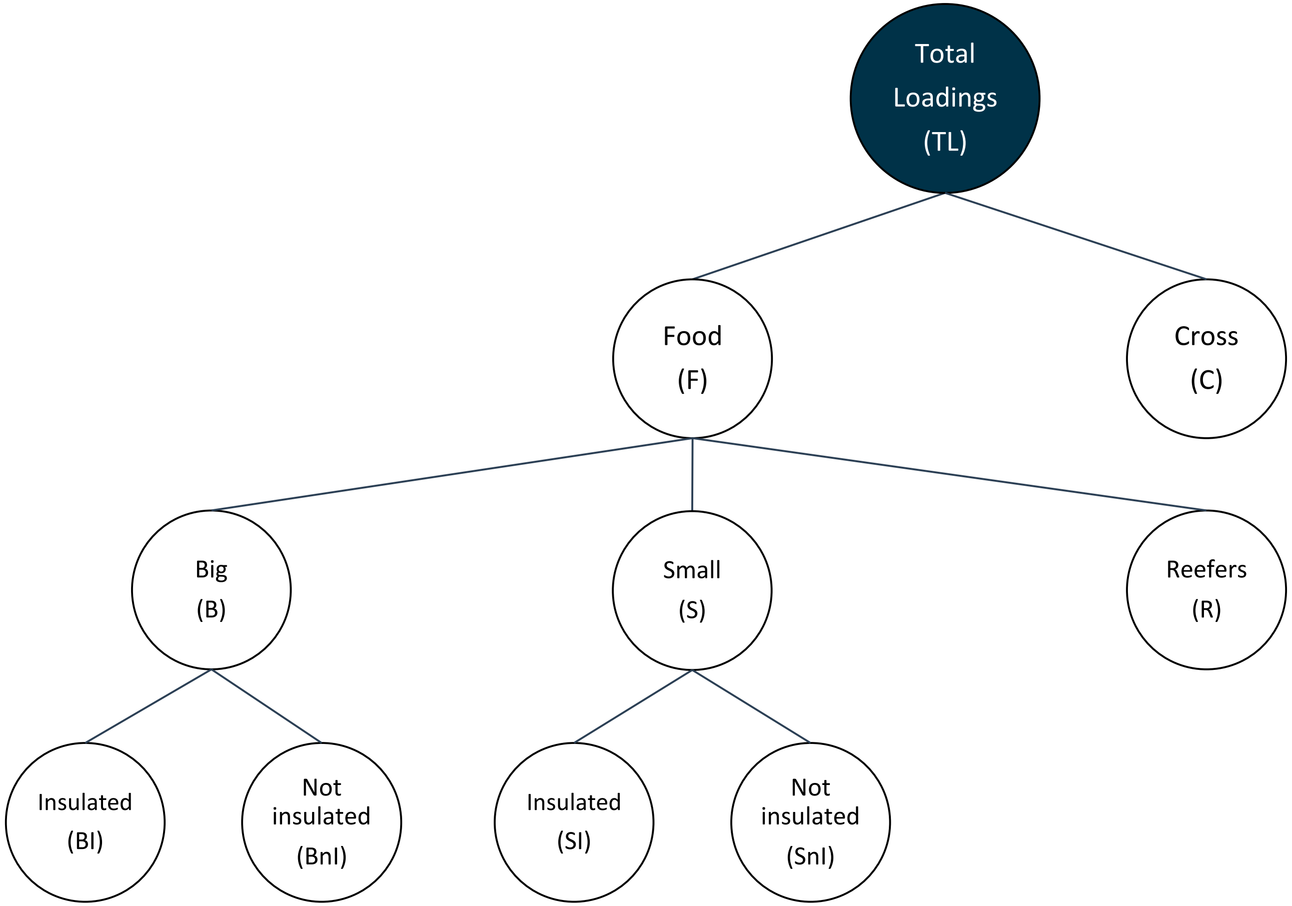
Output

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



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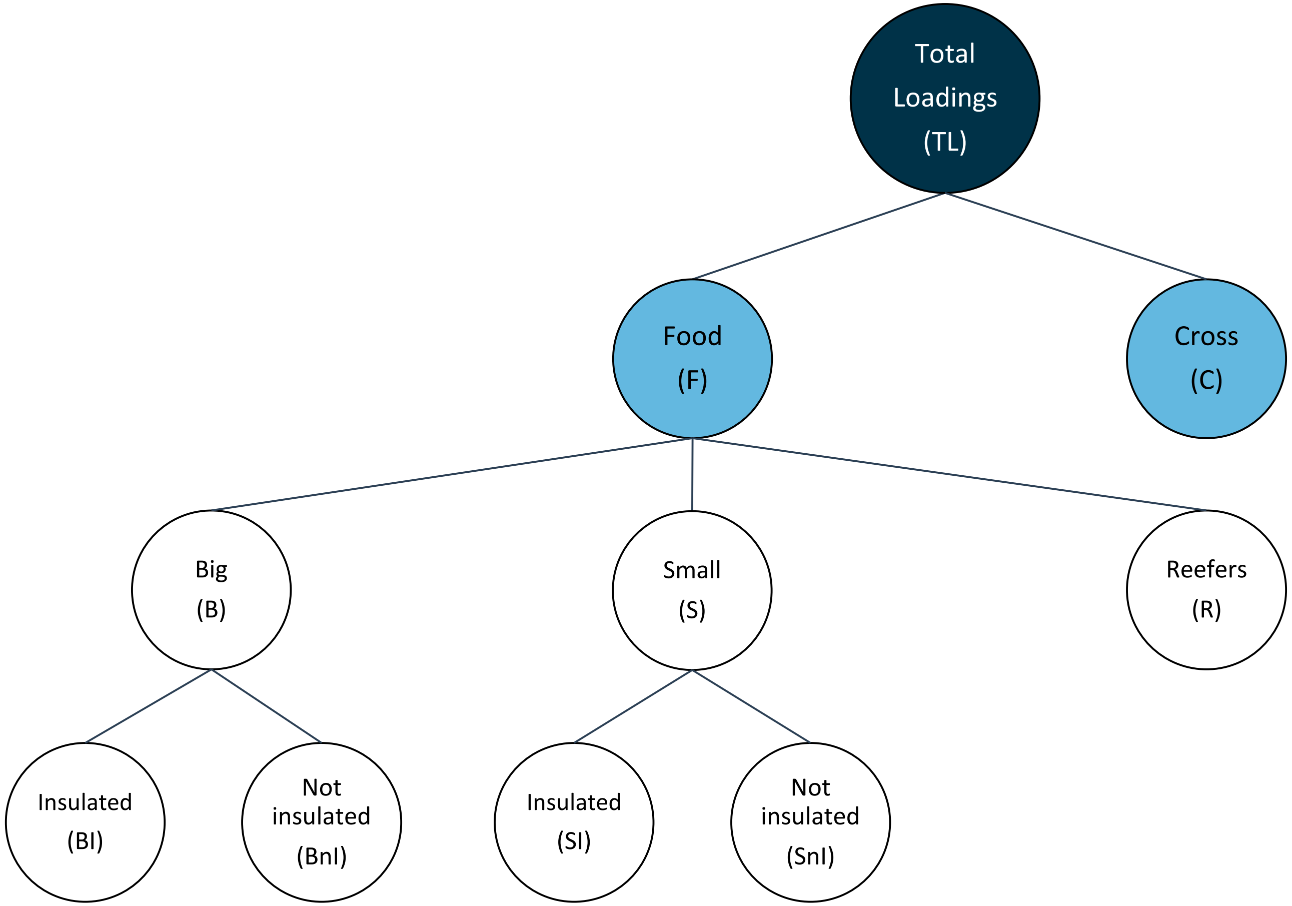

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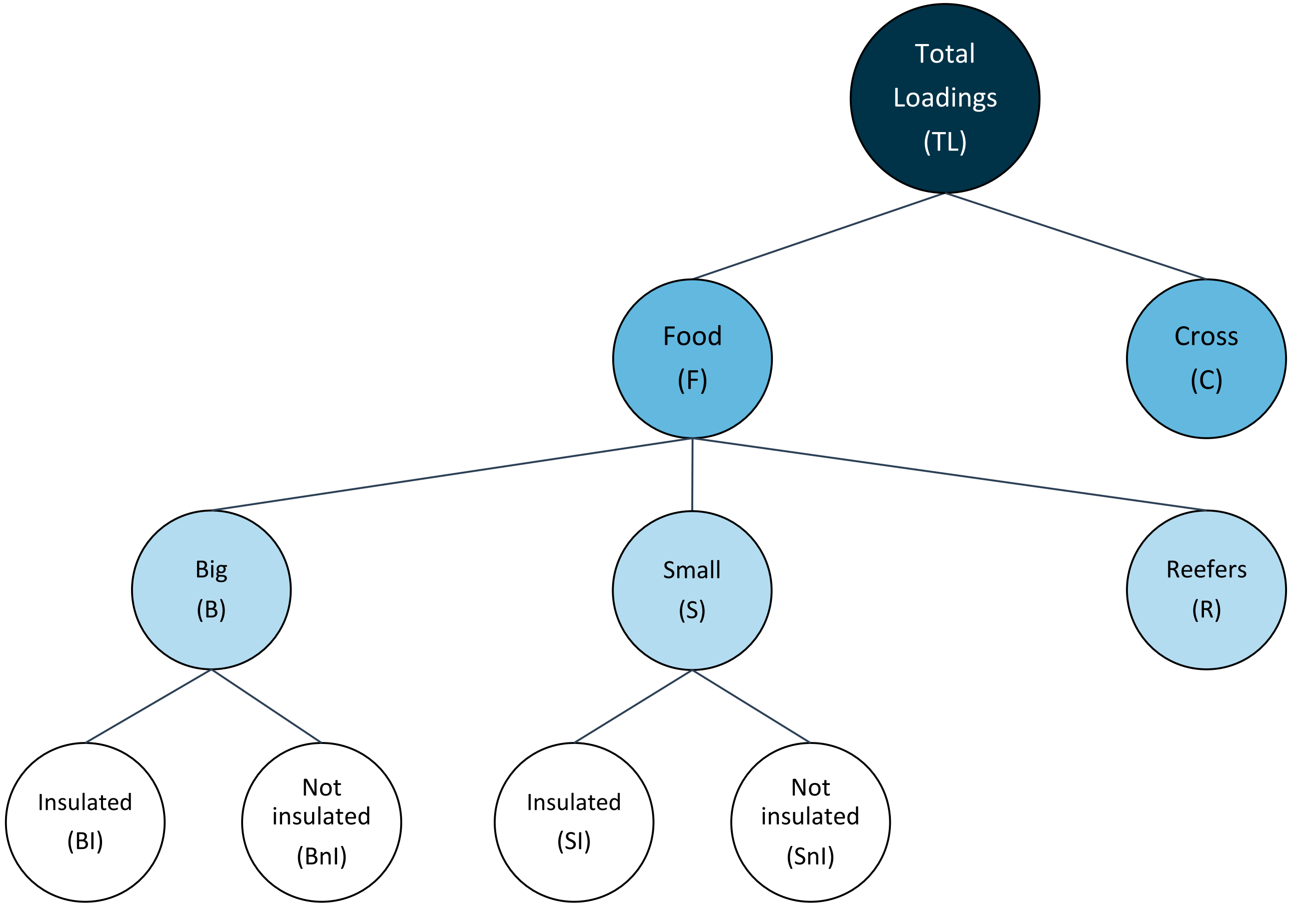

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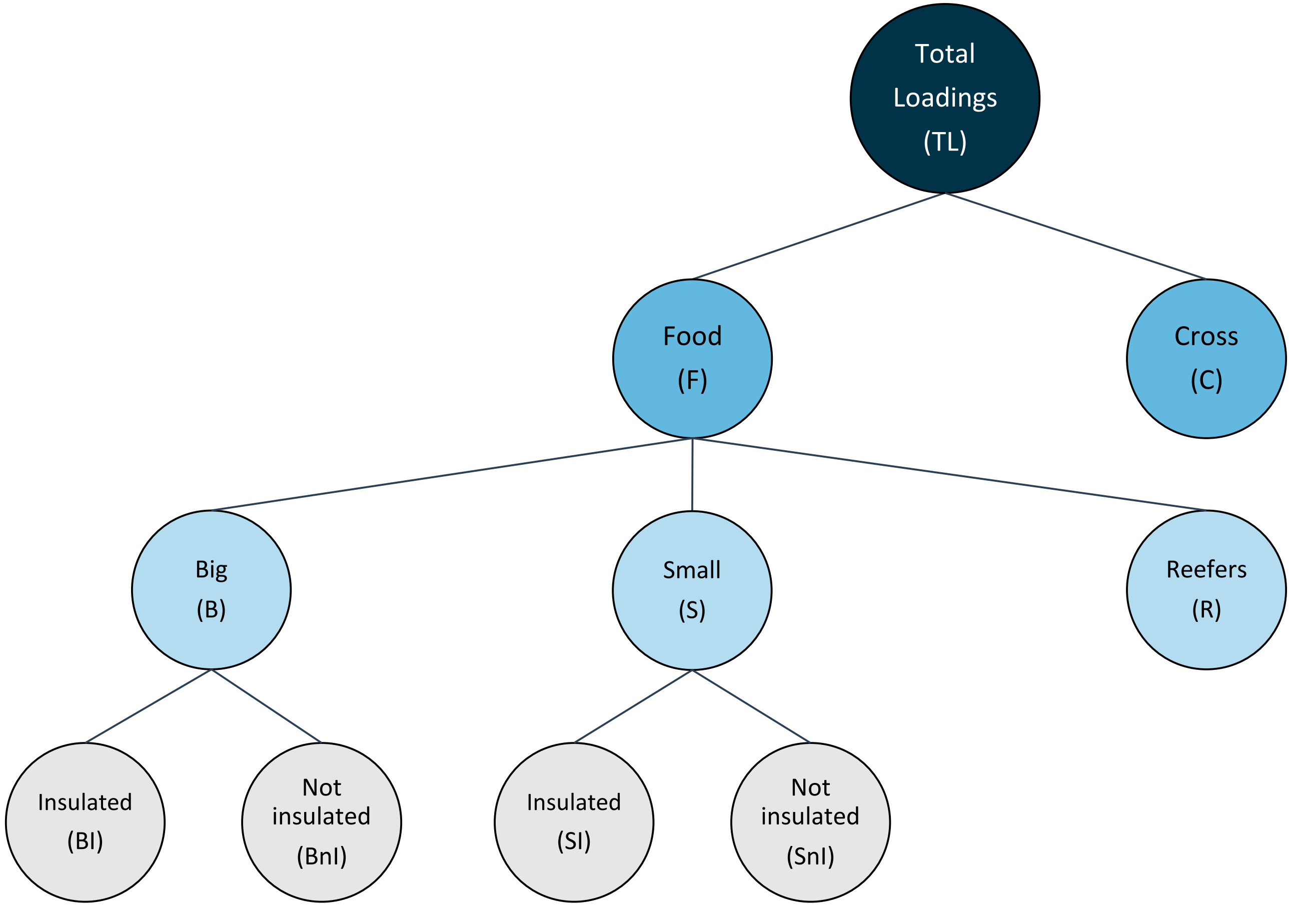
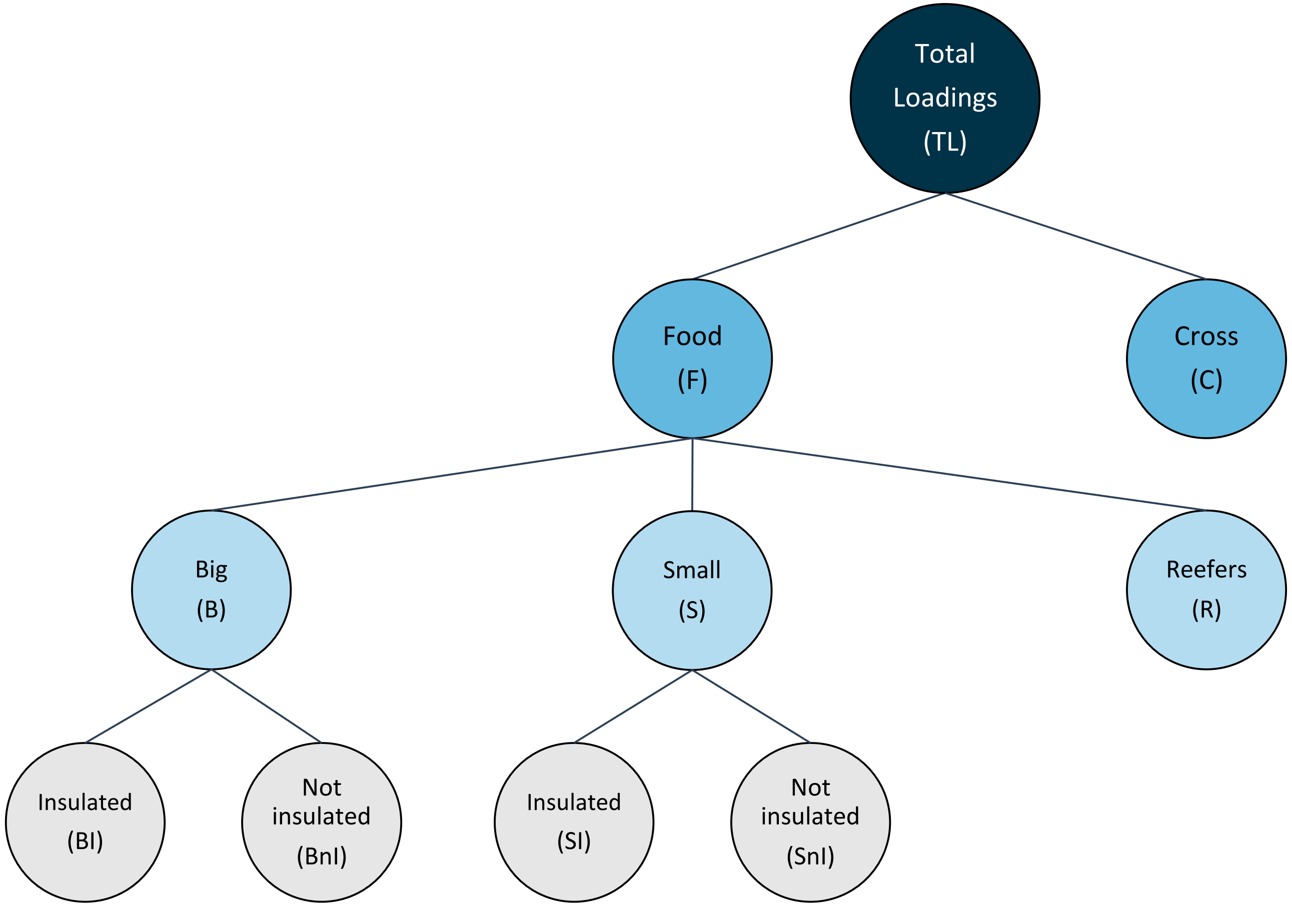


How can a forecast be obtained for every type of tank container?

Tank container forecast



Tank container forecast

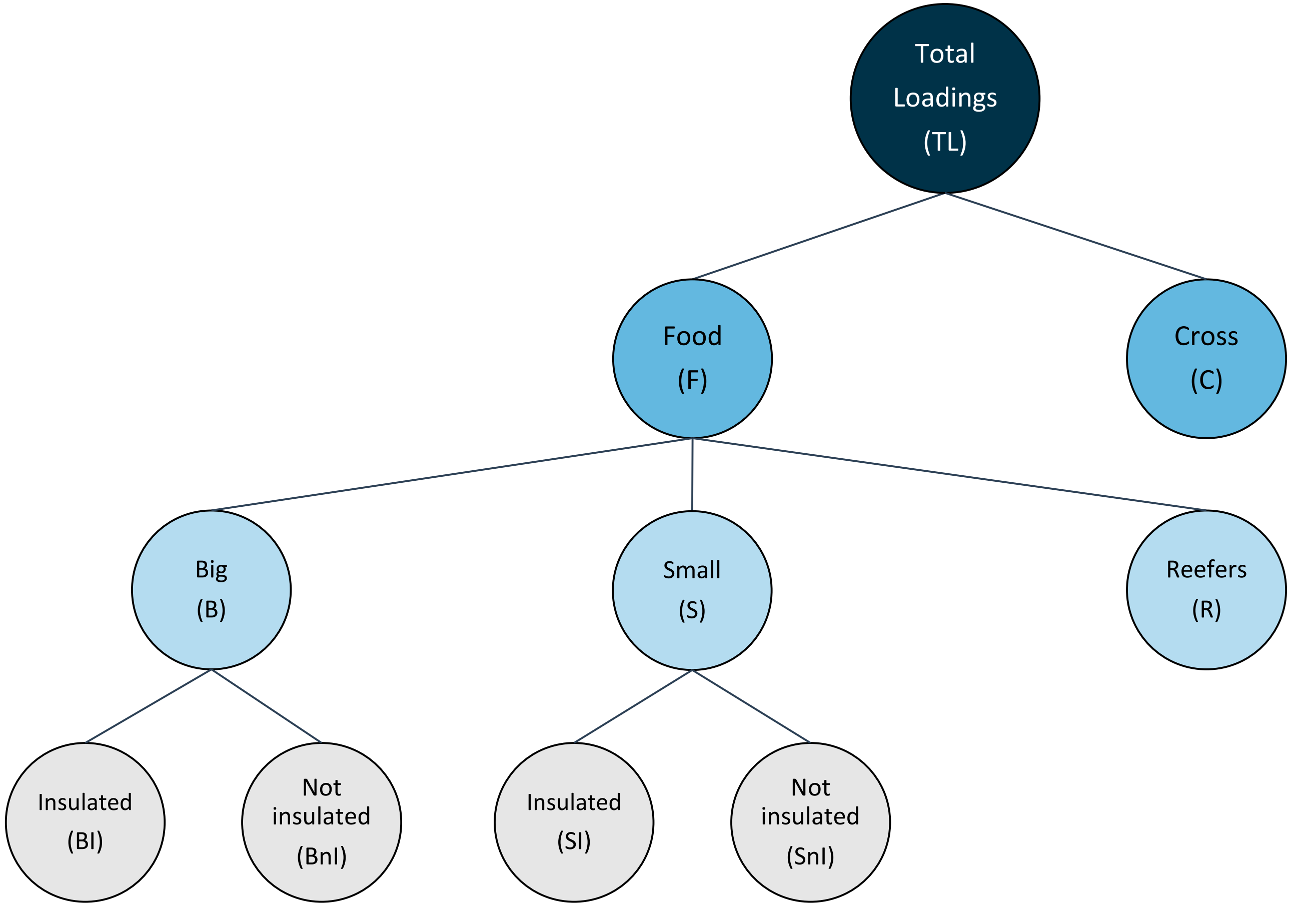
Output Bayesian technique

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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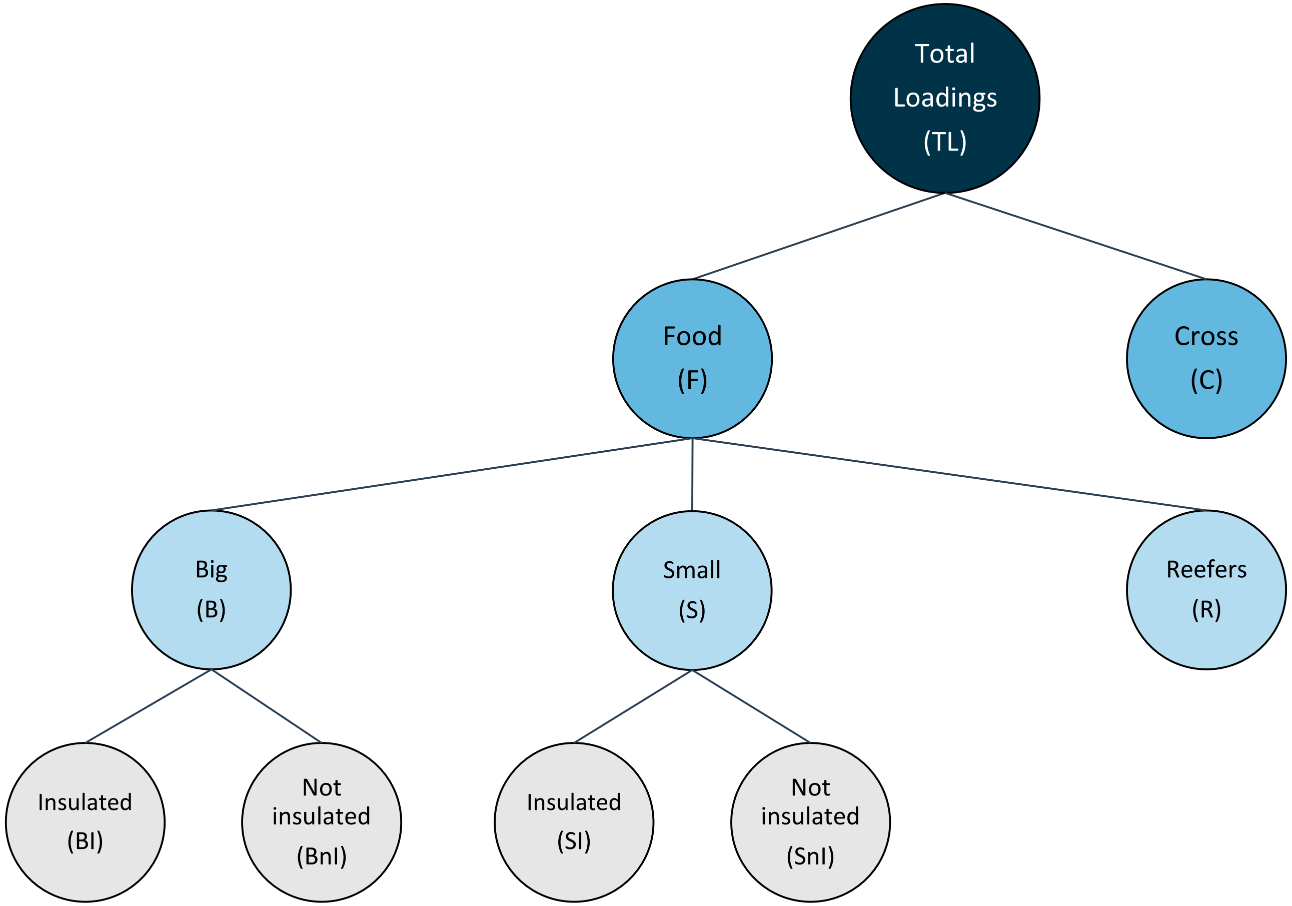

Tank container forecast

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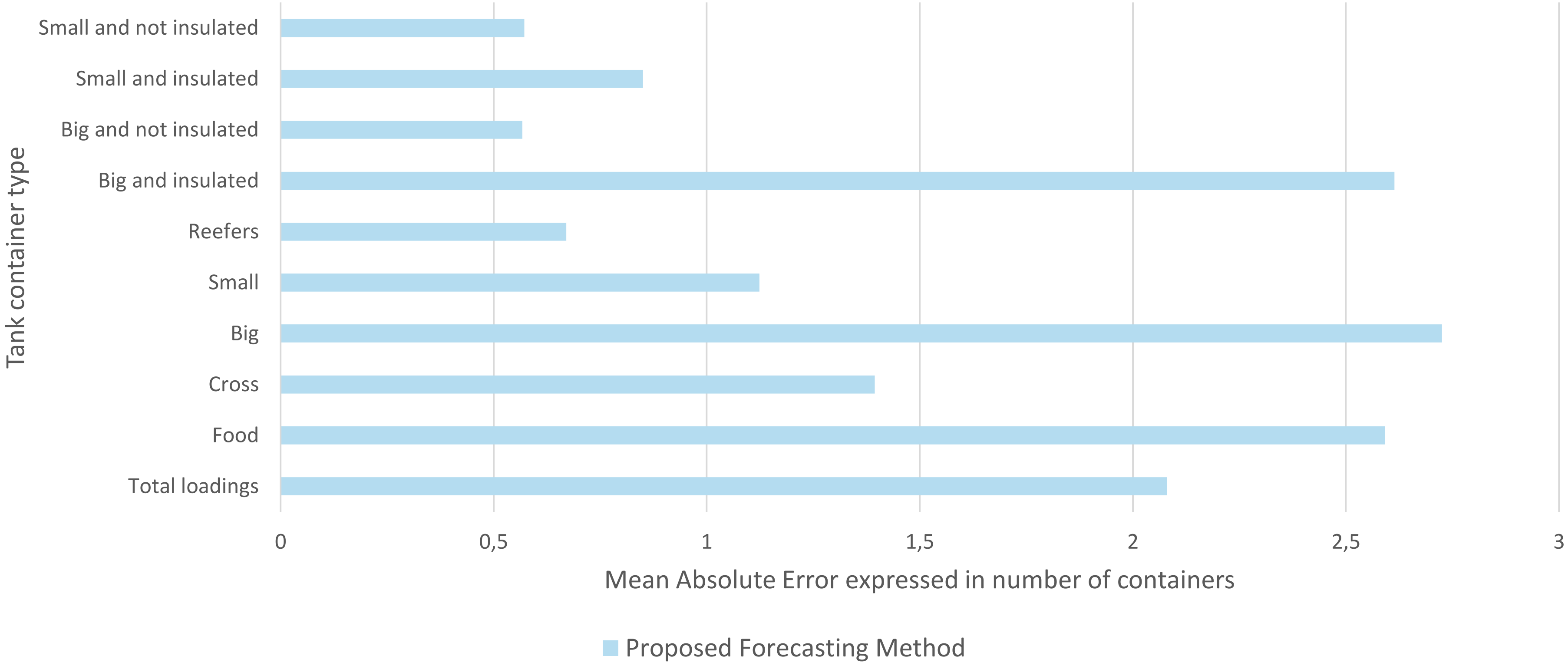
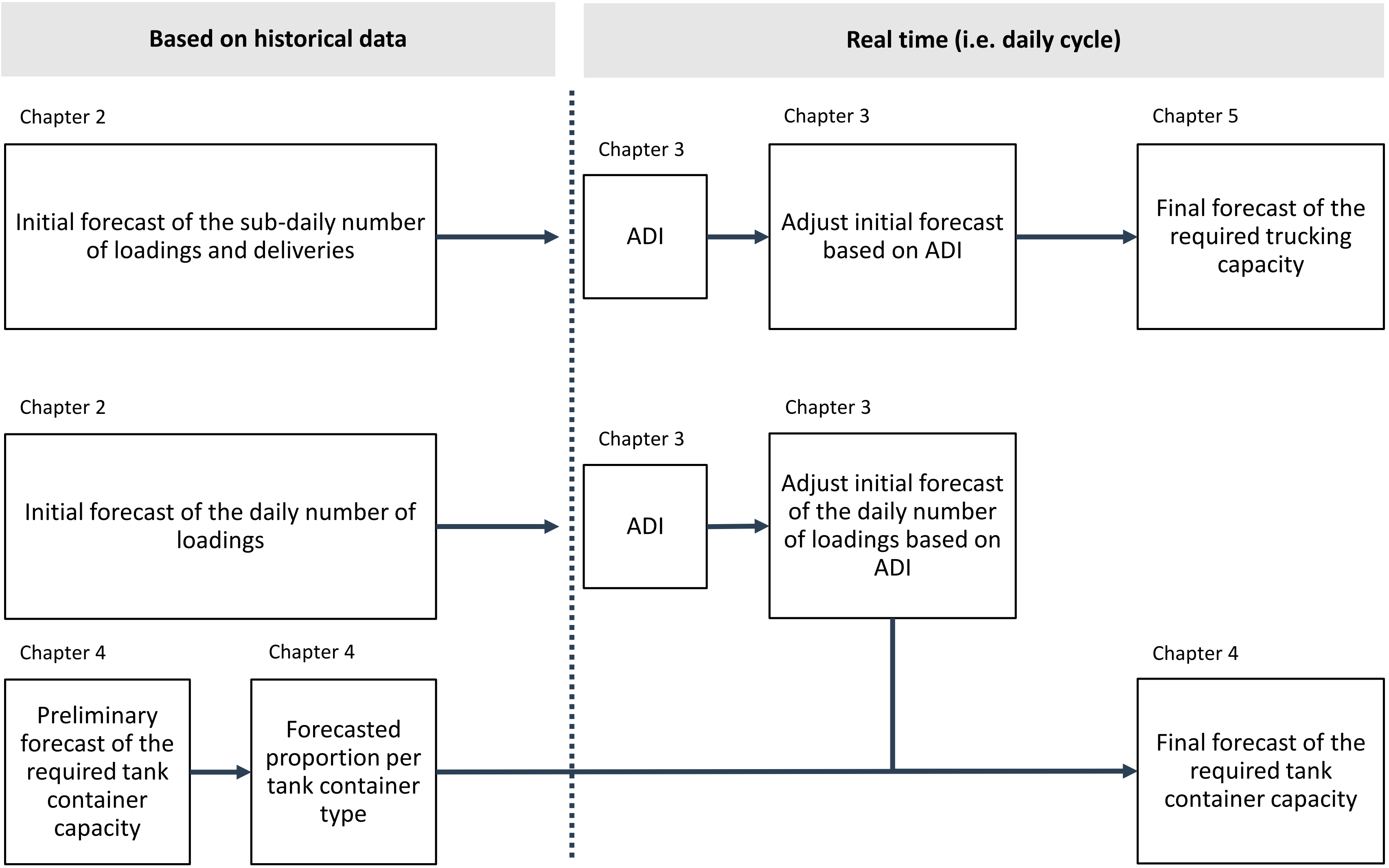
Predictive accuracy tank container forecast in the Rotterdam planning region



Mean Absolute Error differs per type of tank container and varies between approximately 0.5 and 3

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



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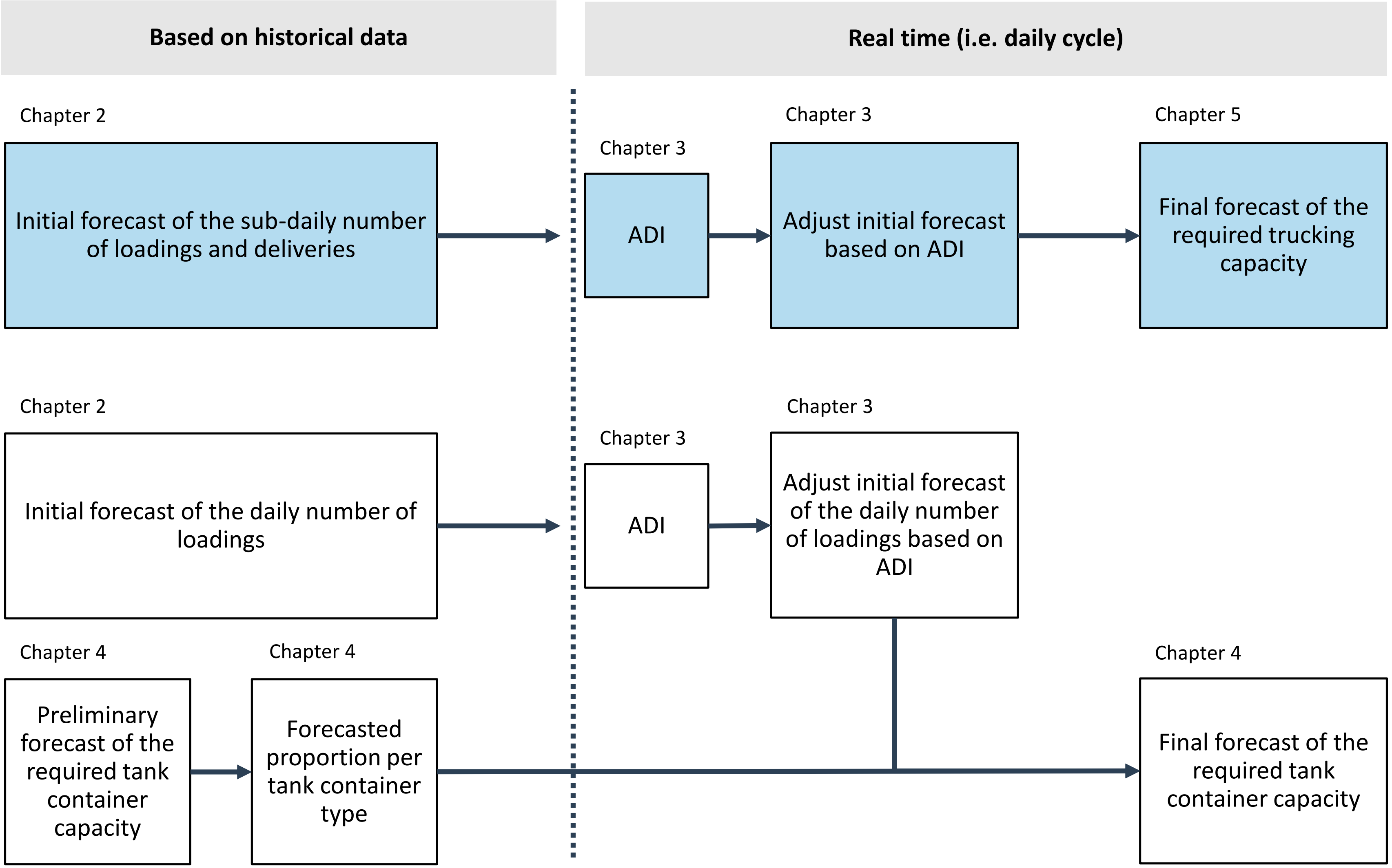
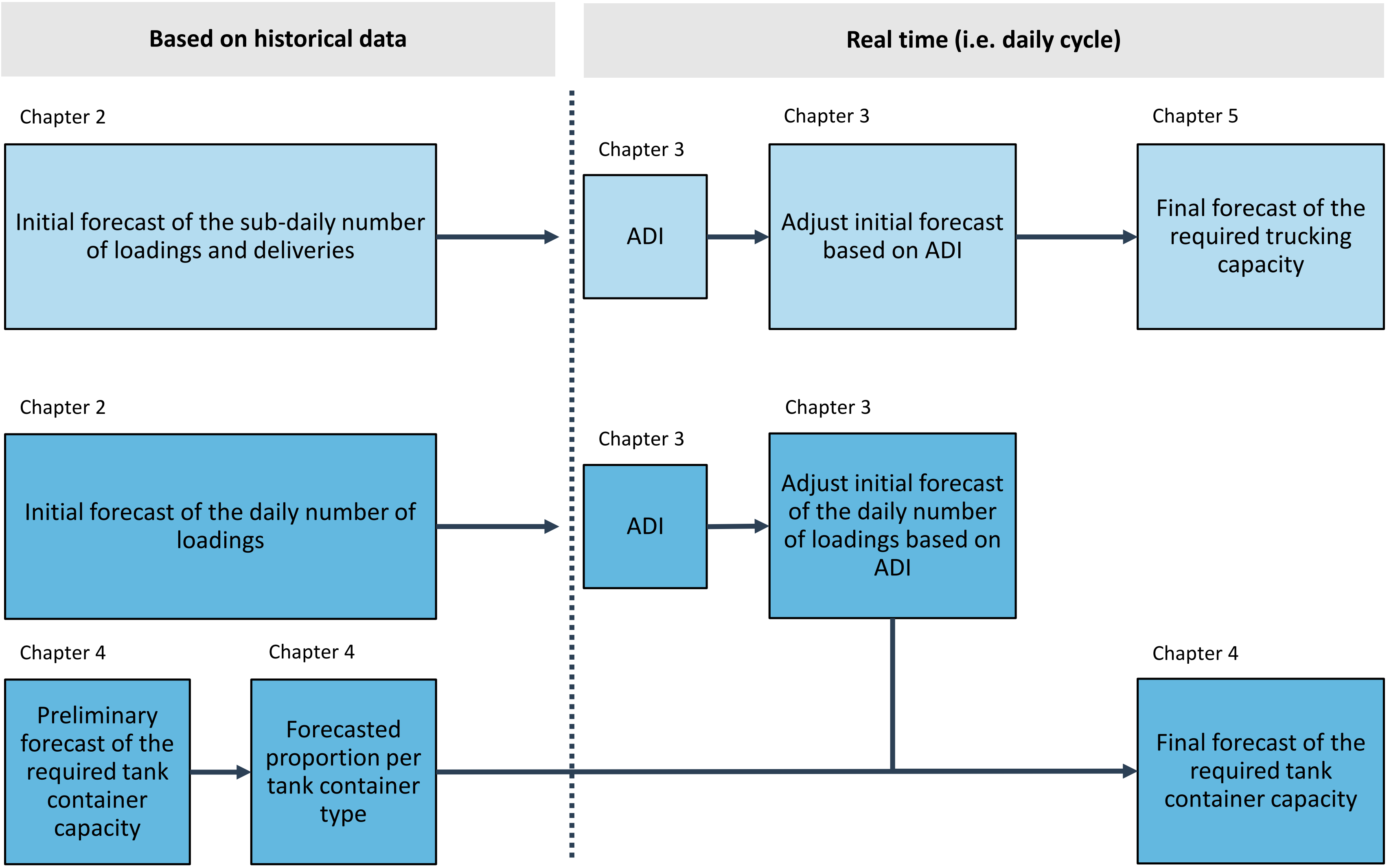


Summary of the proposed forecasting methodology for predicting the number of orders and corresponding capacity requirements



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

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

Commercial managers might use the forecast to proactively look for work for periods in which the demand is expected to be low

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

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
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

The forecasting methodology proposed by this research is now being implemented at H&S (and Den Hartogh)

Implementation project

Stakeholders implementation project

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

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Thanks for your attention