

ADDING **WEATHER DATA** TO ANALYSES OF VEHICLE SYSTEMS

*Performance and
robustness thereof!*

RENO FILLA
TRATON GROUP R&D

2026-02-04

TRATON

WEATHER DATA

*From forecasts
and real observations*



RENO FILLA

PhD from LiU (IEI, 2011)
Fluid Power and Mechatronics

Energy Efficiency
Electromobility and Energy Systems
Automation and Human Factors

20 years at Volvo CE, R&D
Senior Technology Specialist

7+ years at Scania/Traton, R&D
Expert Engineer



WE'VE GOT A PROBLEM

(Industry and Academia)

Performance of any vehicle is affected by weather

- Directly
 - Air temperature
 - Air pressure
 - Air humidity
 - Wind speed + direction
 - Precipitation (rain, snow, hail ...)
 - Cloudiness and solar radiation (effectiveness of solar panels)
- Indirectly: road (friction + rolling resistance)
 - Ice, snow, water on road
 - Surface temperature
 - Ground temperature

Major energy sinks:

- Powertrain losses
- Elevation change
- Air resistance
- Rolling resistance

WE'VE GOT A PROBLEM

(Industry and Academia)

Weather changes all the time

We usually ignore this (or only roughly approximate it)

- in analysis of recorded operation
- in simulation
- in component/system dimensioning

We risk that...

- we write off poor performance as due to bad weather and thus miss real deviations
- we design products with poor performance robustness due to insufficient testing in bad conditions

By picking safe, nominal environmental conditions we ignore the variability that exists in the real world.

We do this at our own peril.

https://inetstgi.com/images/B27/images/3b9562c9.jpg

WE'VE GOT A SOLUTION

(Industry and Academia)

We now have

- data
- tools
- methods

Main idea: Make it easy to combine observed or forecasted weather with vehicle logs

- recorded operation
- simulated missions

(more to come)

data **MDPI**

Article
Using Weather Data for Improved Analysis of Vehicle Energy Efficiency
Reno Filla

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Abstract In moving vehicles, the dominating energy losses are due to interactions with the environment: air resistance and rolling resistance. It is known that weather has a significant impact, yet there is a lack of literature showing how the wealth of openly available data from professional weather observations can be used in this context. This article will give an overview of how such data are structured and how they can be accessed in order to augment logs gained during vehicle operation or simulated trips. Two efficient algorithms for such data extraction and augmentation are discussed and several examples for use are provided, also demonstrating that some caveats do exist with respect to the source of weather data.

Keywords: environmental losses; energy losses; tire losses; rolling resistance; air resistance; air drag; weather data; meteorological observations; recorded weather

1. Introduction

In moving vehicles, the energy losses due to the interaction with the environment are highly significant [1,2] to the point that they become dominant in the case of vehicles with energy-efficient powertrains, such as battery electric vehicles, BEVs. There, these losses have a large impact on driving range and thus determine the installed battery capacity. With the battery being a major cost factor in any BEV, it is therefore of great interest to be able to reliably quantify a vehicle's environmental losses in operation.

In contrast to off-road machines [3], in on-road vehicles, the environmental interactions are only due to the vehicle moving on the road and through the air.

- Energy spent on traversing the road profile;
- Energy spent on overcoming rolling resistance due to tire losses;
- Energy spent on overcoming aerodynamic resistance due to air drag.

The item listed first does not constitute a true loss since a change in elevation also results in a change in potential energy—in both directions. The inability of conventional powertrains with internal combustion engines to recuperate this energy by means of regenerative braking can to a certain degree be mitigated by coasting.

The latter two items in the above list, rolling and air resistance, are true losses because it is not possible to avoid or recuperate this expenditure of energy—though a lot of work is spent in research and development on minimizing these losses as much as possible. For this, it is essential to be able to quantify these losses. Many literature references can be found on tire models [4] and aerodynamic models [5] but, as always, correct results will only be achieved if the models are fed correct input data. Apart from the vehicle design and movement, air drag is affected by the movement and density of the air (wind speed and direction, air temperature, air pressure, humidity, precipitation) while tire losses apart from

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Data 2025, 16, 31 <https://doi.org/10.3390/data1003031>

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Study of Long-Term Variation of Air Resistance of a Tractor with Semitrailer Using Recorded Weather Data Together with Vehicle Data

Reno Filla¹
¹Traton AB, Sweden

Abstract

With air resistance being one of the two major energy losses in on-road vehicles (the other one being tire losses) and therefore heavily contributing to the range of battery electric and fuel cell electric vehicles, it is necessary to account for realistic air resistance in a priori assessments like vehicle range estimations, component dimensioning, and system simulations.

However, lack of input data tempts analysts to instead assume unrealistic "nominal conditions" throughout—a simplification which usually underestimates the amount of energy actually required to overcome air resistance and completely ignores the fact that varying environmental conditions will lead to significant variances in energy consumption and therefore vehicle range. Using "nominal conditions," it is thus impossible to assess the robustness of these measures and, therefore, difficult to design robust systems and to perform meaningful trade-off studies.

In this study, we show how publicly available data from weather observations can be used to assess the long-term variation of air resistance of a truck with a semitrailer. Realistic distributions of energy losses due to air resistance, covering multiple years, are derived—showing not only average values but the complete envelope in which the energy losses vary.

This, in turn, enables to follow up with probabilistic calculations of vehicle performance in order to assess robustness and trade-offs on various system levels of interest. As a consequence, consumption and range predictions of EVs and ICE vehicles can be performed with higher accuracy and confidence.

History
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Revised: 22 Oct 2025
Accepted: 25 Nov 2025
Available: 01 Dec 2025

Keywords
Vehicle range prediction, Environmental losses, Energy consumption, Energy losses, Air resistance, Air drag, Weather data, Meteorological observations, Recorded weather

Citation
Filla, R., "Study of Long-Term Variation of Air Resistance of a Tractor with Semitrailer Using Recorded Weather Data Together with Vehicle Data," SAE Int. J. Commer. Veh. 16(2):0205, doi:10.4271/02-19-02-0010.
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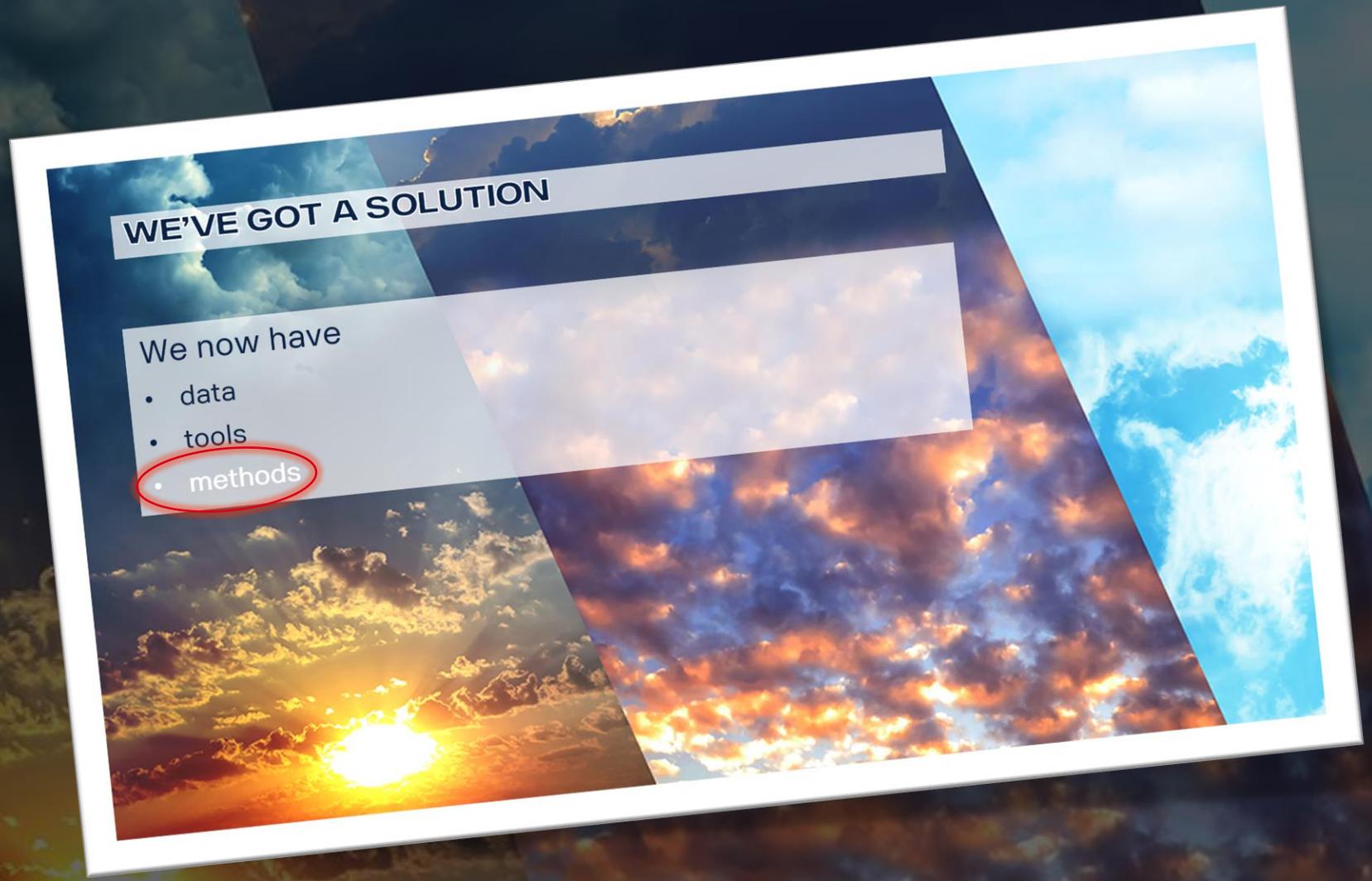
<https://doi.org/10.3390/data10030031>

<https://doi.org/10.4271/02-19-02-0010>

WE'VE GOT A SOLUTION

We now have

- data
- tools
- **methods**



METHODS

Use cases for

- Statistical distributions
- Time series data



ANIA

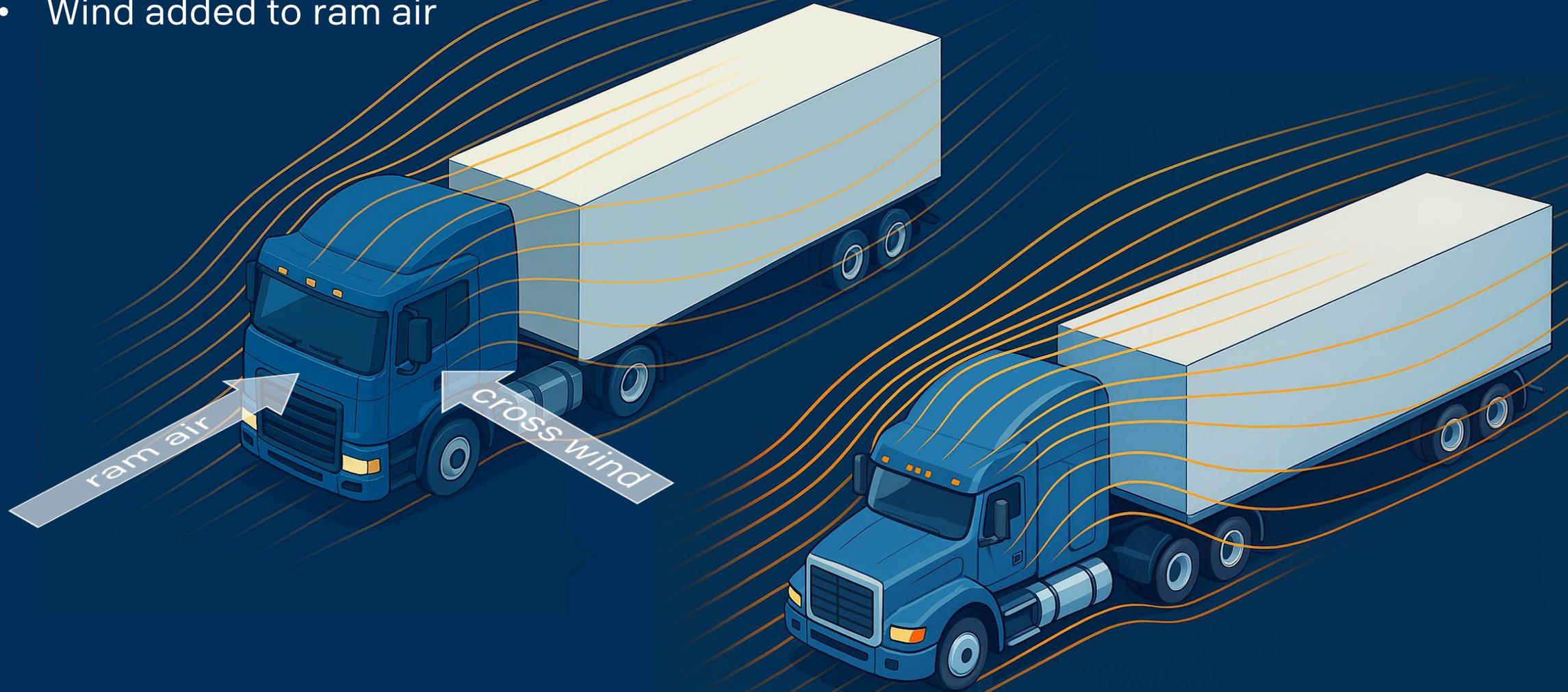
AERODYNAMICS

SCANIA



Air resistance in realistic conditions

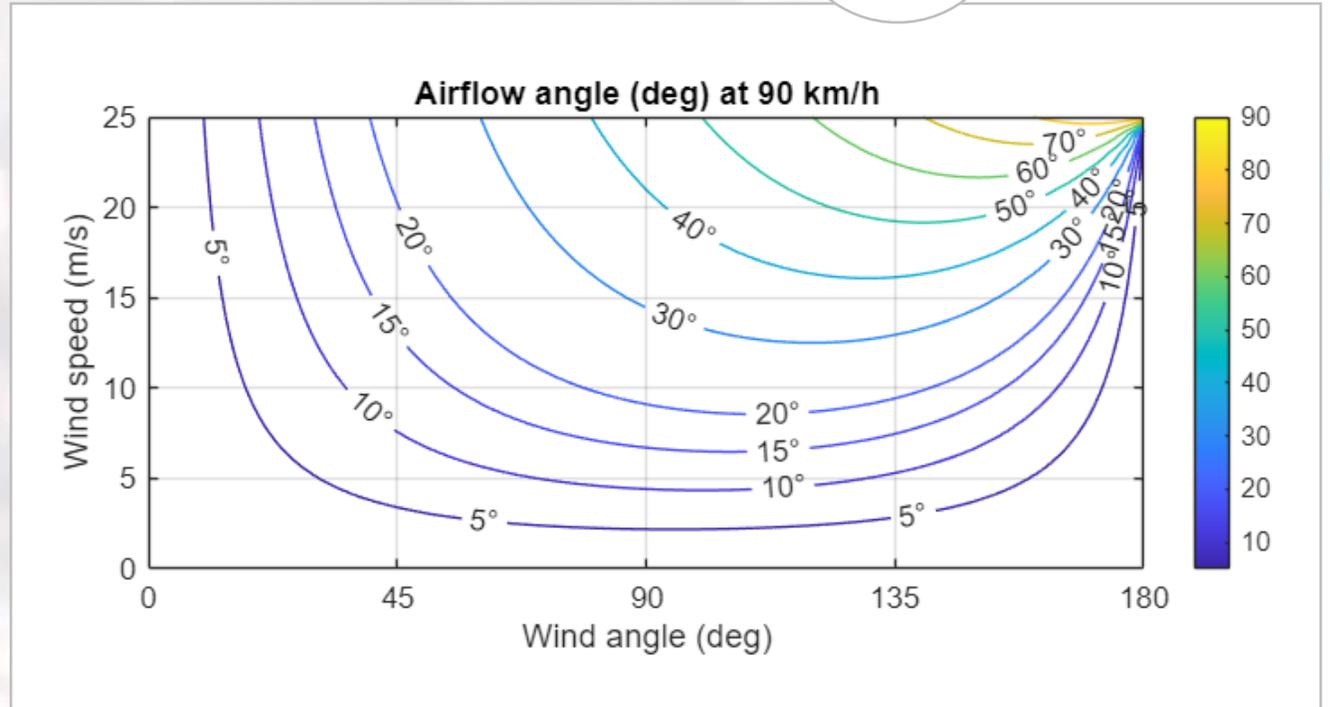
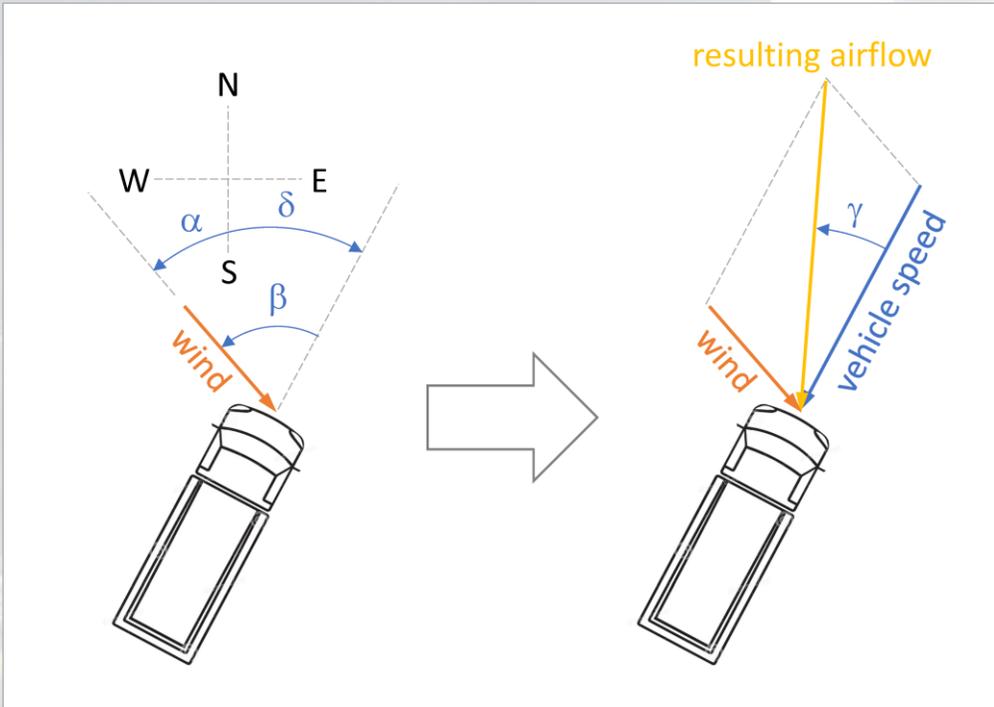
- Wind added to ram air



Air resistance in realistic conditions

- Wind added to ram air

How much do energy losses due to air resistance vary due to weather?

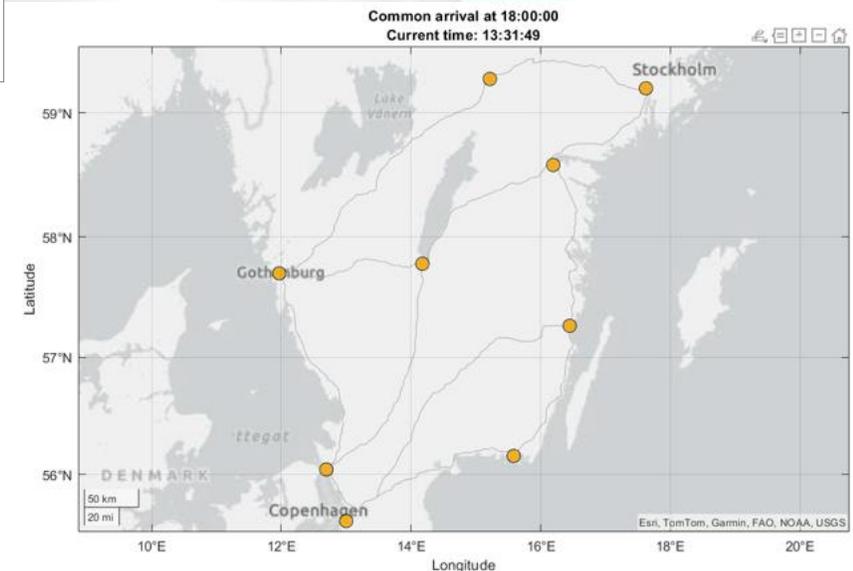
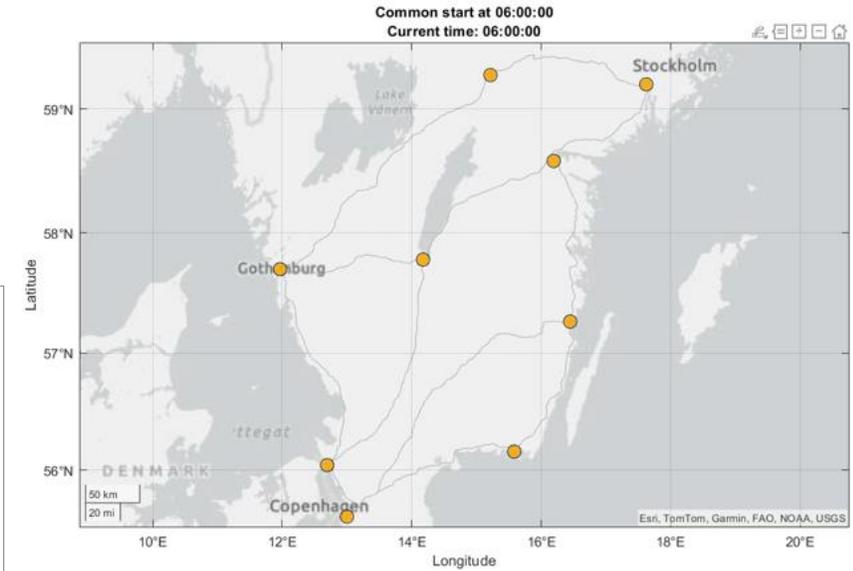


Create + analyse synthetic time-series data

- 11 routes over major roads in Mid/South Sweden
 - Realistic vehicle speed (typical traffic)
 - Speed limits obeyed, max 90 km/h
- Driven 2× a day in both directions
 1. Common start at 06:00 LT
 2. Common arrival at 18:00 LT
- Combine with recorded weather
 - For each day over up to 5 years
- Analyse energy losses
 - Air resistance
 - Rolling resistance

Göteborg	↔	Örebro
Örebro	↔	Södertälje
Göteborg	↔	Jönköping
Jönköping	↔	Norrköping
Norrköping	↔	Södertälje
Malmö	↔	Göteborg
Helsingborg	↔	Jönköping
Malmö	↔	Oskarshamn
Karlskrona	↔	Oskarshamn
Oskarshamn	↔	Norrköping

Advantage of analyzing these two major losses isolated: independent of type of powertrain



Create + analyse synthetic time-series data

Time	Timestamp_UTC	Latitude	Longitude	Distance_incr	Distance_cum	Elevation	Heading	Speed	Speed_limit
0	2024-03-04 11:52:29	57.712	11.968	0	0	1.6533	70.658	5	13.889
2.0211	2024-03-04 11:52:31	57.712	11.968	10.105	10.105	1.6965	70.658	5	13.889
4.0422	2024-03-04 11:52:33	57.712	11.968	10.105	20.211	1.7251	76.829	5	13.889
6.0009	2024-03-04 11:52:35	57.712	11.968	9.7938	30.005	1.8006	70.658	5	13.889
8.022	2024-03-04 11:52:37	57.712	11.969	10.105	40.11	1.8833	77.579	5	13.889
10.097	2024-03-04 11:52:39	57.712	11.969	10.375	50.485	1.9658	76.829	5	13.889
12.056	2024-03-04 11:52:41	57.712	11.969	9.7937	60.279	2.0419	70.658	5	13.889
14.077	2024-03-04 11:52:43	57.712	11.969	10.105	70.384	2.072	113.36	5	13.889

Matlab/Python toolbox

Scania-internal development by Reno Filla, started in 2019

- HERE: routing + typical traffic + speed limits
- Google: resample to high resolution + elevation
25m intervals = 1Hz sampling at 90 km/h
- HERE: match back to road
- Trafikverket: recorded weather (REST API + VViS)
- SMHI: recorded weather

$$E_{air_drag} = \int F_{air_drag} v_{veh} dt$$

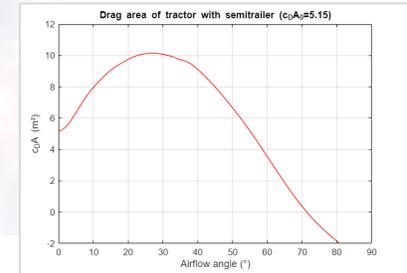
$$F_{air_drag} = \frac{\rho_{air}}{2} v_{air}^2 c_D(\gamma) A$$

Create + analyse synthetic time-series data

Time	Timestamp_UTC	Latitude	Longitude	Distance_incr	Distance_cum	Elevation	Heading	Speed	Speed_limit
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6.0609	2024-03-04 11:52:35	57.712	11.968	9.7938	30.005	1.8006	70.658	5	13.889
8.022	2024-03-04 11:52:37	57.712	11.969	10.105	40.11	1.8833	77.579	5	13.889
10.097	2024-03-04 11:52:39	57.712	11.969	10.375	50.485	1.9658	76.829	5	13.889
12.056	2024-03-04 11:52:41	57.712	11.969	9.7937	60.279	2.0419	70.658	5	13.889
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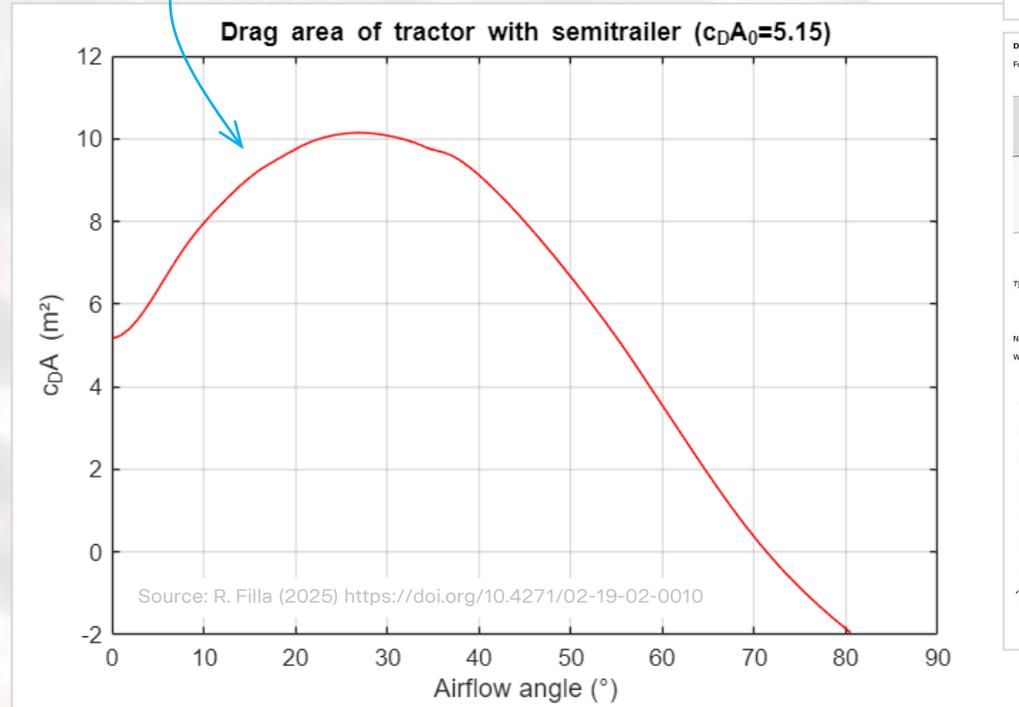
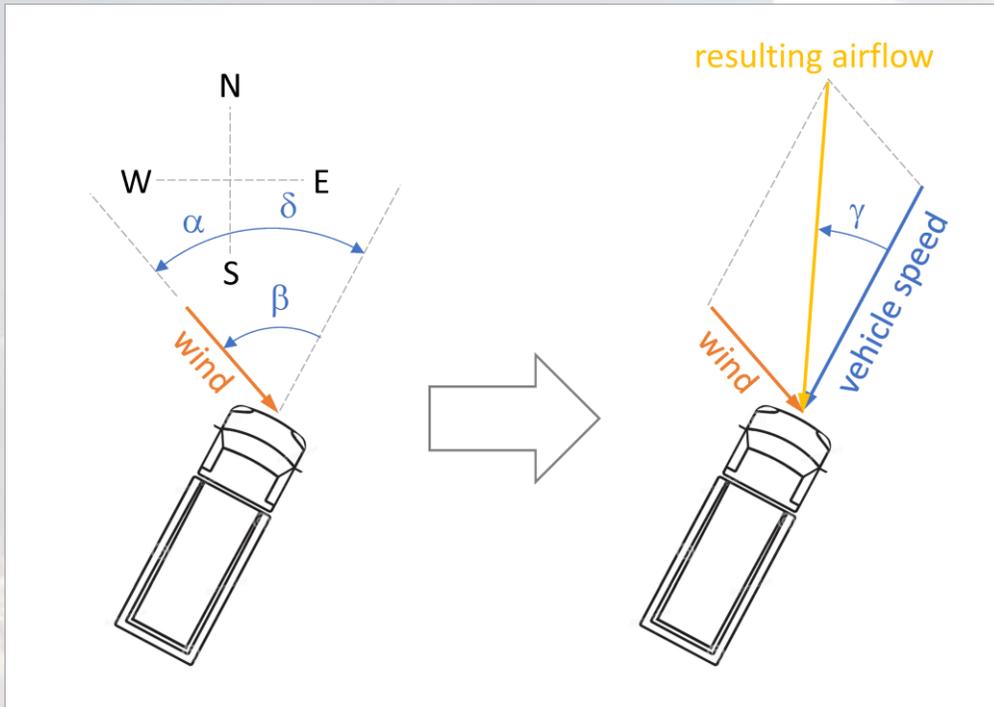


Air resistance in realistic conditions

- Wind added to ram air

back-calculated
combining data from

- M. Askerdal et al. (2024)
- Volvo Trucks PERF



Askerdal, M., Fredriksson, J. and Laine, L.,
Development of Simplified Air Drag Models Including
Crosswinds for Commercial Heavy Vehicle
Combinations, Vehicle System Dynamics 62, no. 5
(2024): 1085-1102, doi:https://doi.org/10.1080/00423114.2023.2213786.

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https://doi.org/10.1080/00423114.2023.2213786

Development of simplified air drag models including crosswinds for commercial heavy vehicle combinations

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^aDepartment of Mechanical Engineering, Chalmers University of Technology, Gothenburg, Sweden;
^bDepartment of Mechanics and Maritime Sciences, Chalmers University of Technology, Gothenburg, Sweden;
^cDepartment of Vehicle Motion and Energy Management, Volvo Group Trucks Technology, Gothenburg, Sweden

ABSTRACT
Accurate range prediction requires good knowledge of the prevailing wind conditions and how they affect the energy consumption of a vehicle. A simplified air drag model is developed that explicitly includes the effect from crosswinds. The model is compared against some observed data. The model is used to estimate the effect from wind speed from the normal air drag equation while the effect from wind is explicit and therefore more transparent. The purpose is to find a low-complexity model complementing CFD models and wind tunnel tests that can be used for range estimation and predictive energy management algorithms. To simplify online estimation, a requirement is that the air drag model only contains few tuning parameters. The model is evaluated against CFD calculations for a few vehicle combinations and the best model shows good accuracy for air angles up to at least 45 degrees. It is shown that the parameters of the simplified model can loosely be connected to some basic geometrical and aerodynamic attributes. This is useful for making a first estimate of the aerodynamic properties of a vehicle combination after major changes in the vehicle, e.g. when adding a trailer. It also highlights that the size and the shape of the vehicle side may be mainly responsible for the high longitudinal air drag sensitivity to crosswinds for large vehicle combinations.

KEYWORDS
crosswinds; simplified model; aerodynamics

1. Introduction
Range anxiety is regarded as one of the real obstructions to a broad public acceptance of battery electric road vehicles [1]. For many commercial transport missions, there are also requirements for delivery on time. The combination of limited range and time requirements is especially bothersome since an attempt to increase the vehicle speed in order to increase the probability of fulfilling the time requirement may decrease the range and the probability of reaching the real destination or a charging spot and vice versa. Range prediction is about estimating available energy stored onboard the vehicle and predicting future

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Drag Coefficient (Cd)
Force (N) for 1m² of frontal area at an air speed of 1km/h.

Typical values FH/FM

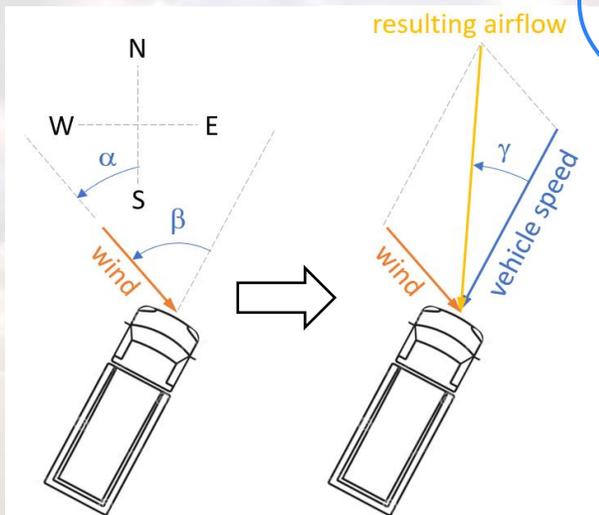
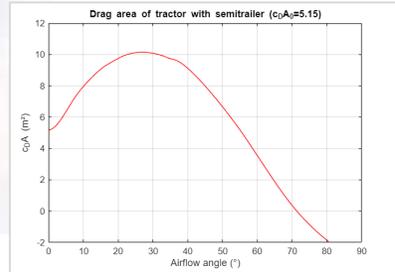
	Single truck	Truck and semitrailer	Truck and trailer
No air-flow equipment.....Cd =	0.7	0.8	
With air flow equipment.....Cd =	0.5	0.7	

Create + analyse synthetic time-series data

Time	Timestamp_UTC	Latitude	Longitude	Distance_incr	Distance_cum	Elevation	Heading	Speed	Speed_limit
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$$E_{air_drag} = \int F_{air_drag} v_{veh} dt$$

$$F_{air_drag} = \frac{\rho_{air}}{2} v_{air}^2 c_D(\gamma) A$$

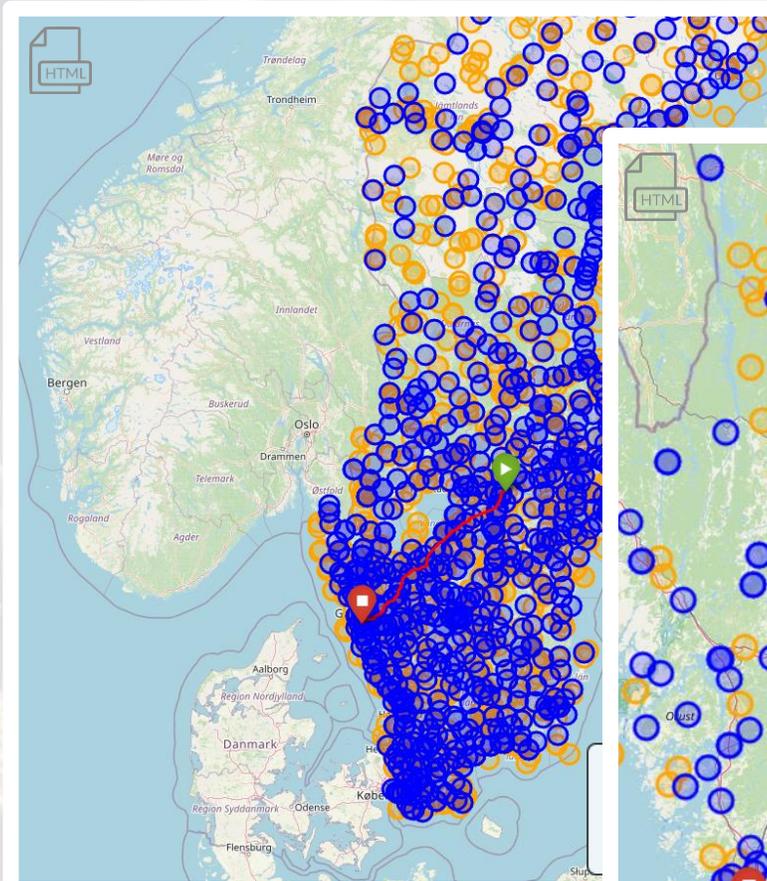


Trv → air temperature
 SMHI { air pressure
 air humidity
 elevation (altitude)

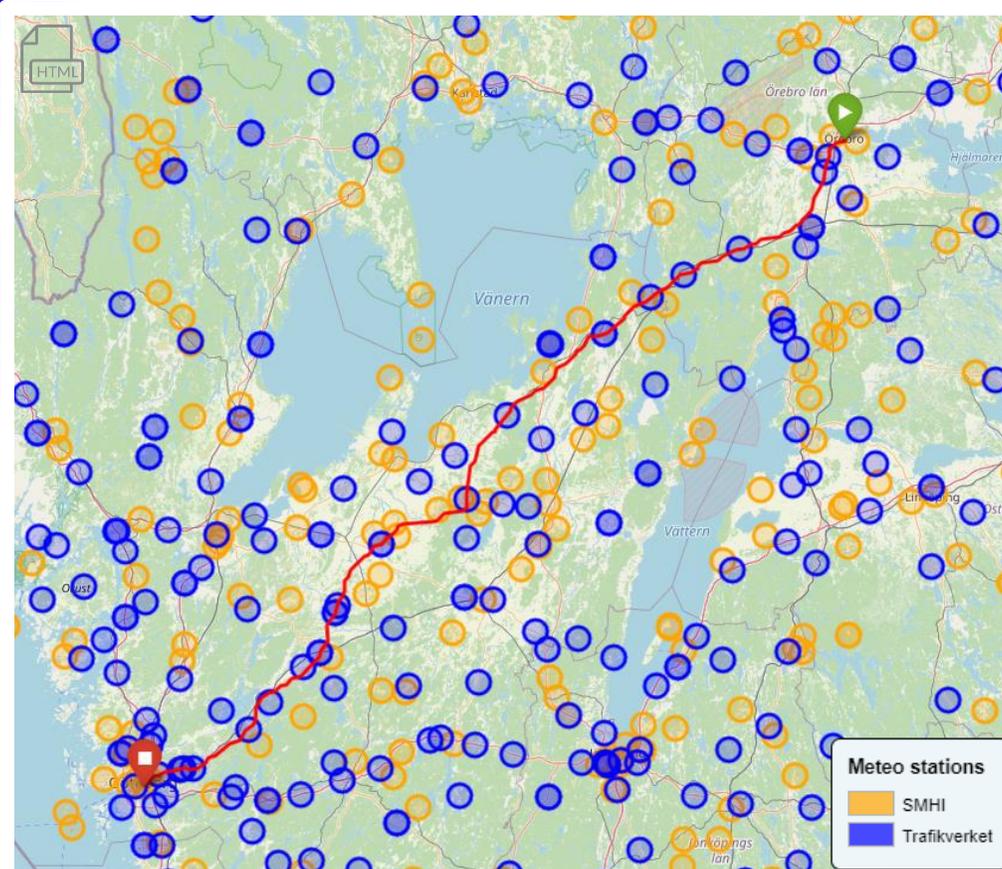
from synthetic vehicle log

wind direction } Trv
 wind speed }
 vehicle heading } log
 vehicle speed }

Create + analyse synthetic time-series data



Örebro → Göteborg



Create + analyse synthetic time-series data

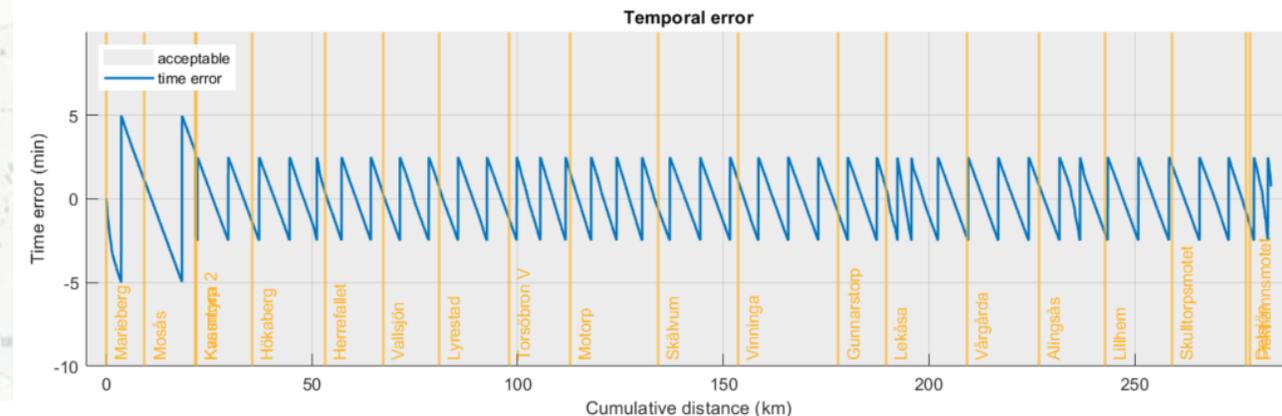
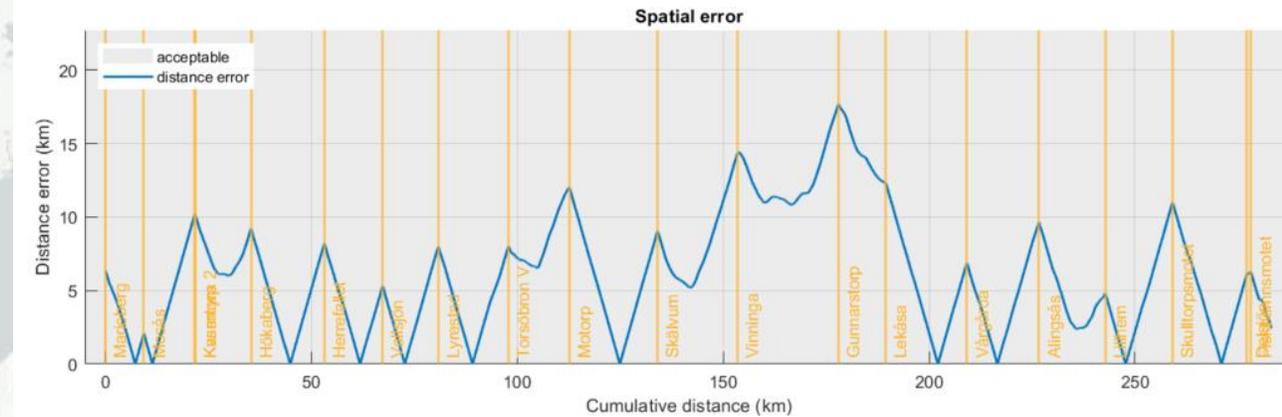
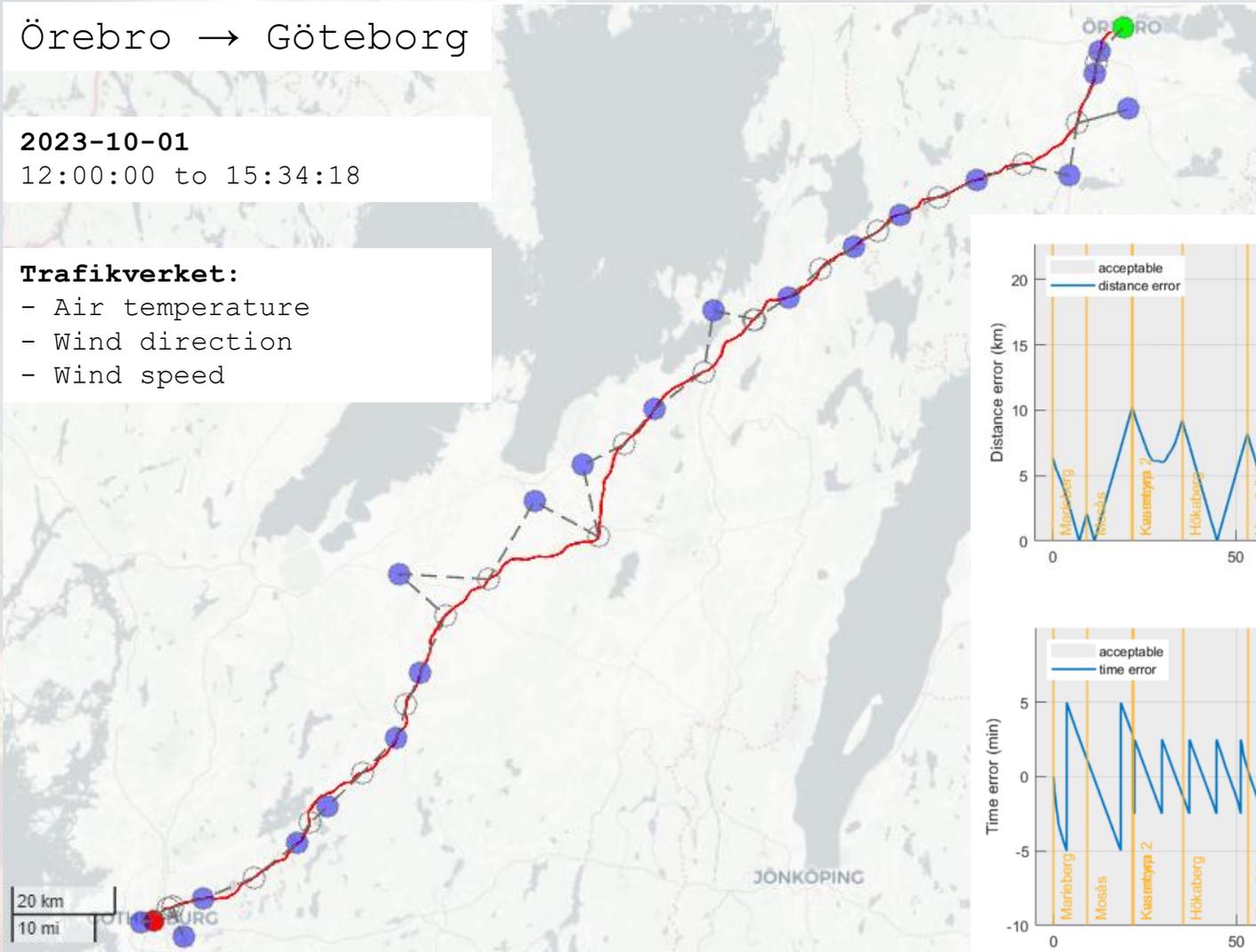
Örebro → Göteborg

2023-10-01

12:00:00 to 15:34:18

Trafikverket:

- Air temperature
- Wind direction
- Wind speed



Create + analyse synthetic time-series data

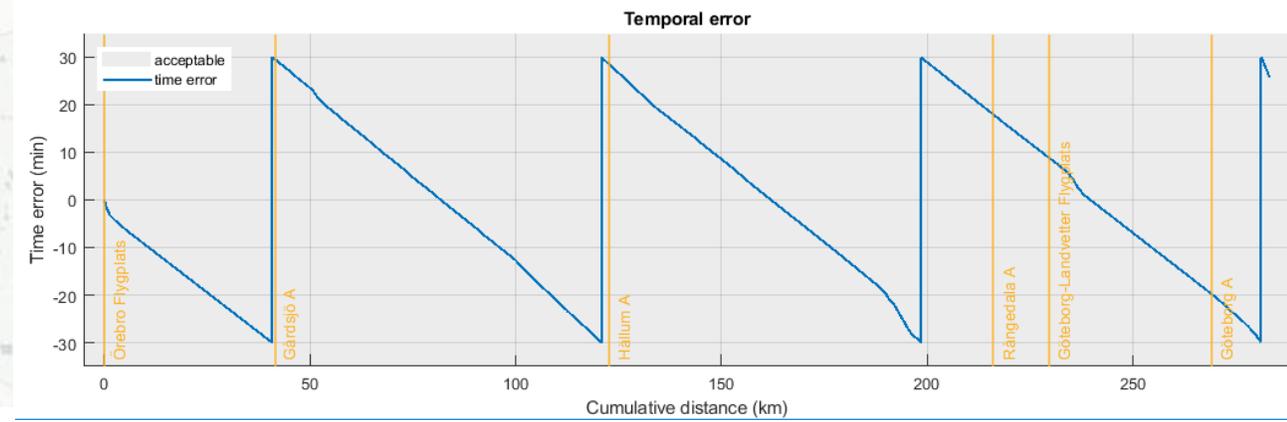
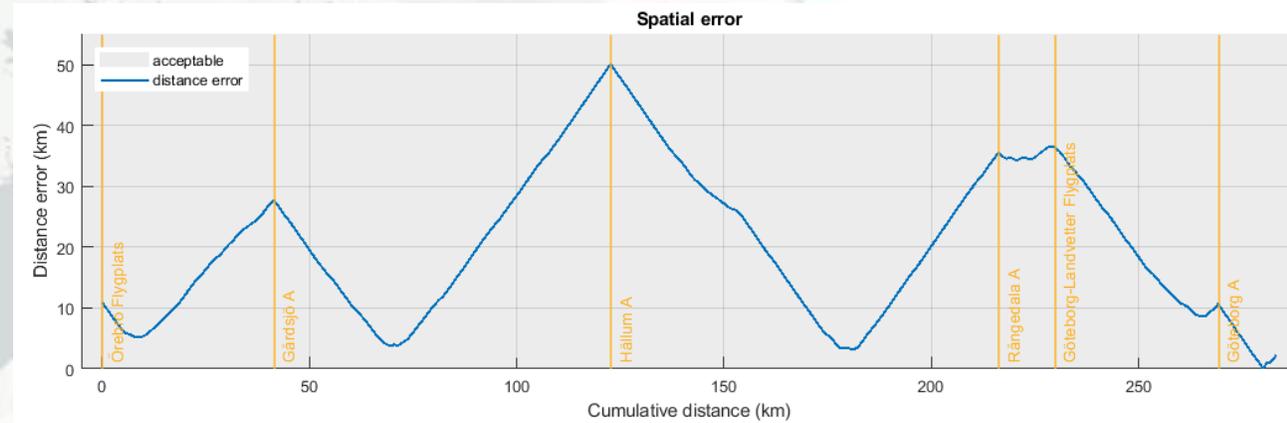
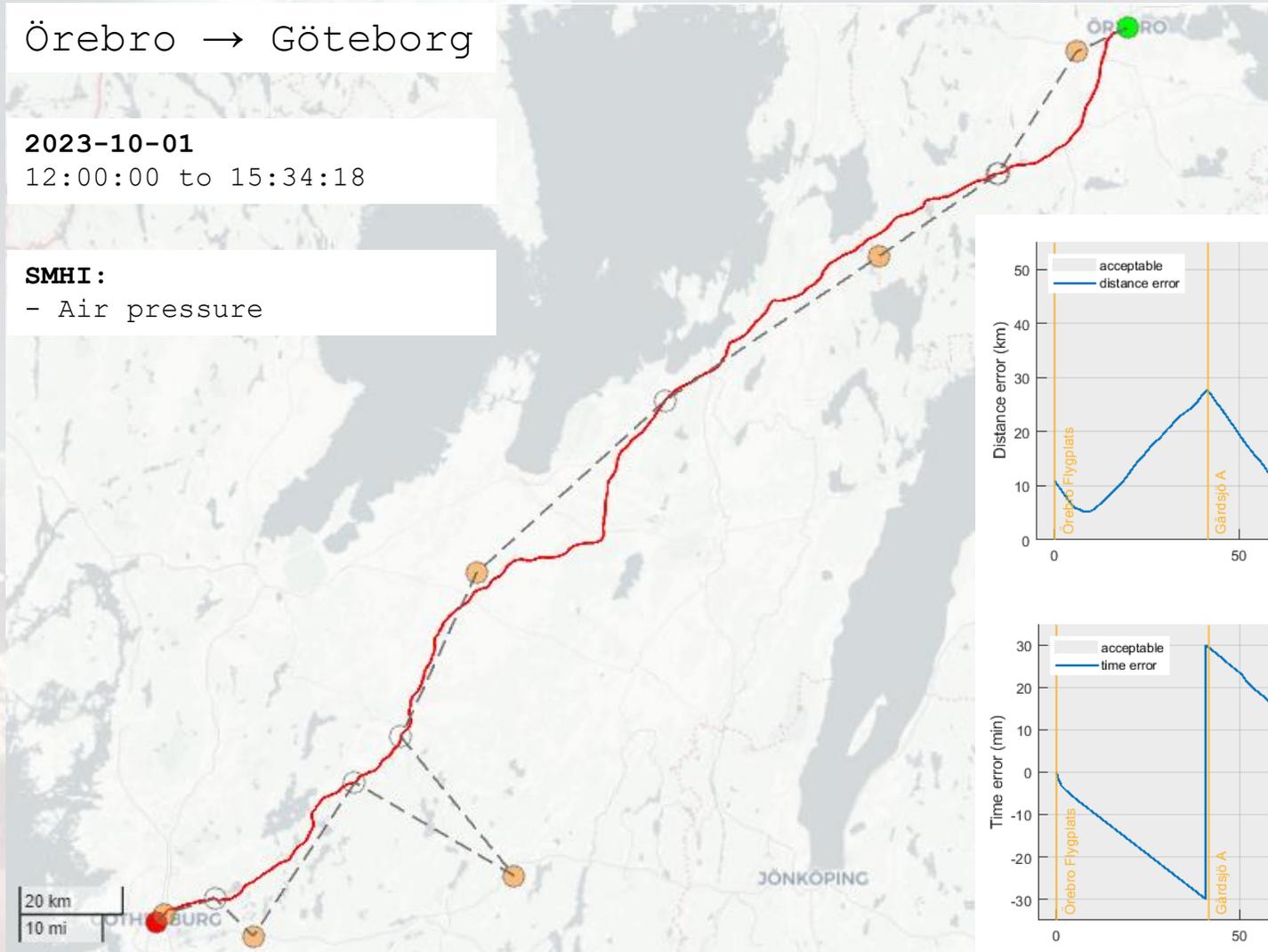
Örebro → Göteborg

2023-10-01

12:00:00 to 15:34:18

SMHI :

- Air pressure



Create + analyse synthetic time-series data

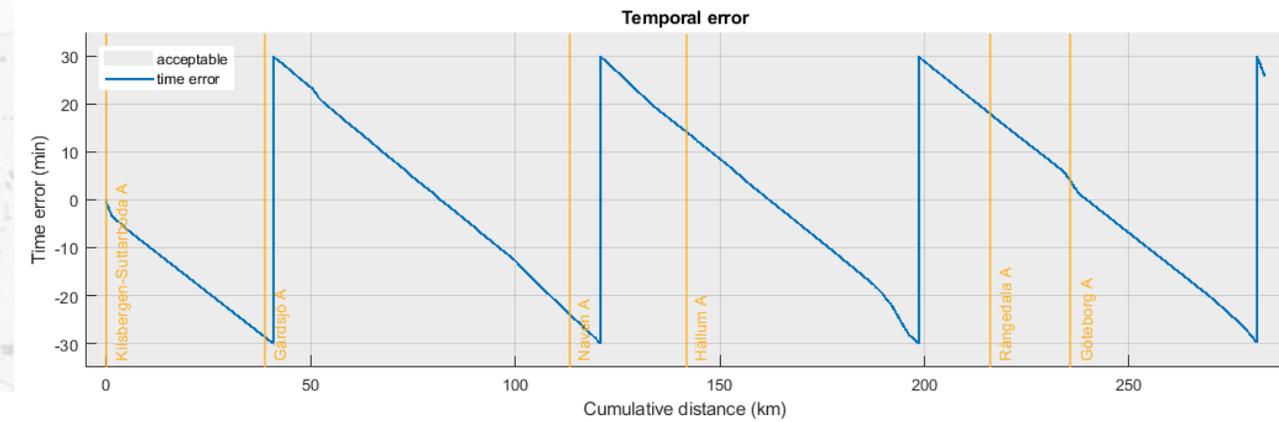
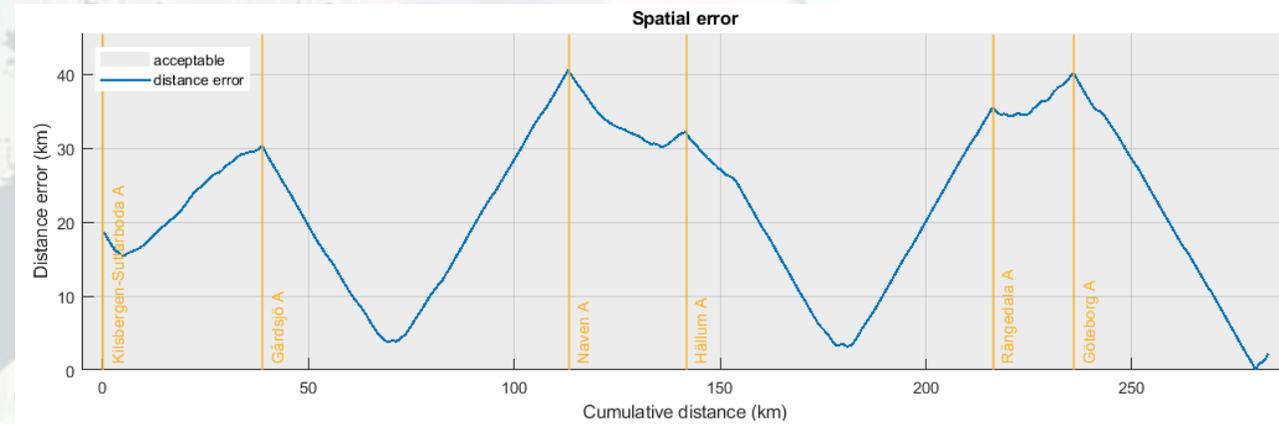
Örebro → Göteborg

2023-10-01

12:00:00 to 15:34:18

SMHI :

- Air humidity



Create + analyse synthetic time-series data

from synthetic vehicle log

Computed and aggregated for

- 11 routes
- 2 directions
- 2 times a day
- each day for 5 years

= 190 h of processing
(one-time effort)

from CFD simulations

TrV

SMHI

air t

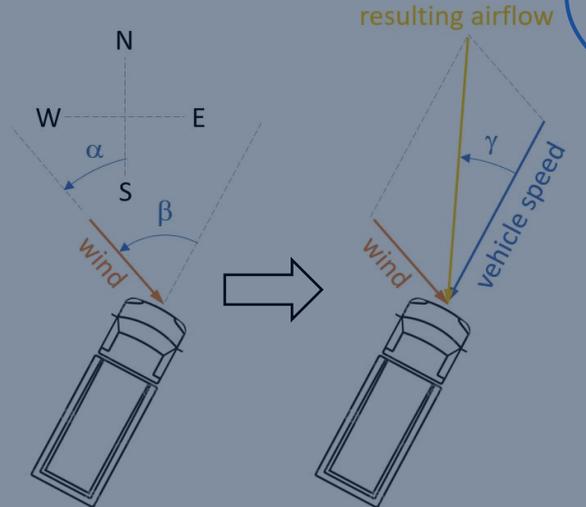
air p

air humidity

elevation (altitude)

from synthetic vehicle log

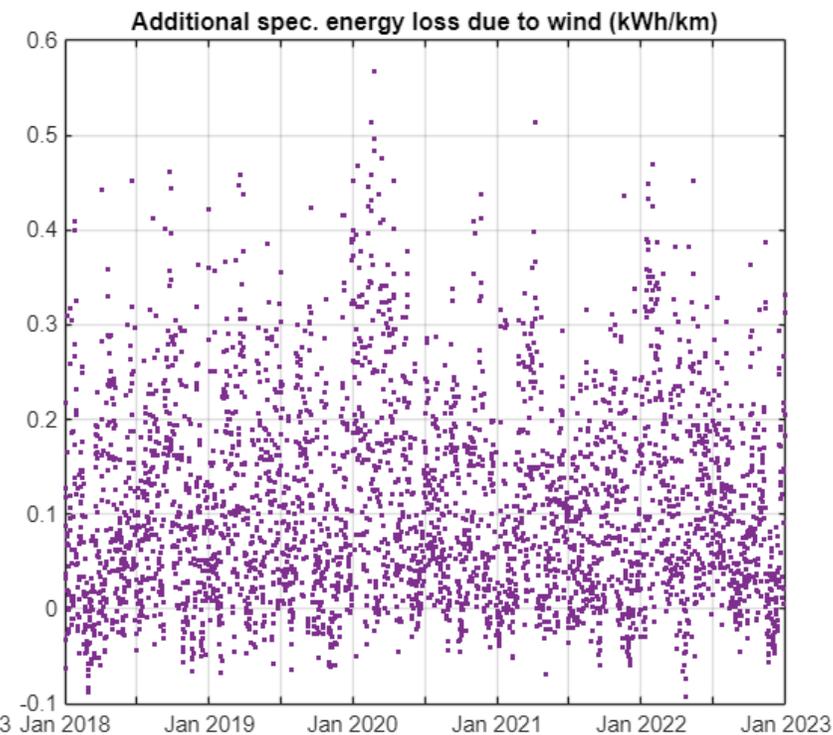
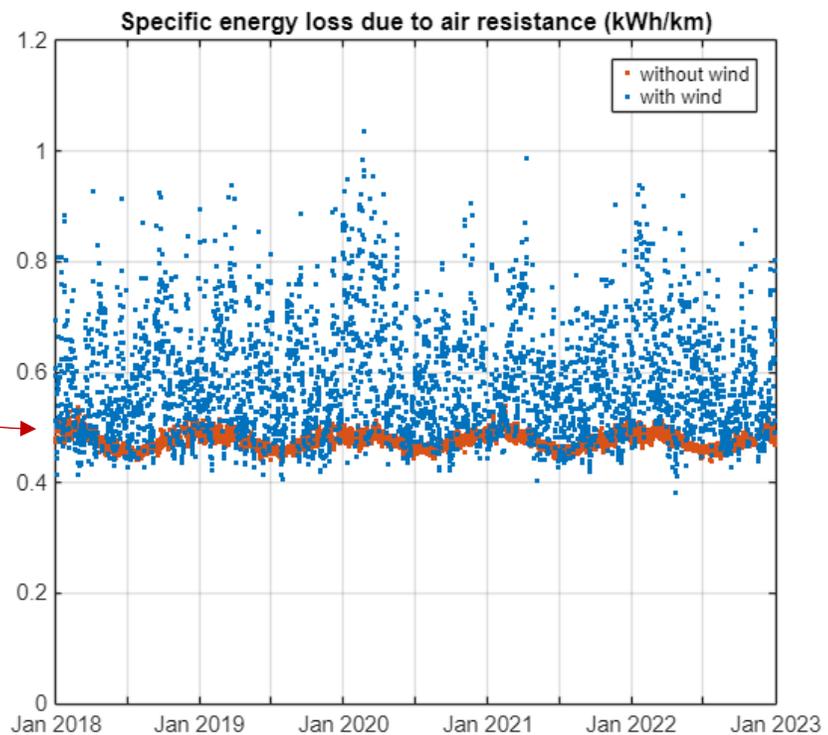
$$\frac{1}{2} v_{air}^2 C_D(\gamma) A$$



wind direction } TrV
wind speed }
vehicle heading } log
vehicle speed }

diff with wind to without wind
= robustness

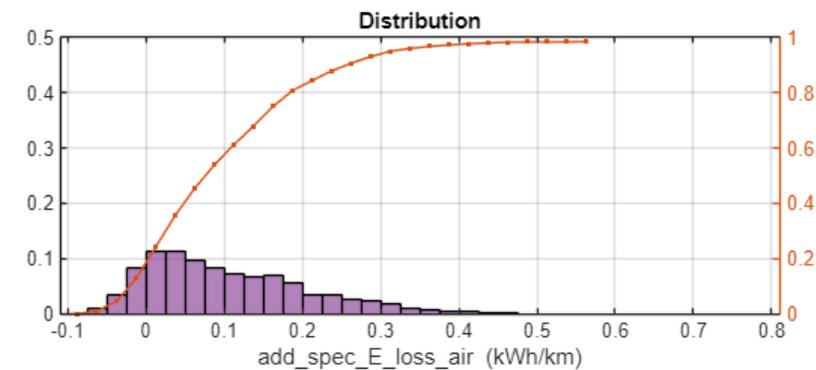
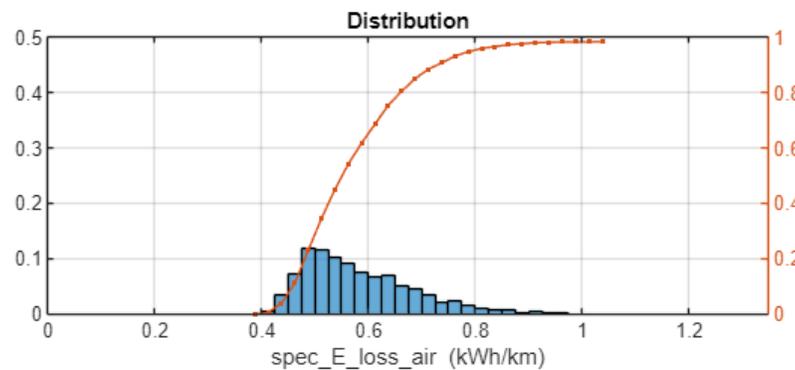
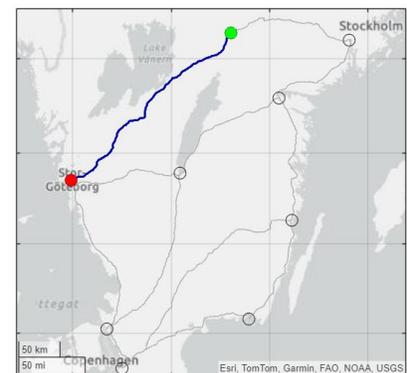
Route 12: Örebro - Göteborg



plot without wind
is not a horizontal line
due to air density changing
with air temperature, pressure,
and humidity

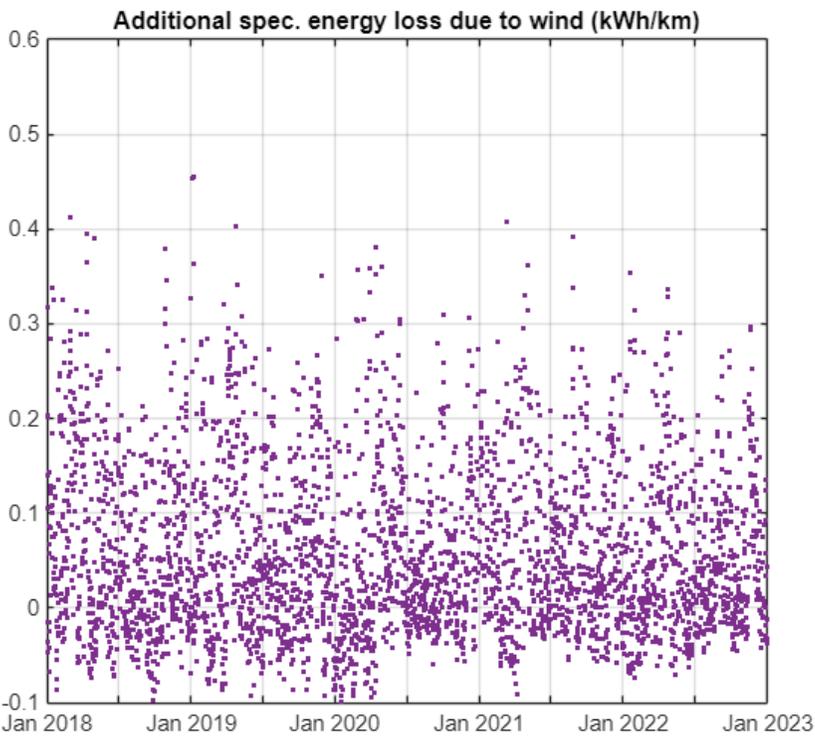
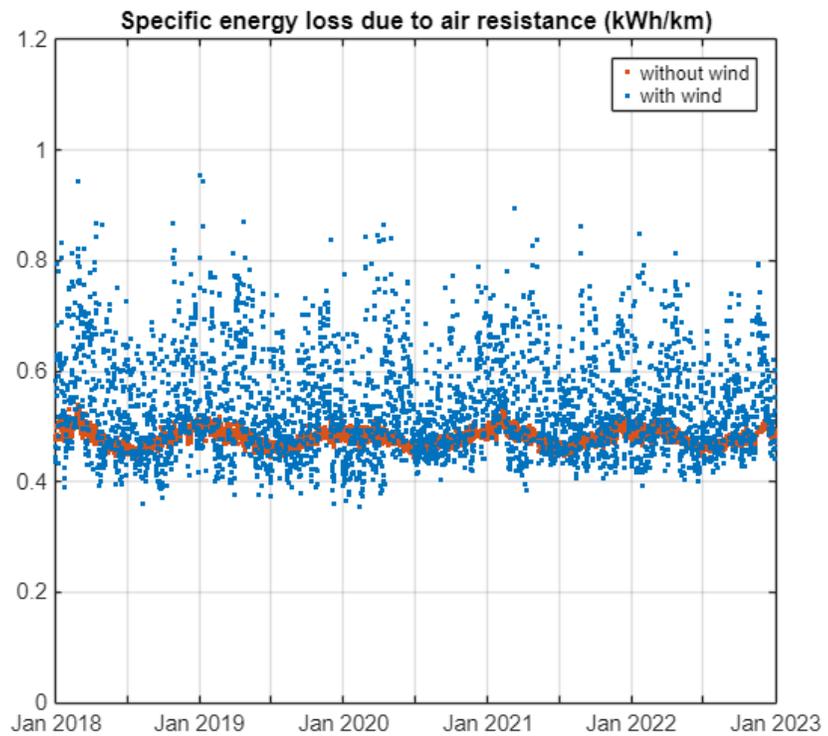
sinusoidal variation
due to the seasons
(winter vs summer)

Örebro → Göteborg

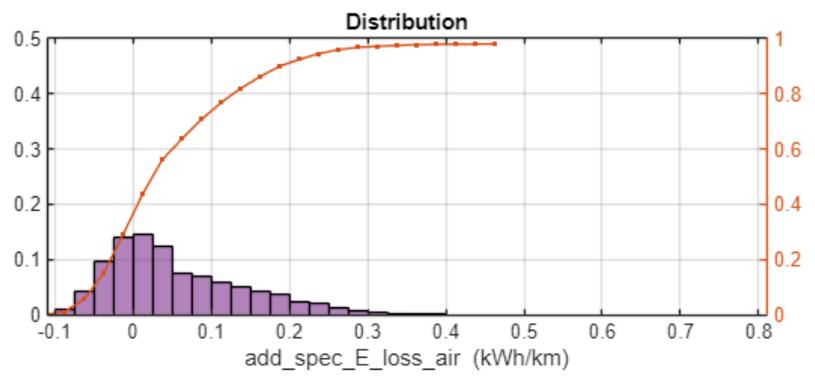
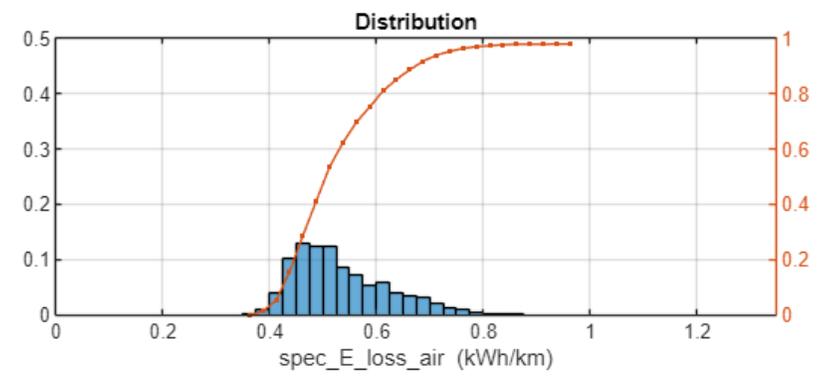
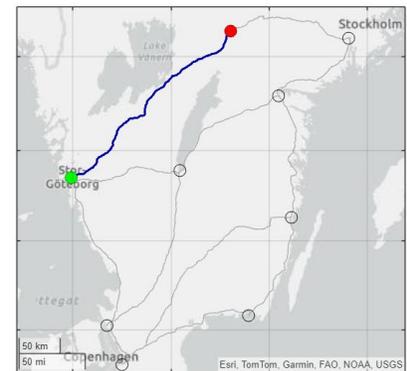




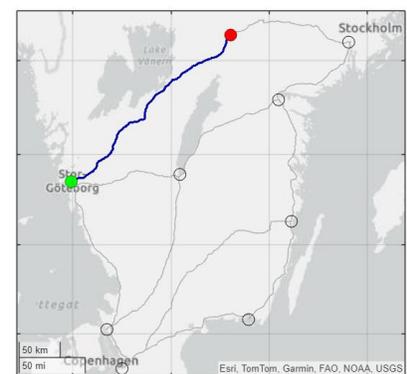
Route 1: Göteborg - Örebro



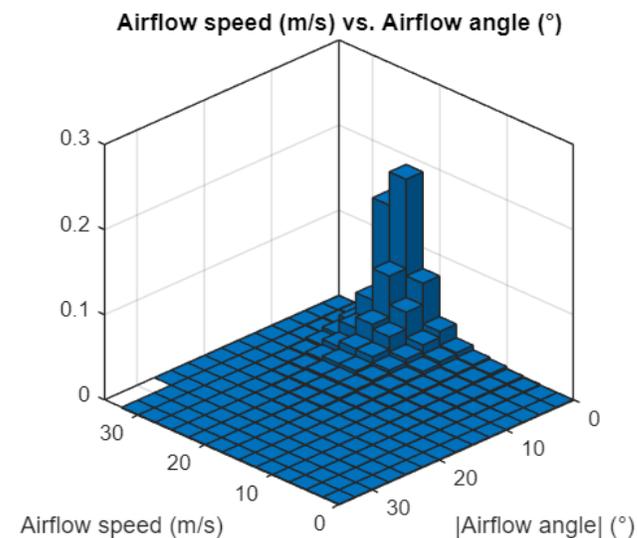
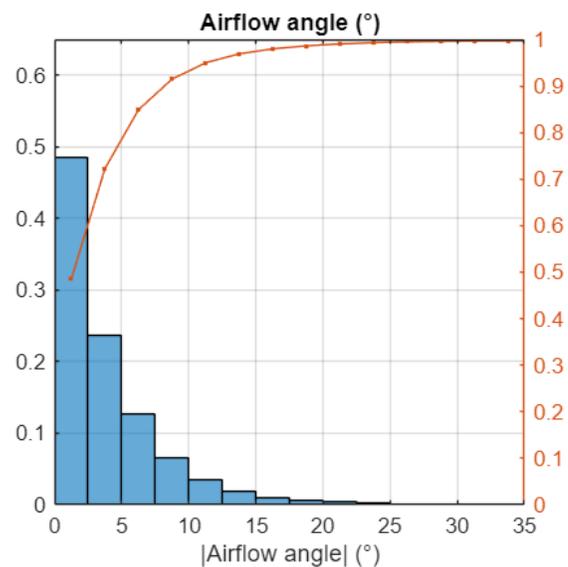
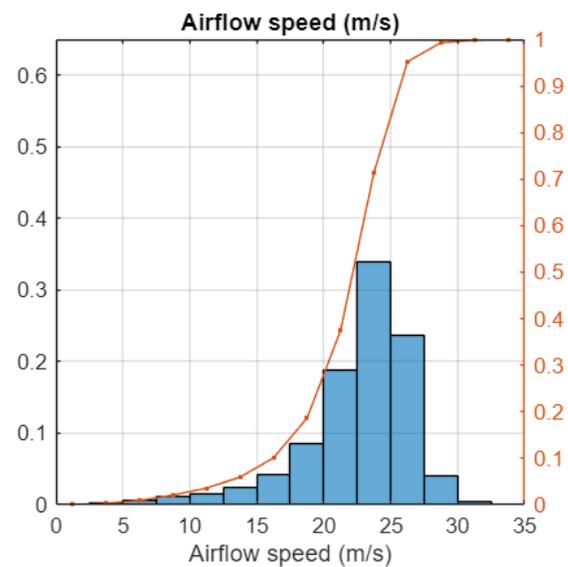
Göteborg → Örebro



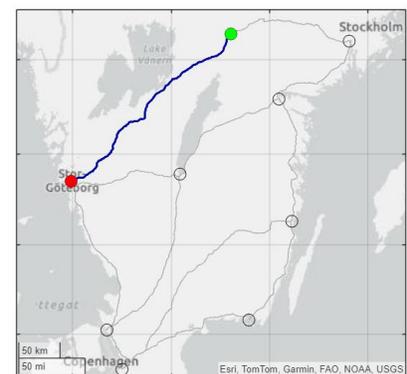
Göteborg → Örebro



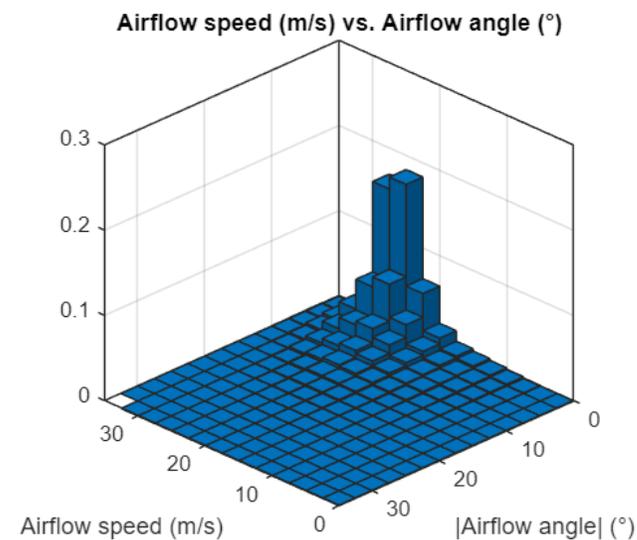
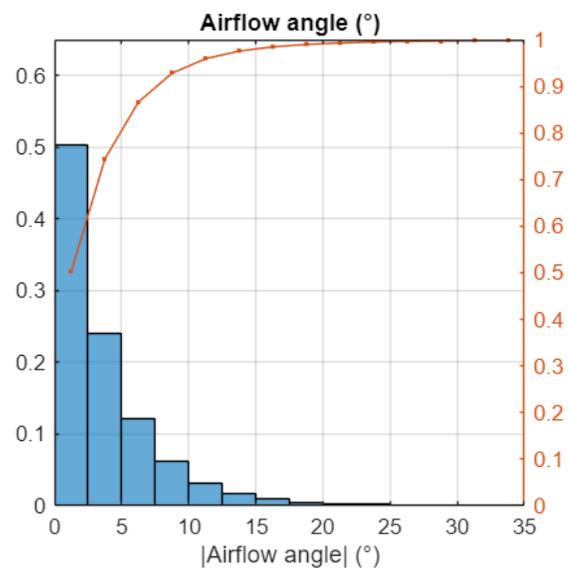
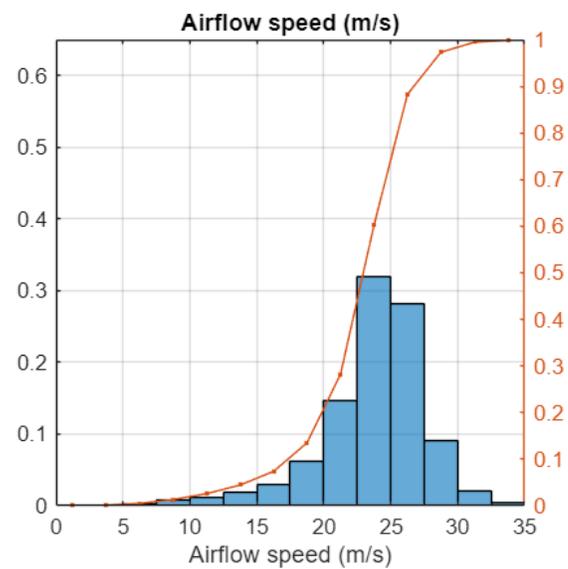
Route 1: Göteborg - Örebro



Örebro → Göteborg



Route 12: Örebro - Göteborg

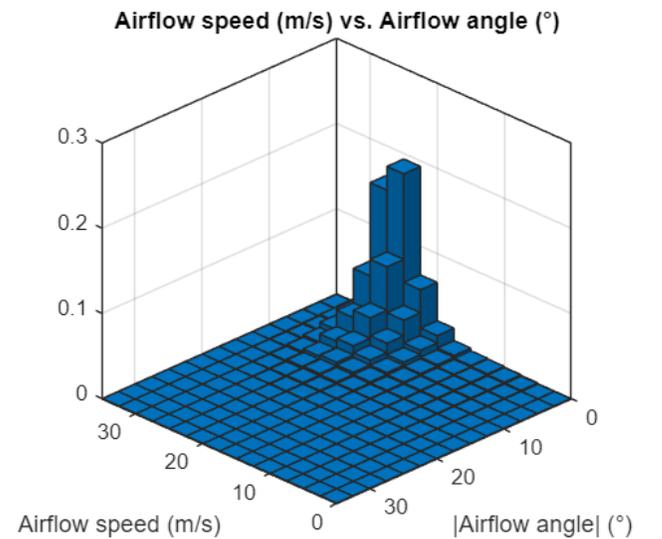
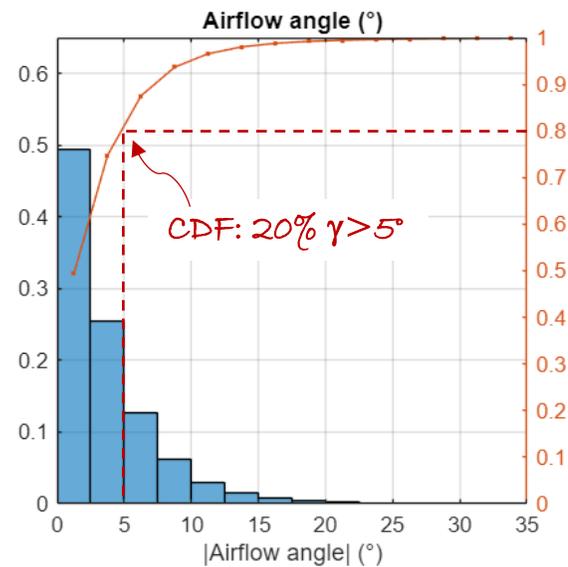
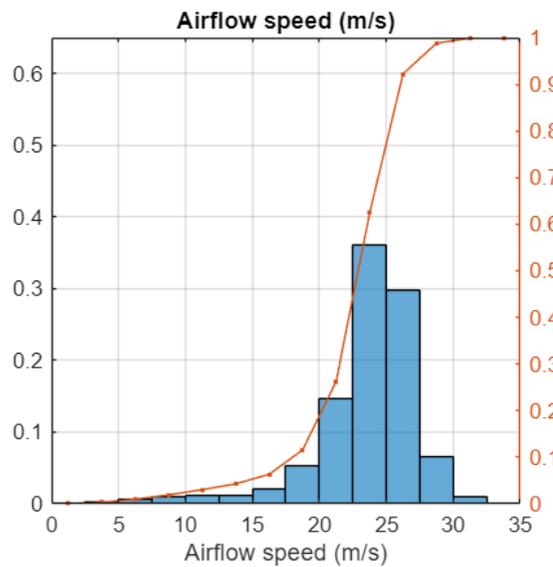


How useful are historic weather patterns in the times of climate change?

All routes



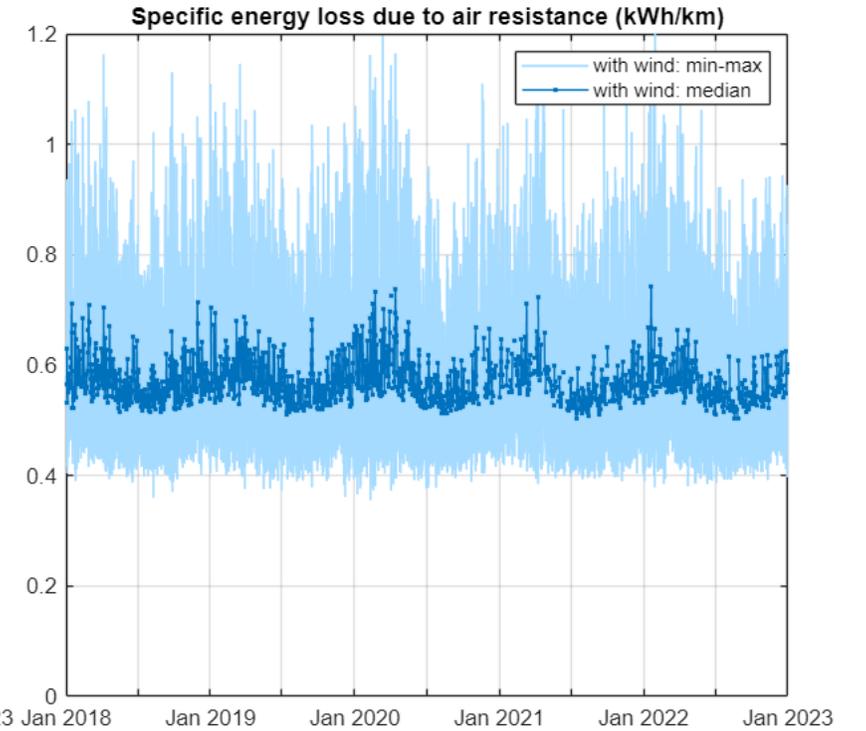
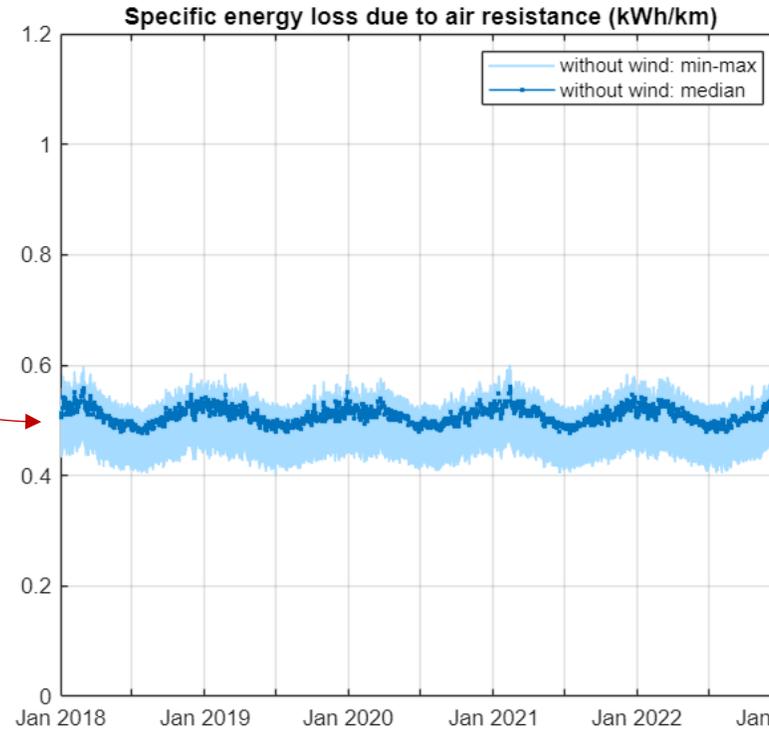
All routes compounded



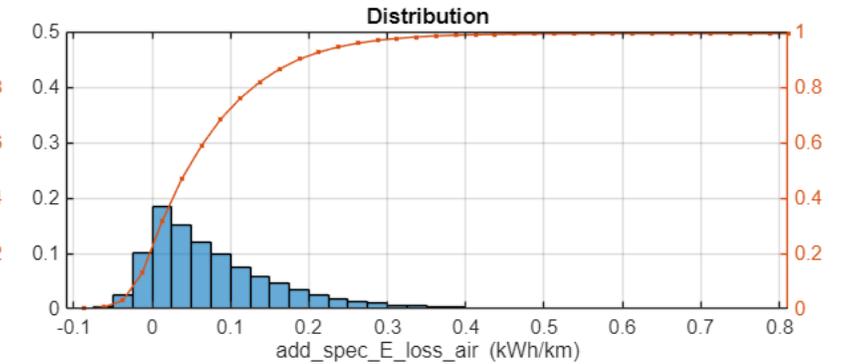
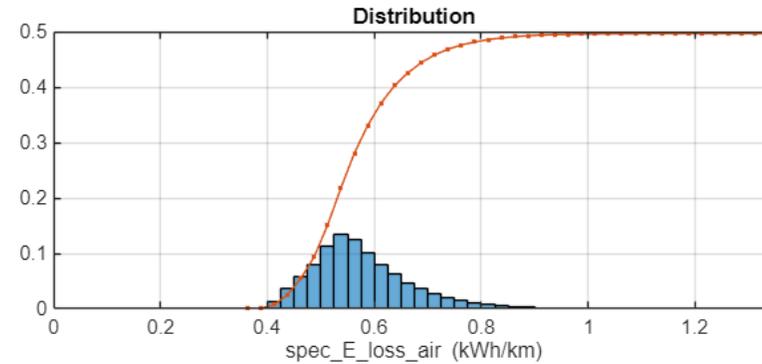
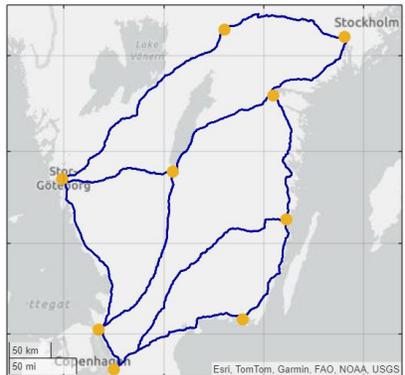
44 data points per day,
all with different air density
due to different air temperature,
pressure, and humidity

sinusoidal variation
due to the seasons
(winter vs summer)

All routes



All routes



CONCLUSION

Create + analyse synthetic time-series data

Time	Timestamp_UTC	Latitude	Longitude	Distance_incr	Distance_cum
0	2024-03-04 11:52:29	57.712	11.968	0	0
2.0211	2024-03-04 11:52:31	57.712	11.968	10.105	10.105
4.0422	2024-03-04 11:52:33	57.712	11.968	10.105	20.211
6.0009	2024-03-04 11:52:35	57.712	11.968	9.7938	30.005
8.022	2024-03-04 11:52:37	57.712	11.969	10.105	40.11
10.097	2024-03-04 11:52:39	57.712	11.969	10.375	50.485
12.056	2024-03-04 11:52:41	57.712	11.969	9.7937	60.279
14.077	2024-03-04 11:52:43	57.712	11.969	10.105	70.384

Matlab/Python toolbox

Scania-internal development by Reno Filla, started in 2019

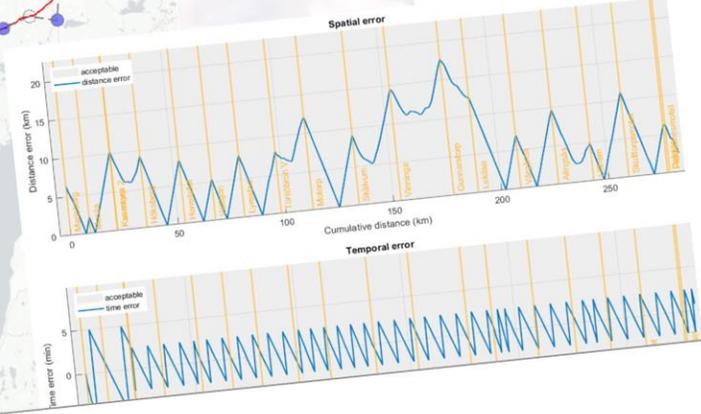
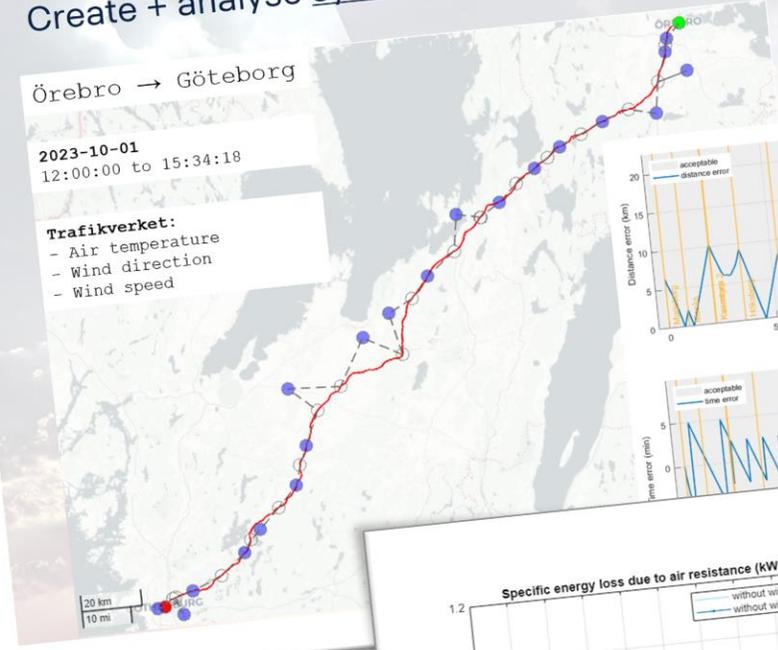
- HERE: routing + typical traffic + speed limits
- Google: resample to high resolution + elevation
25m intervals = 1Hz sampling at 90 km/h
- HERE: match back to road
- Trafikverket: recorded weather (REST API + VVIs)
- SMHI: recorded weather

Create + analyse synthetic time-series data

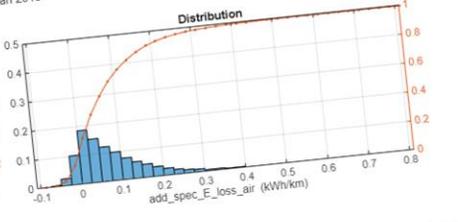
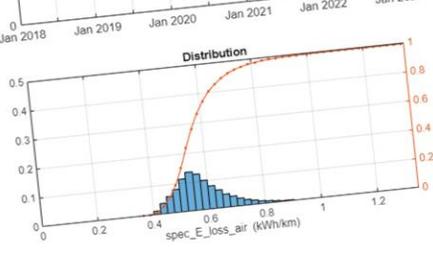
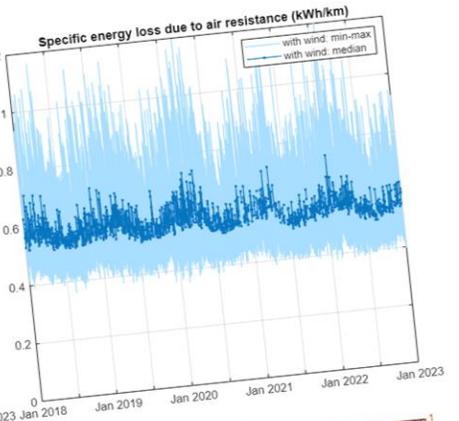
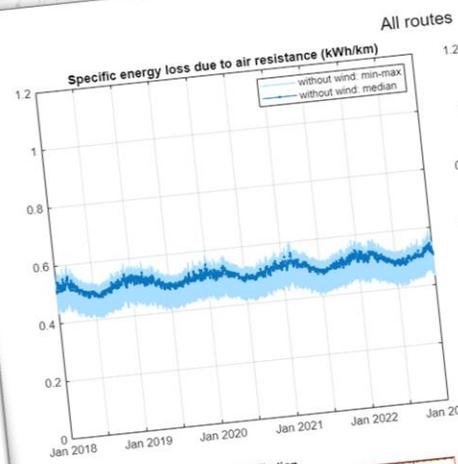
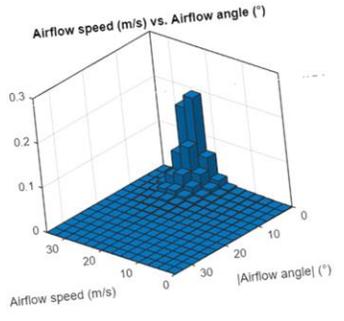
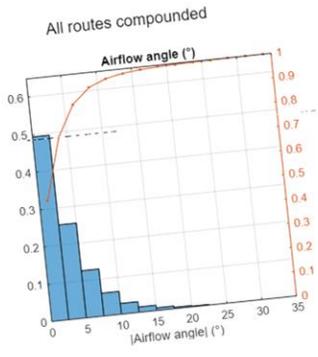
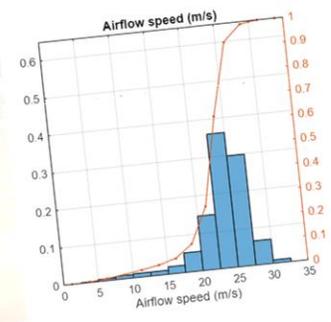
Örebro → Göteborg

2023-10-01
12:00:00 to 15:34:18

Trafikverket:
- Air temperature
- Wind direction
- Wind speed



All routes



CONCLUSION

(Industry and Academia)

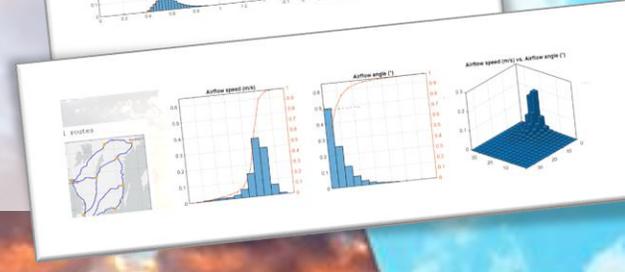
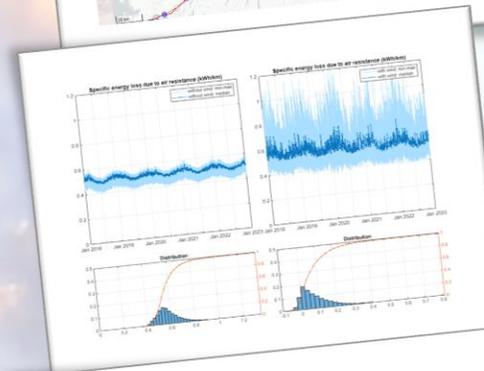
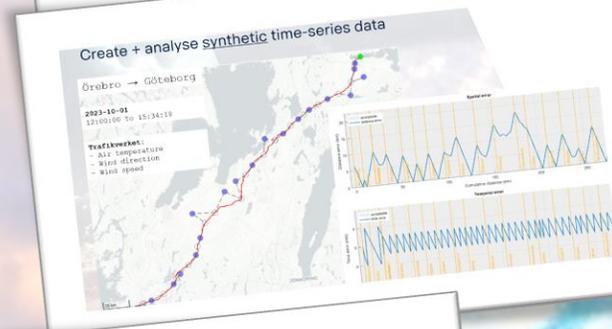
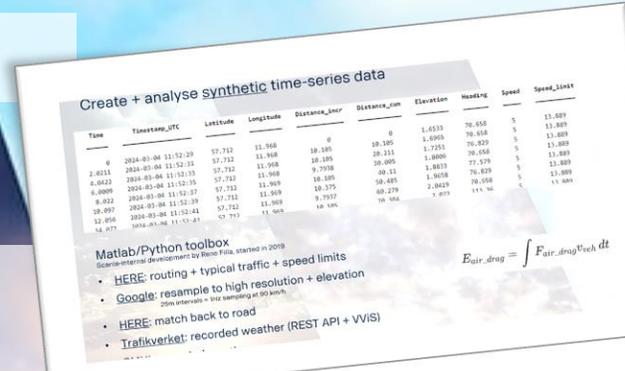
Weather changes all the time

Now we have the data, tools and methods to include this

- in analysis of recorded operation
- in simulation
- in component/system dimensioning

Now we have no more excuses...

- for writing off poor performance as due to bad weather and thus missing real deviations
- for designing products with poor performance robustness due to insufficient testing in bad conditions



<https://ine.tsgj.com/images/827/images/3b9562c9.jpg>

THANK YOU!

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