

Predicting Weather Inflicted Train Delays

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Photo by Kalevi Lehtonen 1955. Not published until Commons in 2014.
https://fi.wikipedia.org/wiki/Tiedosto:Finnish_class_Dm4_locomotive_number_1607_in_the_year_1955.jpg

We aim to predict disruption of rail traffic caused by weather

Operation center can take several actions:

- Reduce train shifts
- Communicate

Project timeline: 01/2018-10/2018

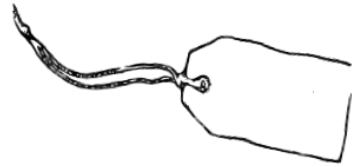
Project partners: FMI, FTA, Trafi, VR

Area: Finland

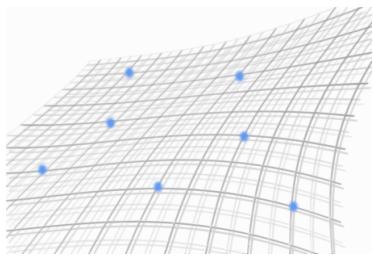
Time range: 2 days ahead

Time step: 1 hour



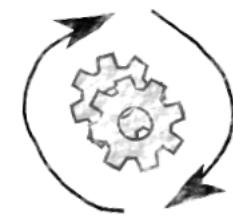


+



Label
data

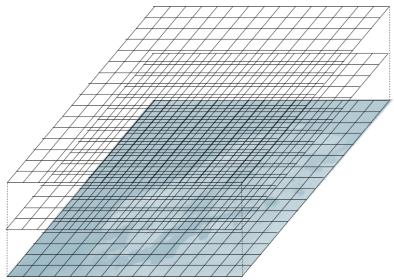
Feature
data



Method Results



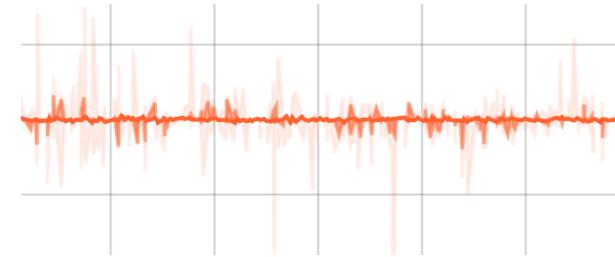
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NWP



Method



Prediction

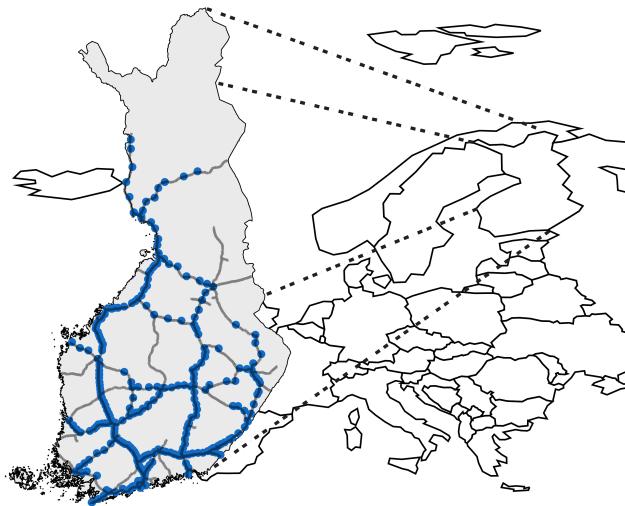


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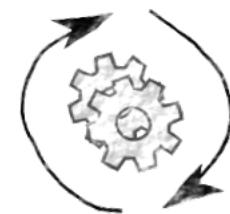
Data consist of train delays and corresponding weather observations

Delay between stations

- Passenger trains
- 514 stations

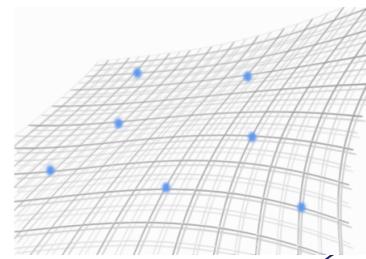


Data Liikennevirasto (CC4)



Weather observations

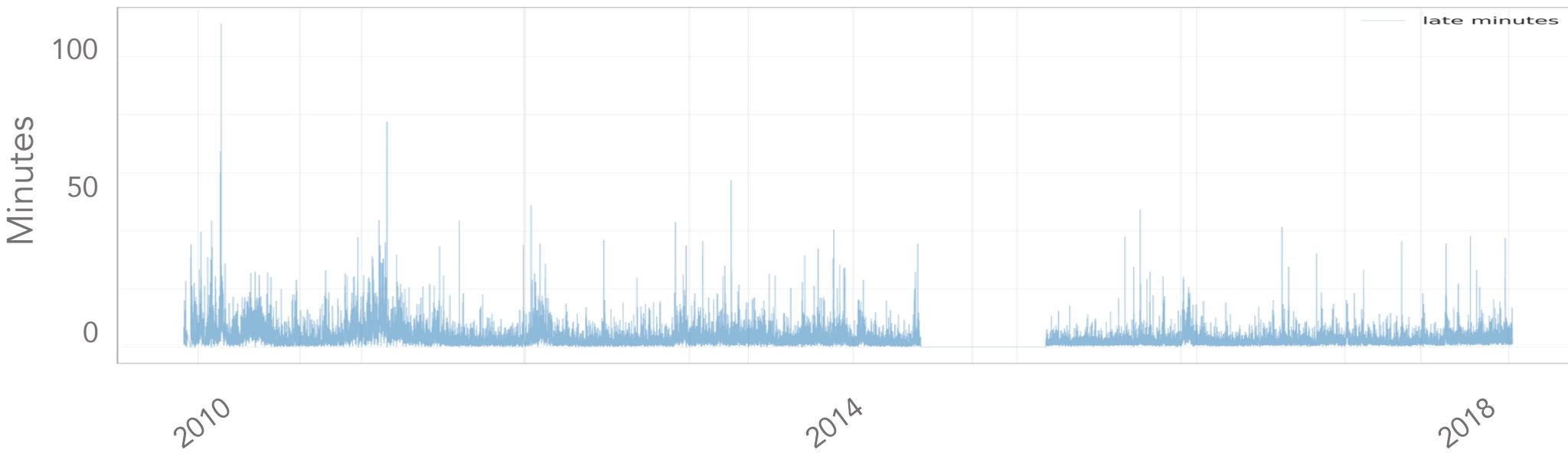
- 19 parameters



- Data from 2010 – 2018
- 30 M rows | 5.5 GB data

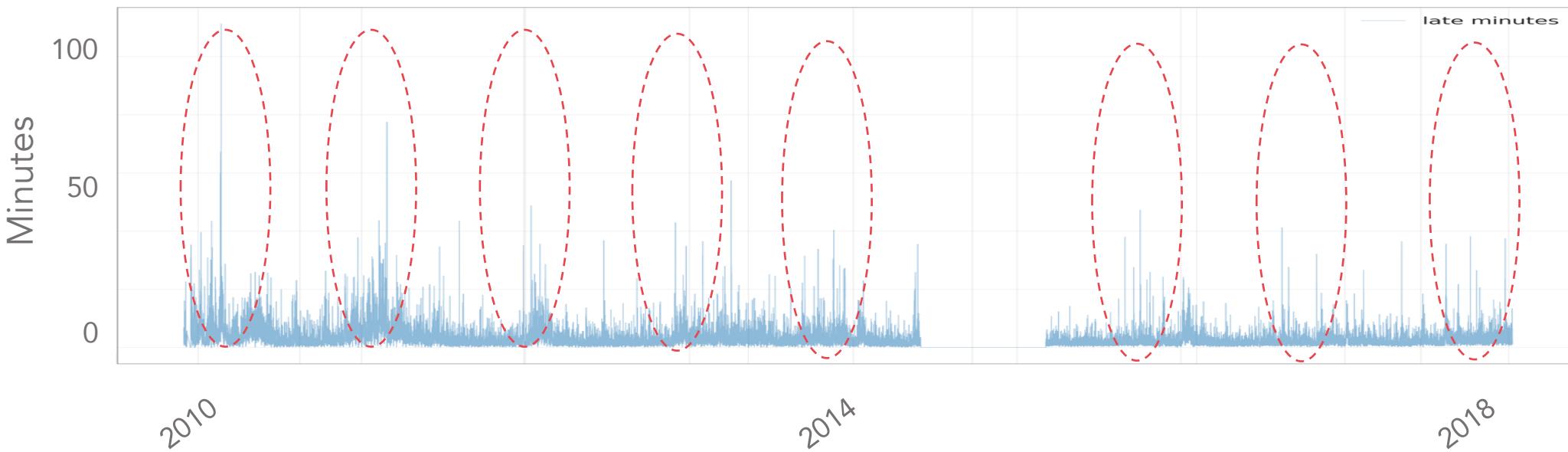
Most trains run in time

Mean delay over all stations



Most trains run in time

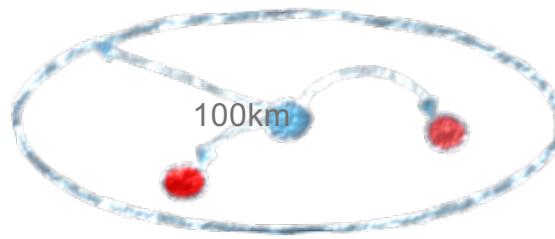
Mean delay over all stations



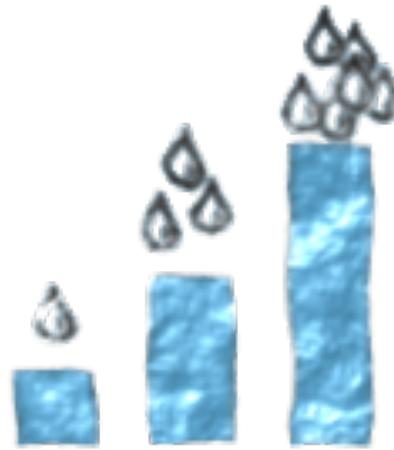
But severe delays happen quite regularly every year

Various pre-processing methods used

Observations
fetched with 100 km
radius from train
station using
aggregation



Calculated 3h and 6h
precipitation
accumulation sums



Tried PCA, ICA and
K-Means clustering

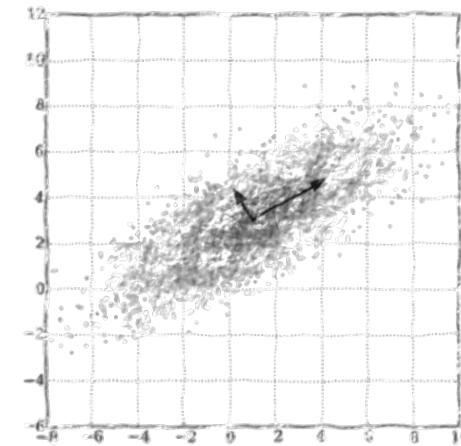
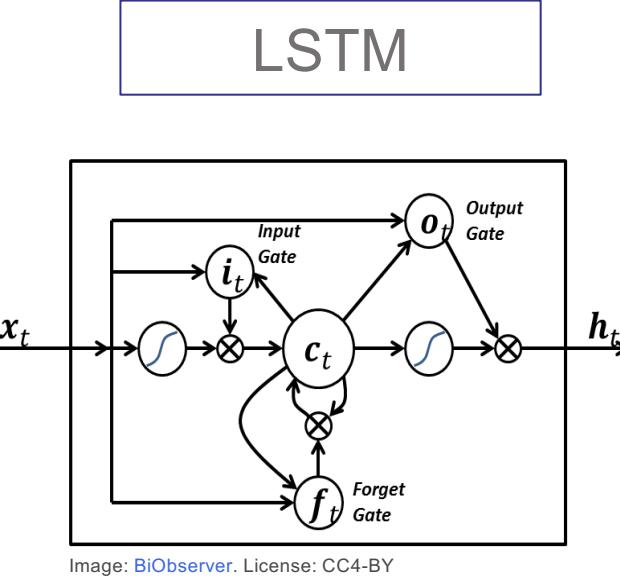
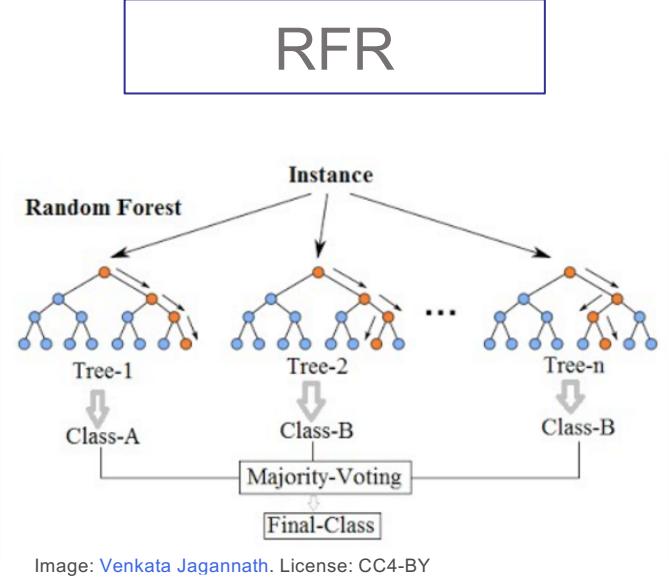
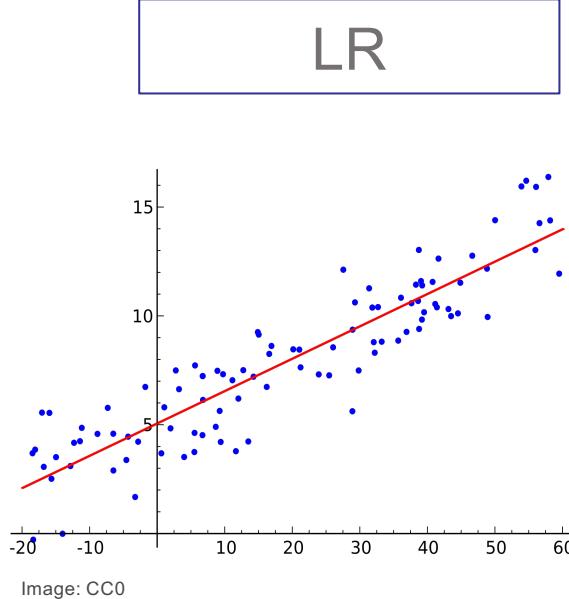


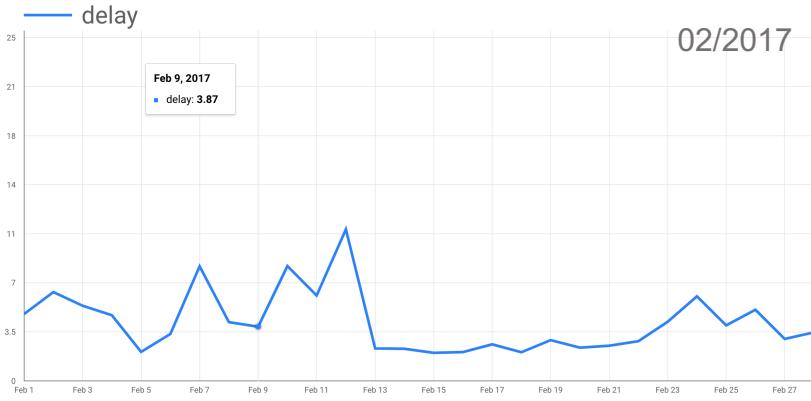
Image: Roope Tervo 2018.
Original image: [Nicoquaro](#). License: CC4-BY.

Three ML methods considered



Random search used for finding optimal hyper parameters of LR and RFR

Three selected months picked out for testing performance



- Rest of the dataset splitted randomly to train and validation dataset with ratio 70/30 %

Results

LR

RMSE: 5.59
MAE: 3.11
BSS: 0.08

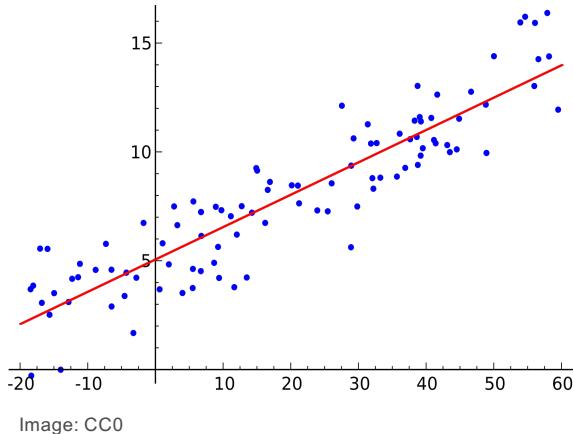
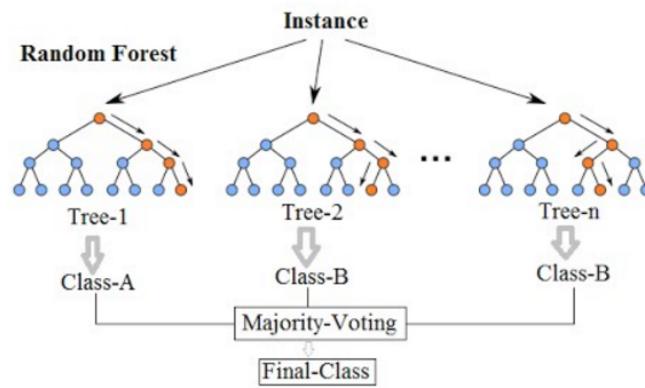


Image: CC0

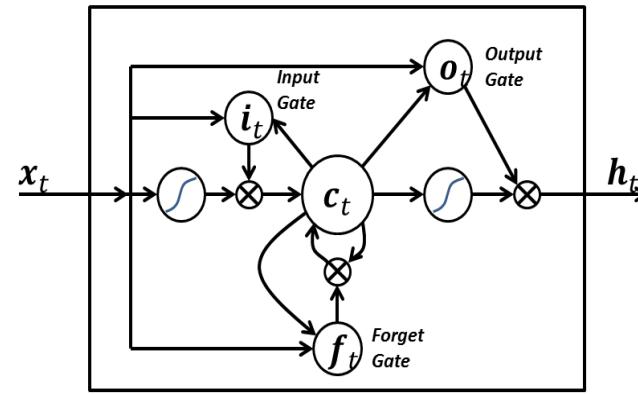
RFR

RMSE: 5.37
MAE: 3.21
BSS: 0.11



LSTM

RMSE: 4.35
MAE: 2.75
BSS: 0.01



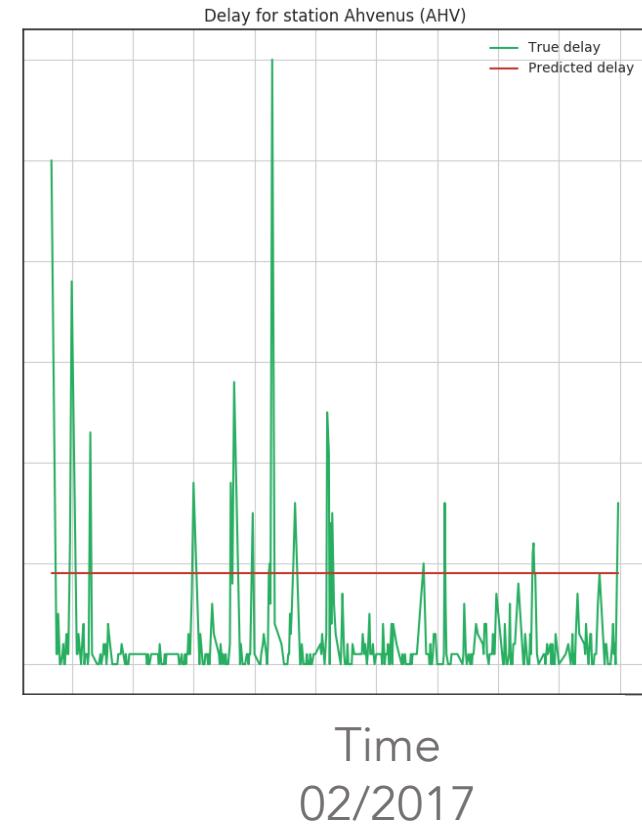
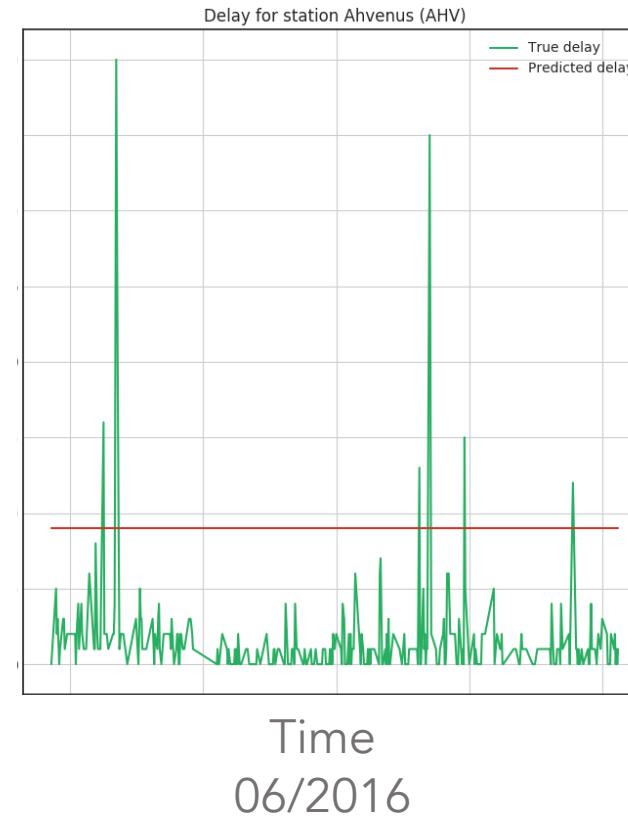
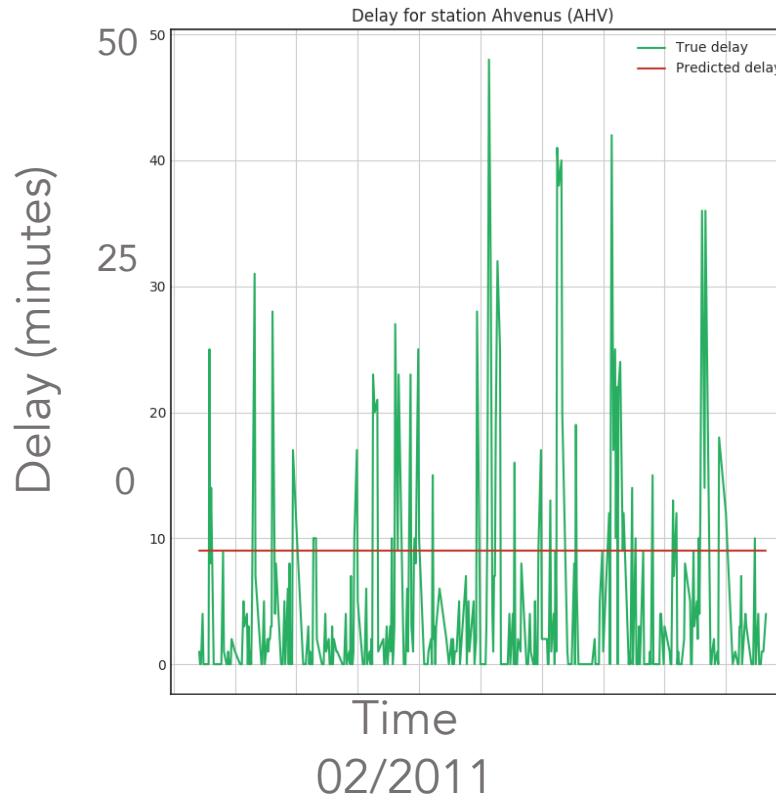
$$BSS = 1 - \frac{RMSE}{RMSE_{ref}},$$

where $RMSE_{ref}$ denotes root mean square error calculated with a mean value over the whole dataset

LSTM shows no real skill

— Predicted delay
— True delay

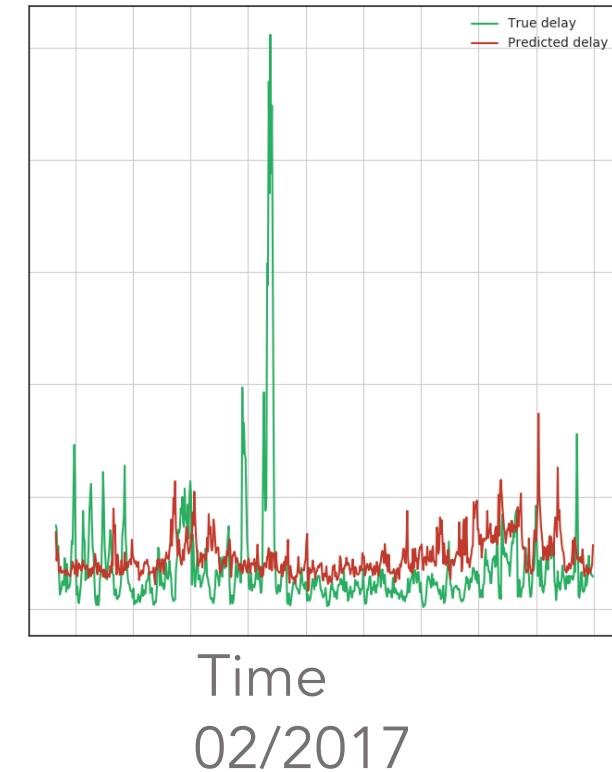
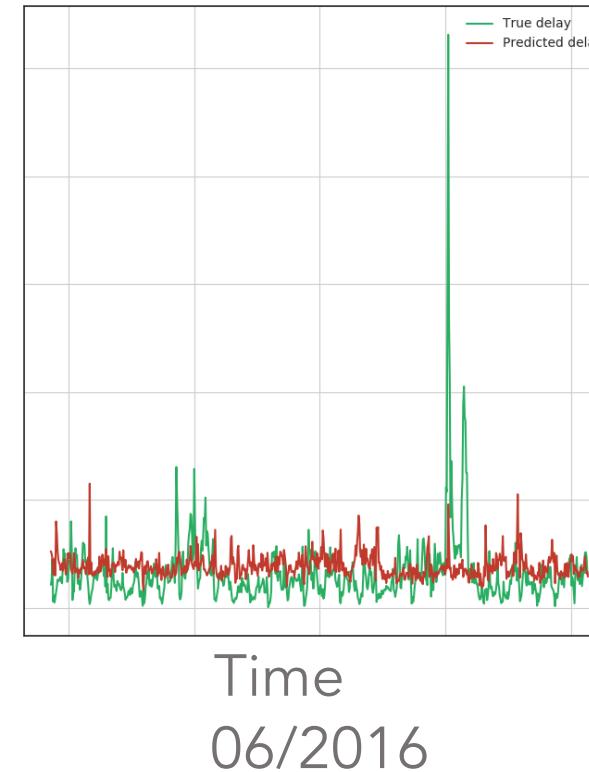
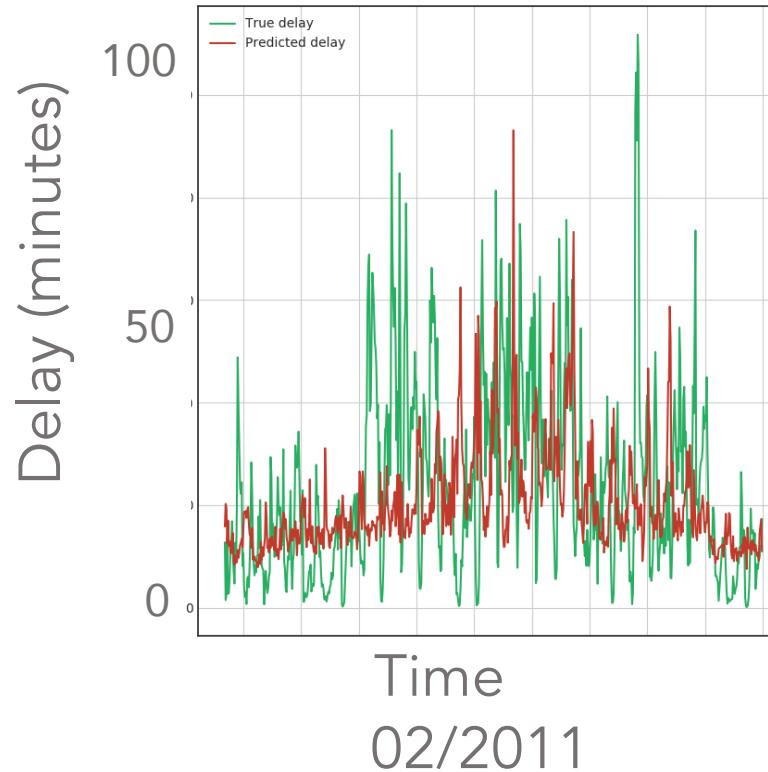
Predicted vs. true delay, case Ahvenus



RFR works relatively well

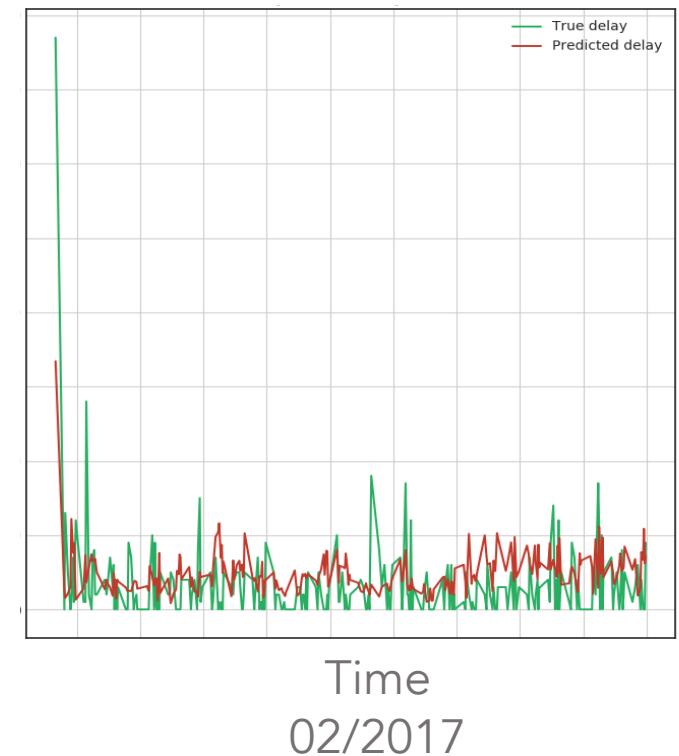
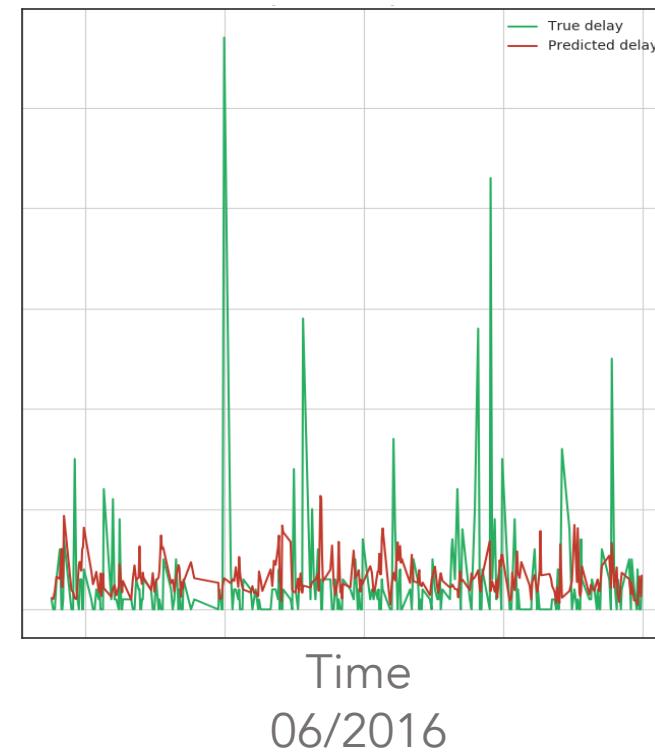
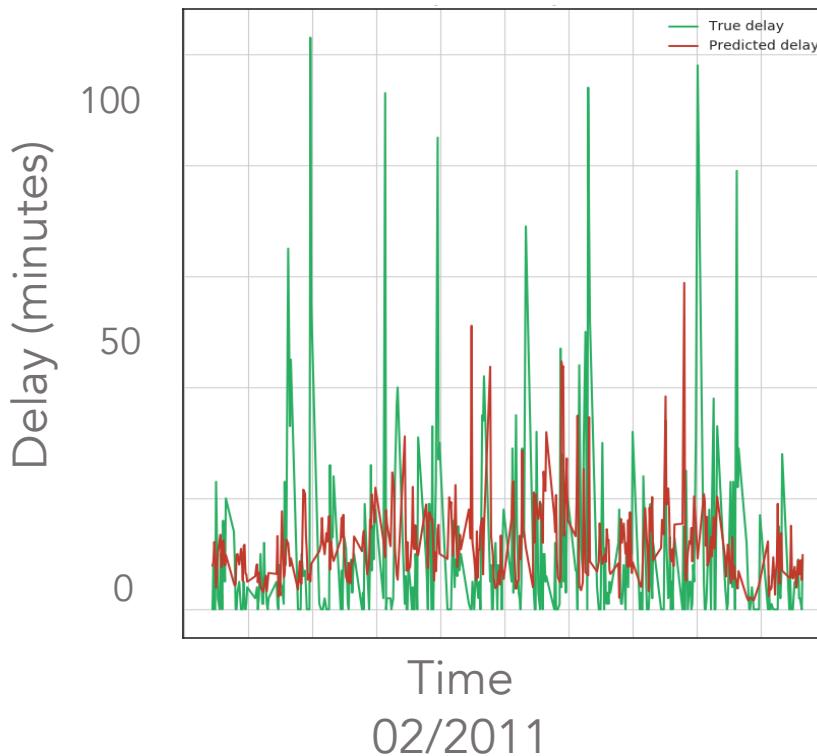
— Predicted delay
— True delay

Predicted vs. true delay, average over all stations



RFR works well for most individual stations

Predicted vs. true delay, case Kyrö

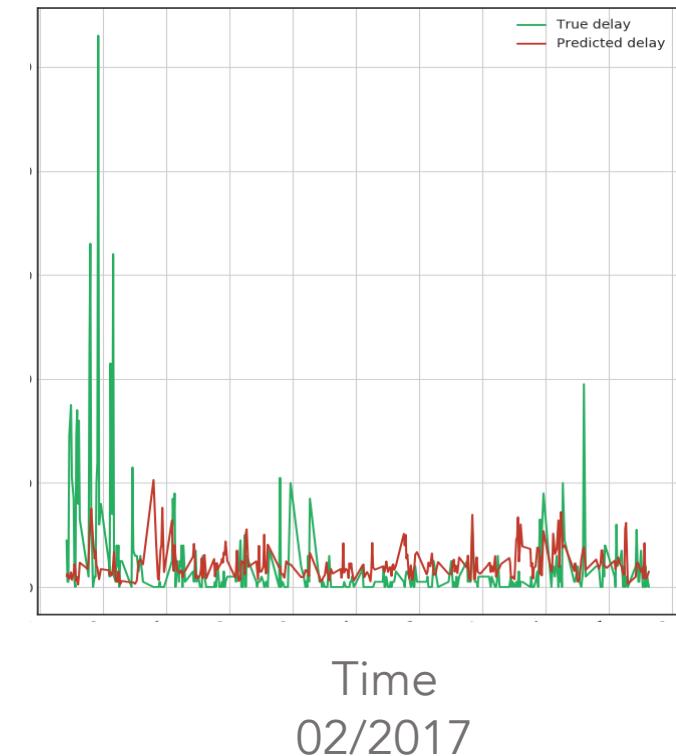
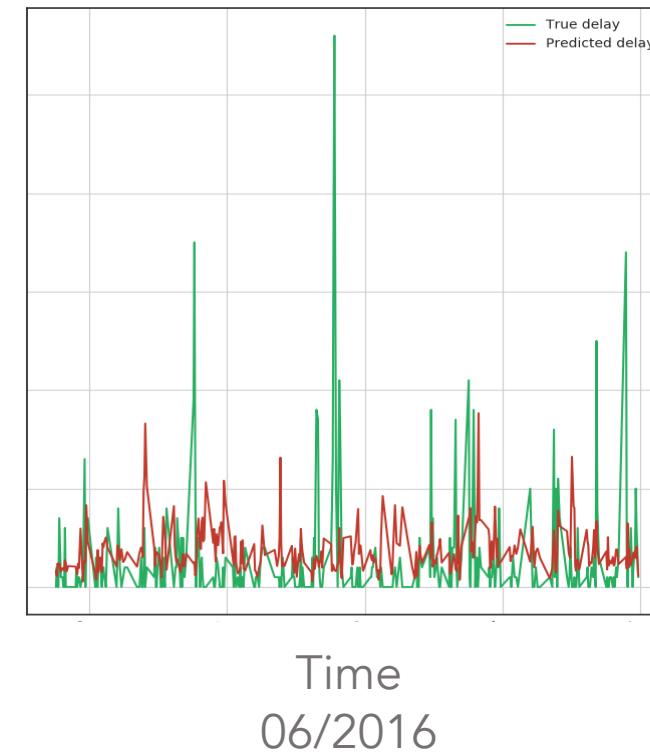
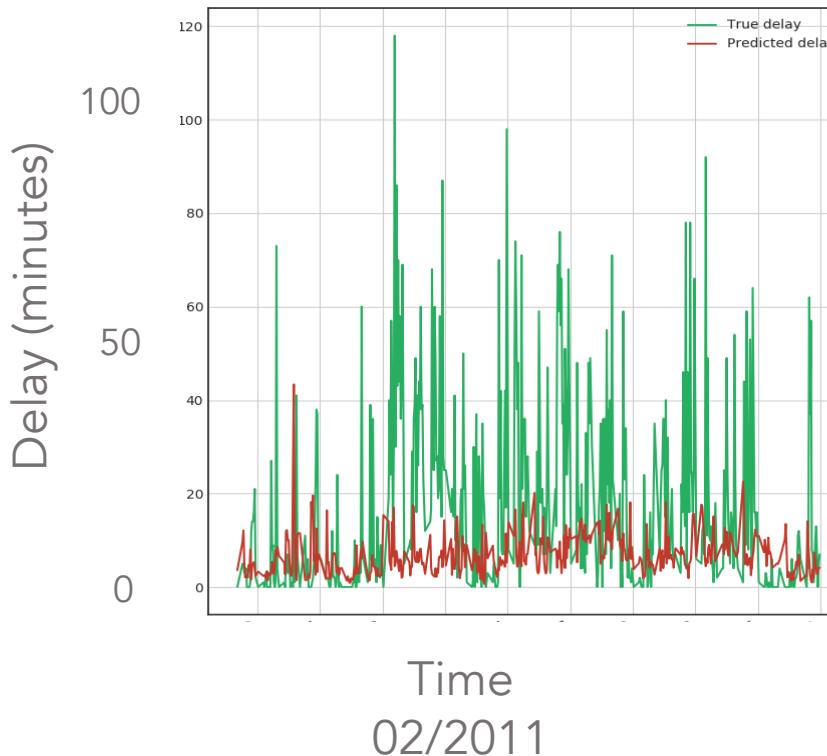


RFR don't work for all cases

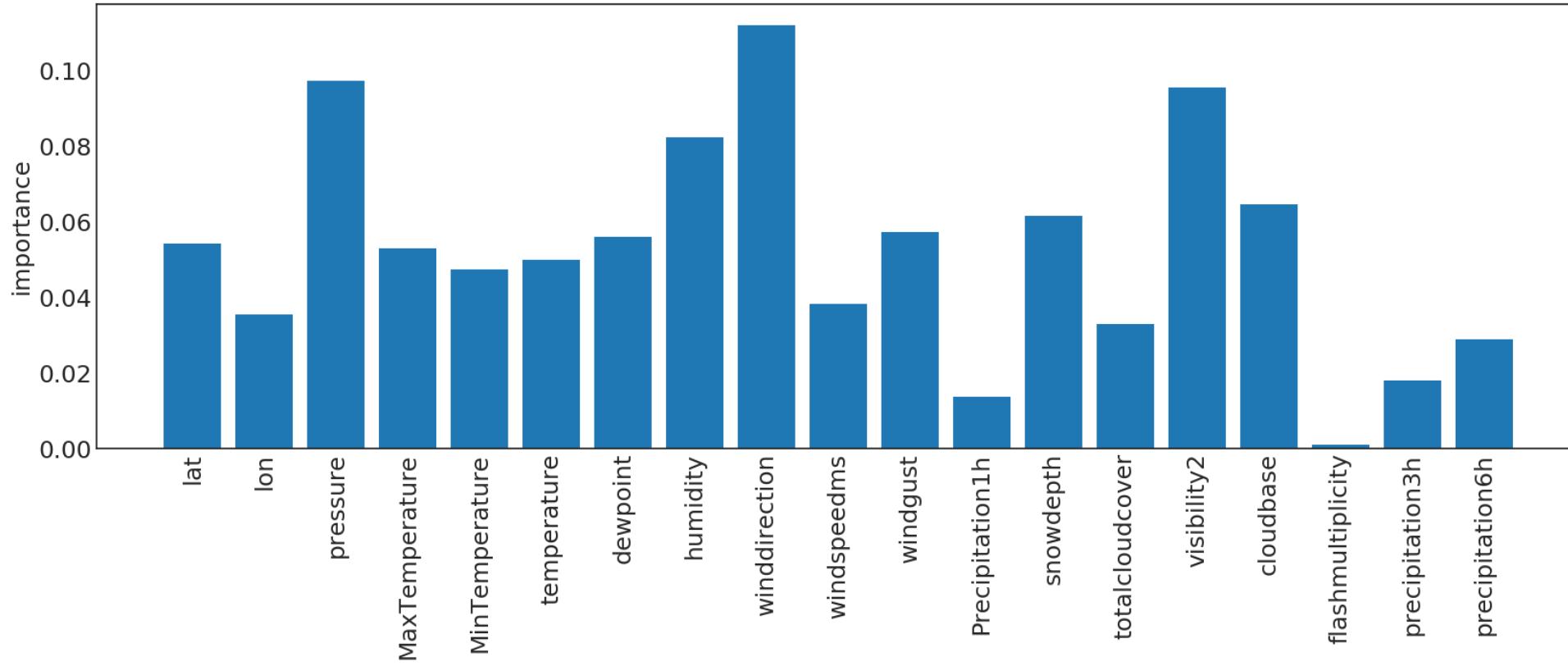
Predicted delay

True delay

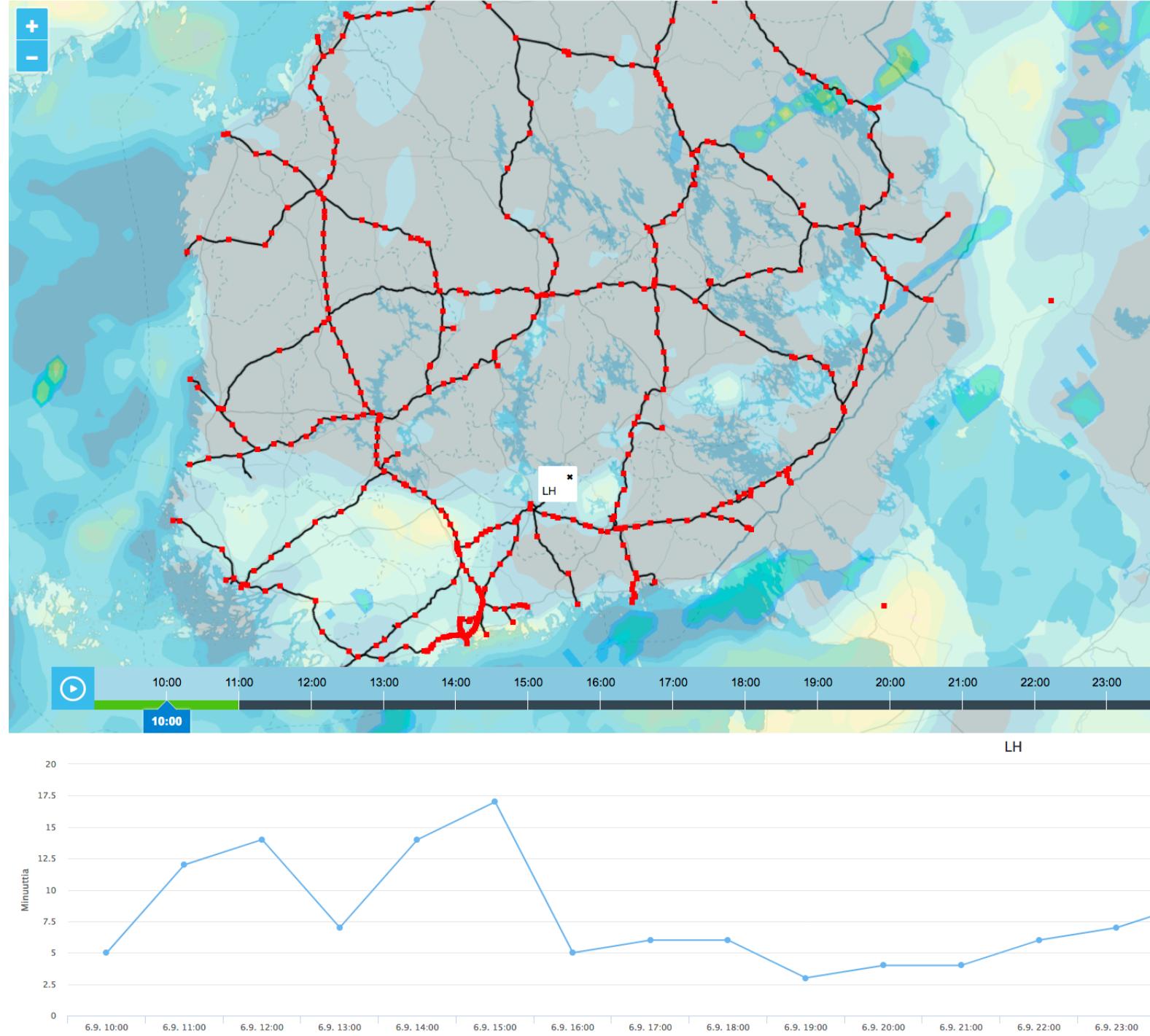
Predicted vs. true delay, case Karjaa



Wind direction, pressure and visibility are the most important features



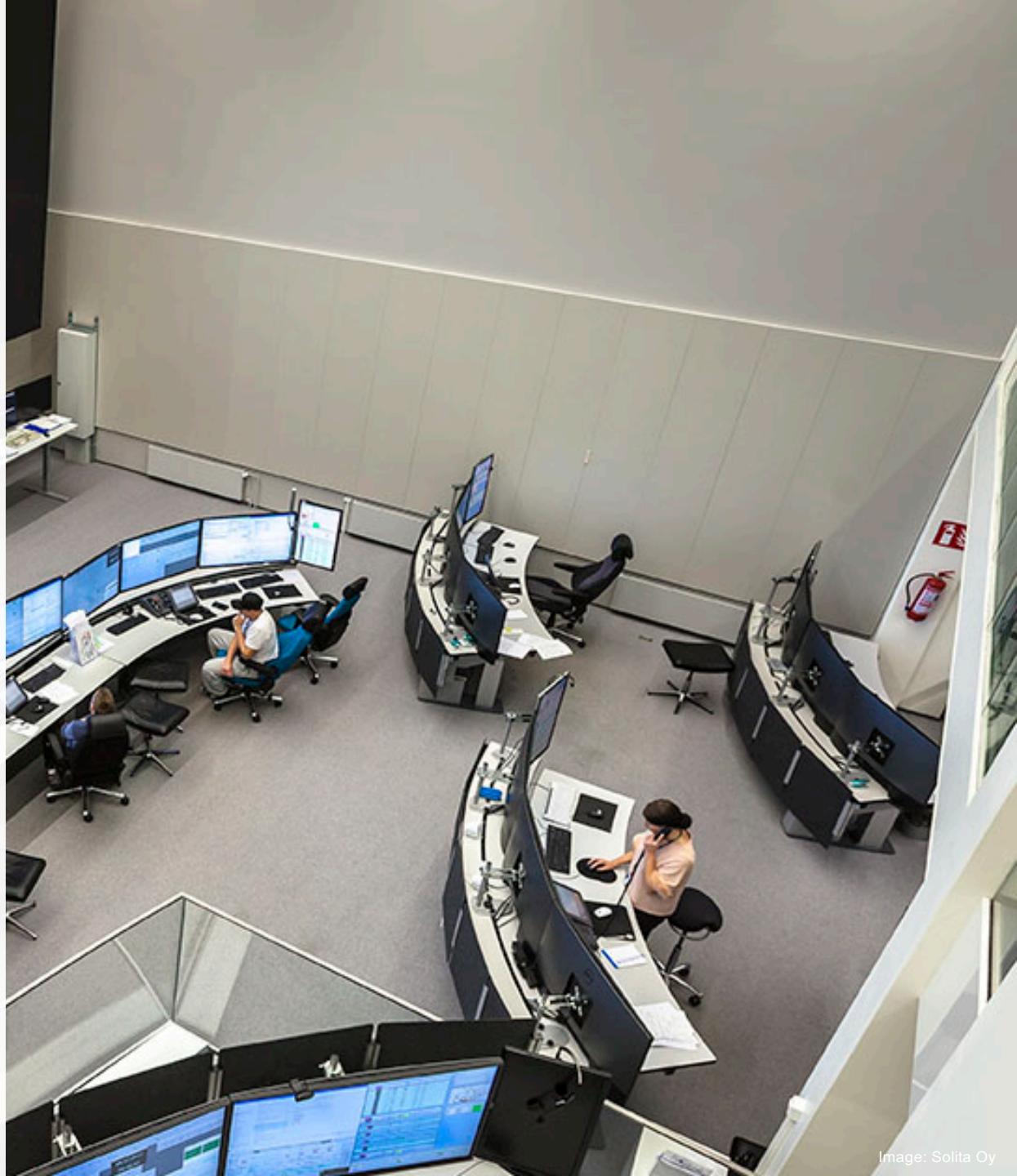
Predictions are delivered to end users via web interface



Train delays can be predicted based on weather conditions

RFR gives the best average prediction

...although its performance is not steady



Questions

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CC0. Image by: Simon Jowett

