CEVOLVER

Connected Electric Vehicle Optimised for Life, Value, Efficiency and Range

Fleet data based electric driving Range Predictor (FRP)

FRP

The Fleet Range Predictor can predict the energy demand of any vehicle for a specific route based on fleet aggregated data. The feature does this in two steps. One being accumulating correction factors for the whole street network by a fleet. The other one being the prediction of the energy demand based on this info. First analyses show that this procedure can be used vehicle type and brand independent. In addition, the type of impact on the energy demand does not matter. All kind of effects will be distributed to the next upcoming vehicles.

Energy Prediction

When the driver puts a route into the nav-system the feature can split this route into segments. For each of these segments there is a correction factor which can be taken to evaluate the Energy for each of those segments.

$$\mathbf{E_{prediction}(segment) = E_{calculated\ ideal}(segment) * CF(segment)}$$

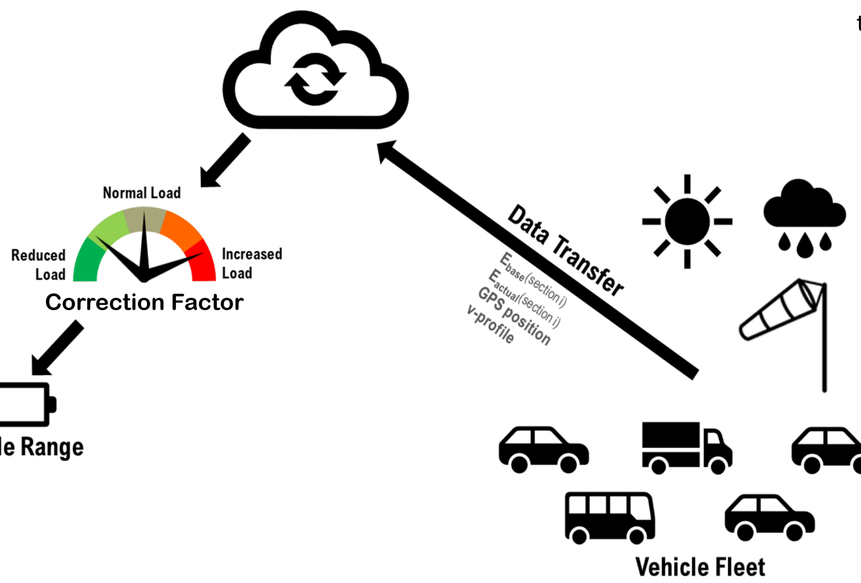
Correction Factor (CF)

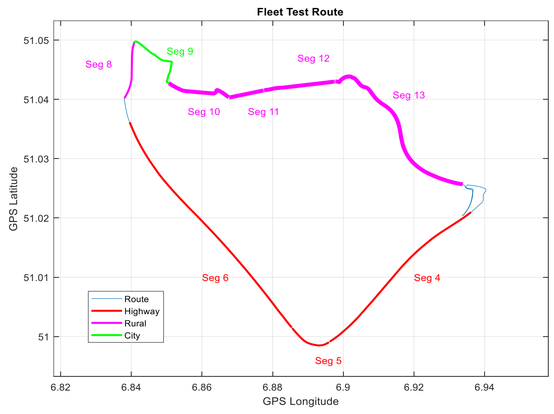
The correction Factor describes a normalized factor for a specific road segment which reflects the ratio of the real used propulsion energy to the propulsion energy the vehicle would have used in ideal conditions. This means, taking physical formulas to calculate the road resistance without any wind, traffic, rain or other environmental influence. First tests have shown, that this normalized factor can be transferred independent of the vehicle type.

$$\mathbf{CF}\ [\%] = \frac{\mathbf{E_{measured\ real}}\ [\mathbf{W}]}{\mathbf{E_{calculated\ ideal}}\ [\mathbf{W}]}$$

Constraints

- In the current feature layout propulsion energy is predicted
- Driver requests a route
- Speed profile prediction (EcoDriving can provide a speed proposal)



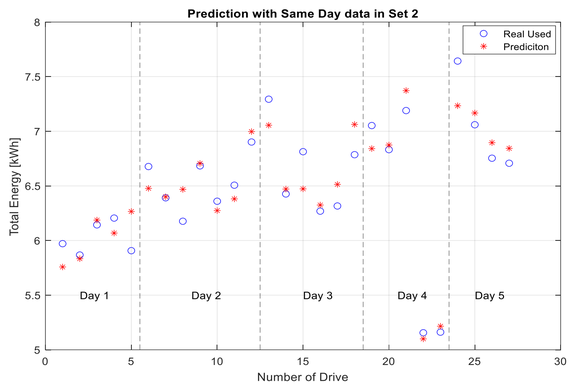


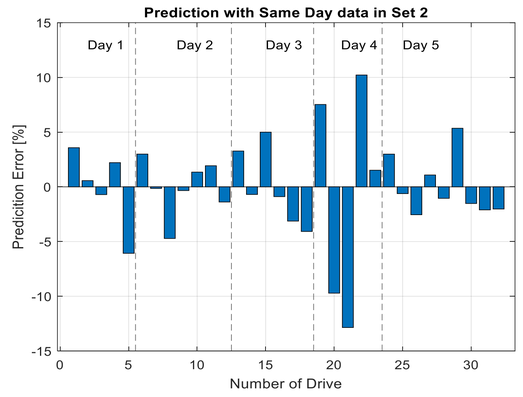
Test Route

To verify the concept a test route was driven repeatedly with a van and a c-class SUV EV. This Route is 21km long and has three different road types:

- Highway
- Rural
- City

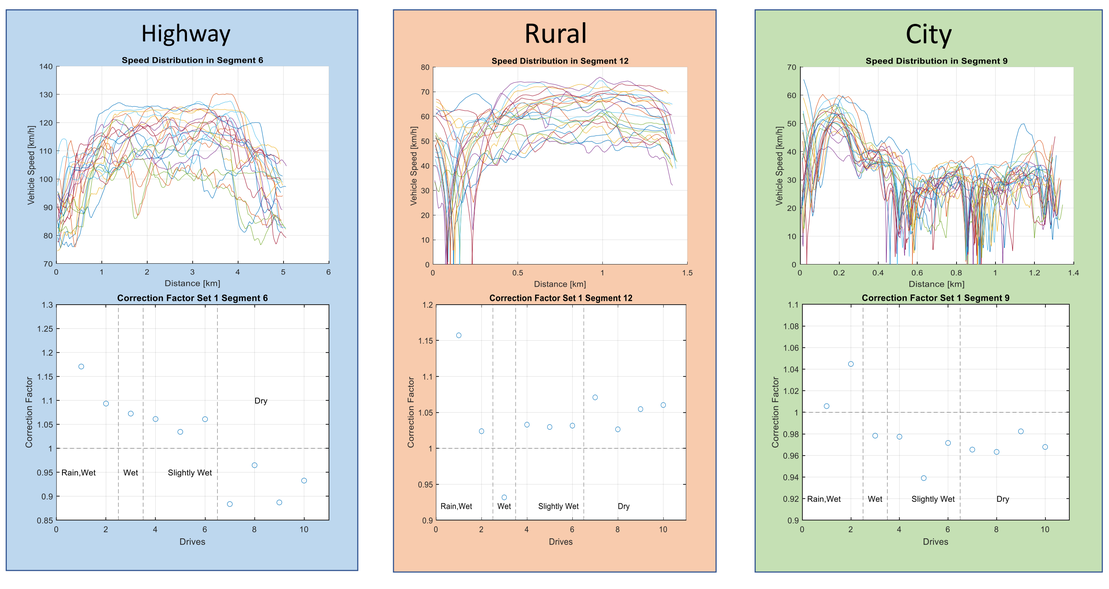
First Results





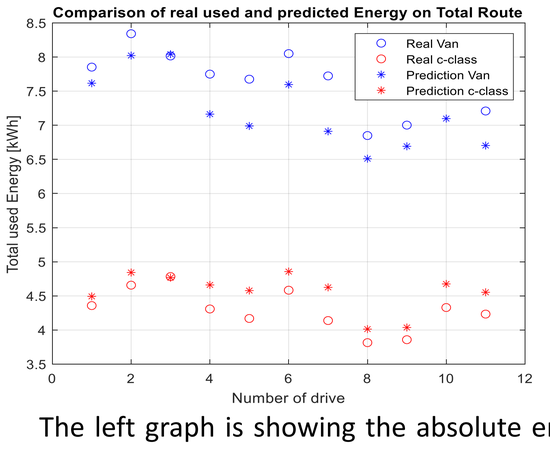
Because there was no fleet to test the feature with, the test route was driven several times. Taking one drive and assuming the other drives of the same day were the fleet feeding the CF, a prediction for each drive was done. The left graph compares the prediction with the real used energy while the right graph shows the corresponding error. Most predictions were with an accuracy of more than 90%. With more data and some refinements, a more robust analysis with a real fleet and more datapoints with recent CF could lead to a robust 90%.

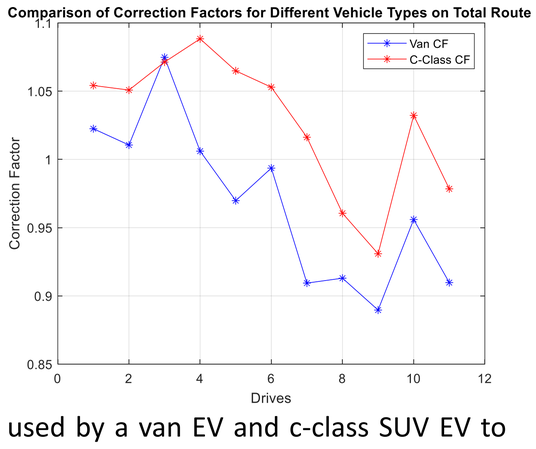
Impact of environmental influences (example of rain)



These graphs show the results of an analysis of the impact of wet roads on the correction factor for a van class vehicle. Hence all drives had tailwind, the dry condition CF is below 1. While on highway, with higher speeds, the impact is higher and more visible, in lower speed segments the spread is higher and the overall average of correction factors are lower.

Vehicle Type Comparison





The left graph is showing the absolute energy used by a van EV and c-class SUV EV to show the different levels for the overall route (21km). Using the CF of one vehicle, applying it to the other, is resulting in an accuracy error of about or under 10%. Looking at the overall trend of prediction there seem to be a systematic drift value. Also, the spread is still quite high (between 4-5kWh for c-class vehicle). A higher number of datapoints would give a better view on the statistical analysis and could lead to an higher accuracy in prediction.

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement no. 824295

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