Vehicle Independent Road Resistance Estimation Using Connected Vehicle Data

Mikael Askerdal, Chalmers University of Technology/Swedish Electromobility Centre
E-mail: mikask@chalmers.se
Jonas Fredriksson, Chalmers University of Technology
E-mail: jonas.fredriksson@chalmers.se

This paper is investigating if it possible to use vehicle log data to estimate vehicle independent road resistance parameters that can have large local variations and change rapidly, such as wind speed, wind direction and road surface conditions. The estimated parameters can be used to improve range estimation, route planning and vehicle energy management. The advantage with using vehicle independent parameters is that data from any vehicle can be used to improve the estimation and that all vehicles can benefit from the estimated data. An analytical solution previously presented for parameter estimation is verified on vehicle log data. Results show that the method works reasonably well for wind speed estimation and that changes in road conditions can be detected. Side wind affects need to be considered in future work.

Topics: Vehicle Automation and Connection, Vehicle Dynamics and Chassis Control

1. INTRODUCTION

Battery electric vehicles (BEV) have many advantages compared to vehicles with conventional powertrains. Nevertheless, the limited range between charging is still a considerable disadvantage. Range estimation is needed to determine how far the vehicle can run before the battery is empty. However, range estimation suffers from a number of difficulties. One of them is uncertainties in the road resistance, i.e. the total braking force from the road and the environment affecting the vehicle. It contains three separate components; rolling resistance, air resistance and gravitational force from the road slope. The road resistance is depending on both internal vehicle parameters such as vehicle mass, tire- and aerodynamic properties, and environmental conditions such as wind, road slope and road surface. Improved information on the environmental conditions would simplify the range estimation of BEVs considerably.

Road resistance estimation is mainly used for predicting the vehicle energy consumption of a road segment. In [1], it is shown that the energy consumption of a vehicle is mainly depending on three factors apart from the vehicle itself. First, the driver has a large influence. An aggressive driver uses the brakes a lot and a considerable amount of energy is lost. Some of it may be recuperated in electric and hybrid vehicles but some parts are always lost, either as losses in the powertrain or due to power limitations in the recuperation. Second, the surrounding traffic affects the possibilities to drive in an energy optimal way. If the vehicle ahead is braking hard, there are no other options than to brake hard as well, i.e. there is no room to select an energy optimal speed trajectory. The traffic flow that sets the pace. Finally, the road resistance has a large influence on the energy consumption. The energy consumption is much larger on a muddy dirt road than it is on dry highway and head wind has a large negative effect on energy consumption especially at high speeds. To be able to accurately predict a vehicle's energy consumption all these three factors need to be considered. Given the massive ongoing research in automated vehicles ([2],[3]) but also in driver behavior modelling ([4],[5]) and traffic simulations, it is motivated to complement that research with research around road resistance.

Road resistance estimation is nothing new, in fact, recursive algorithms like Kalman-filters have been implemented in vehicles for the purpose of estimating grade resistance and vehicle mass, see e.g. [6]. However, a major problem with using on-line data in a single vehicle for doing these estimates is that it can only be done on data from the road segments already passed. As road surfaces and wind conditions can change rapidly, for example when making a sharp turn a windy day, prediction of energy consumption based on past data might be very wrong. This is the main motivation for looking into the field of connected vehicles to improve the estimation. On roads with at least moderate traffic, other vehicles than the ego vehicle have travelled the road ahead. If the energy consumption of each vehicle is normalized into vehicle independent measures of the parameters affecting energy consumption, any vehicle passing the same road segment later on could use the information for estimating its own energy consumption and improving the possibility to predict the vehicle energy consumption more accurately. This is especially important for BEVs that need good range estimation to be trusted by its driver.

This article focus on practical verification of a previously developed framework for vehicle independent road resistance estimation [7]. Measurements from a vehicle is used to verify the ability to estimate the correct average wind speed and rolling resistance coefficient on a segment of a public road. The sensitivity to errors in measurements and vehicle parameters is also investigated.

Chapter 2 describes the notation and the parameter values used in the examples all through the paper. Chapter 3 contains the problem formulation and chapter 4 the estimation method used. Chapter 5 holds the results from estimation using vehicle measurements and chapter 6 evaluates the sensitivity of the estimation to errors in the models, measurements and parameters used. Chapter 7 discusses the results and chapter 8 holds some final conclusions.

2. PROBLEM FORMULATION

To describe the longitudinal vehicle speed, a simple vehicle dynamic model can be used:

$$ma = F_v - \frac{\rho_{air} A_f c_d}{2} v^2 - mgc_r \cos(\alpha) - mgsin(\alpha) \quad (1)$$

where m is the vehicle mass, a the vehicle acceleration, F_v the propulsion force of the vehicle, ρ_{air} the air density, A_f the frontal area, c_d the air resistance coefficient of the vehicle, v the relative air speed, g the gravitational constant, c_r the rolling resistance coefficient and α the road slope. Equation (1) contains one vehicle independent parameter, namely the road slope α, and two parameters that are depending on both the vehicle itself and the surrounding conditions, namely the relative air speed v, and the rolling resistance coefficient c_r. The problem discussed in this paper is how to estimate two unknown parameters, namely the wind speed component of v and c_r with only one equation. The idea of using vehicle log data to estimate static information such as road slope information has been investigated in previous research (e.g. [8]). Therefore, in this work the focus is on how to estimate the vehicle independent parts of the relative air speed and the rolling resistance.

3. ESTIMATION METHOD

Wind speed can be fluctuating a lot and change quite rapidly and measurements of parameters like acceleration and slope can be very noisy. It is therefore motivated to use methods that estimate the average value of the parameters over a road section, using energies rather than forces, such as the vehicle estimation method developed in [7], instead of continuous estimation. Somewhat simplified, the algorithm can be described as:

1) Measure total wheel energy over the segment ran in both directions
2) Calculate sum of rolling resistance and air resistance by removing changes in potential and kinetic energy over the segment
3) Calculate sum of rolling resistance and energy loss from wind by removing air resistance energy assuming zero wind.
4) Assume same rolling resistance in both directions -> the difference in resulting energy using measurements from running the same segment in each direction is the effect from the wind Calculate wind speed estimate using this difference and aerodynamic properties of vehicle.
5) Calculate rolling resistance coefficient using estimated wind speed in step 4.

If the same vehicle is used to do all measurement, normalization is not needed. [7] gives an explanation how this can be done if multiple vehicles with different properties are used. The estimation method has been tested against real vehicle log data from a single vehicle.

3.1 Vehicle measurements

The vehicle measurements were done on a segment on a public road with a truck equipped with a wind sensor that is able to measure the relative air speed and air direction. By subtracting the vehicle speed the actual wind speed and wind direction was calculated. The selected road segment that is shown in figure 2 is located south of Gothenburg, Sweden.

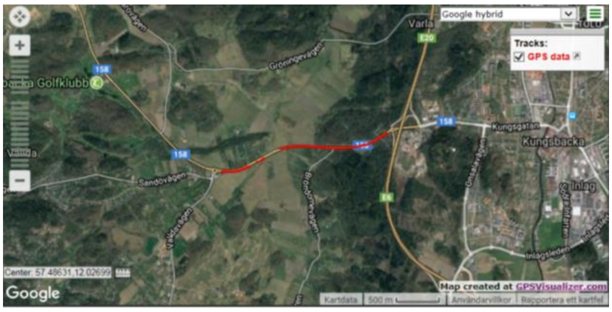

Fig. 2 Measured Road Segment

It is 2060 meters long including both a downhill and an uphill as can be seen in figure 3 together with a typical vehicle speed profile. The measurements were collected by running the road segment several times in both directions.

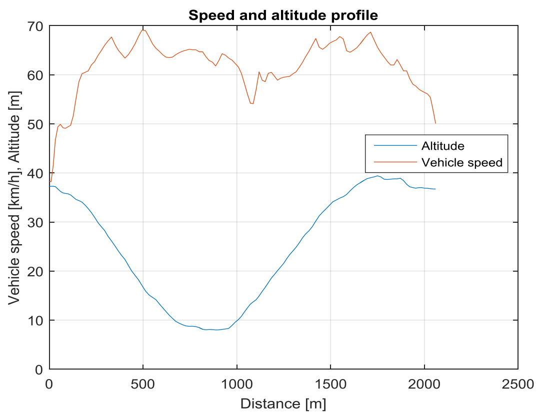

Fig. 3 Speed and Altitude Profile of Measured Road Segment

Table 1 summarizes the measured average wind speed, average wind direction and road surface conditions during the measurements.

Table 1 Vehicle Measurements

Date	Wind speed	Wind direction	Surface
20171123	*2.7*	100°	Dry
20171220	*1.8*	158°	Moist
20181504	*2.0*	194°	Dry
20180508	*1.4*	101°	Dry

Figure 4 illustrates the truck travelling in forward direction with average wind speeds and wind directions during measurements marked. 0° means direct tail wind (in forward direction) and 180° means direct head wind.

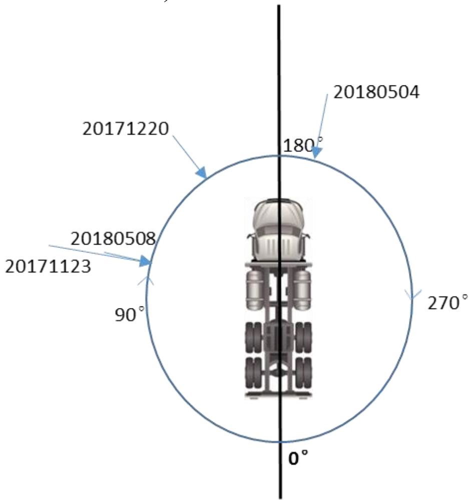

Fig. 4 Average Wind Speed and Wind Direction during Measurements

The reported wind speed from SMHI (Swedish Meteorological and Hydrological Institute) at the time and location for the measurements was between 4 and 9 m/s and the wind direction either head or side wind (or a combination). However, the measured wind speed was much lower, < 3 m/s.

7.1 Estimation Based on Vehicle Measurements

Real vehicle data includes effects from the side wind. The method tested is assuming that there is no side wind and the results from this show that the method is capable of determining if there is head or tail wind but the magnitude of the wind speed is estimated somewhere in between the actual wind speed and the head wind component when the side wind is significant as shown in figure 5 and table 2.

Table 2 Measured and Estimated Wind Speed

Date	Measured wind speed	Estimated wind speed	Measured head wind
20171123	*2.7*	-1.4	-0.5
20171220	*1.8*	-2.0	-1.7
20181504	*2.0*	-1.9	-2.0
20180508	*1.4*	-0.6	-0.3

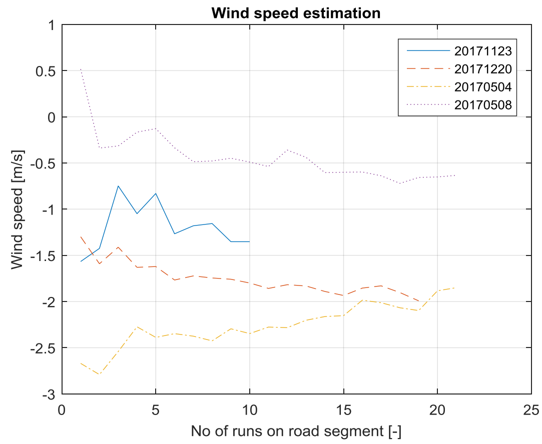

Fig. 5 Wind Speed Estimation on Measurements

Figure 6 shows the estimated rolling resistance coefficient. The value is in general higher than expected. The measurements from 20171220 done on moisty asphalt shows the highest estimated road resistance coefficient.

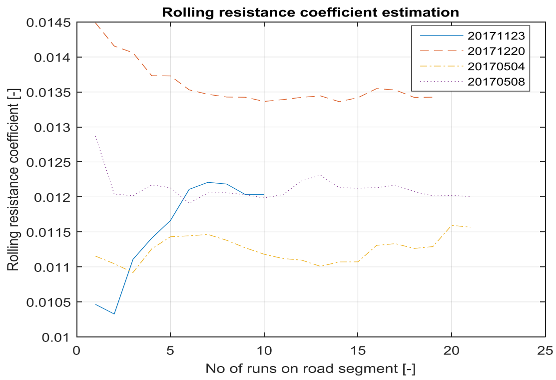

Fig. 6 Rolling Resistance Coefficient Estimation

4. SENSITIVITY ANALYSIS

The sensitivity of errors in different parameters with respect to wind speed and rolling resistance coefficient estimates is analyzed in this chapter. In section 4.1 errors in vehicle parameters and measurements are analyzed and in 4.2 errors from differences in vehicle collective and road conditions in the two directions are analyzed.

4.1 Sensitivity to Errors in Vehicle Parameters and Measurement

According to [7], if the same vehicle is ran in both directions on a road segment the wind speed (in head/tail direction) can be estimated by:

$$v_w = \frac{J_{roll\_wind\_bw} - J_{roll\_wind\_fw}}{2\rho_A A_f C_d S v_{v\_aver}} \quad (2)$$

and the rolling resistance coefficient by:

$$c_r = \frac{J_{roll\_wind\_fw} + J_{roll\_wind\_bw} - \rho_A A_f C_d S_h \left({v_{vaver}}^2 + {v_w}^2\right)}{2mgS_h} \quad (3)$$

$J_{roll\_wind\_bw}$ and $J_{roll\_wind\_fw}$ denotes the measured energy consumption from rolling resistance and wind resistance (assuming zero wind) in backward (_bw) and forward (_fw) direction of the road segment. The sensitivity in wind speed estimation and rolling resistance coefficient estimation from errors in these parameters can be calculated by taking the partial derivatives of the estimates with respect to the parameters according to:

$$\frac{\partial V_w}{\partial (J_{roll\_wind\_bw} - J_{roll\_wind\_fw})} = \frac{1}{2\rho_A A_f C_d S v_{v\_aver}} \quad (4)$$

$$\frac{\partial C_r}{\partial (J_{roll\_wind\_bw} + J_{roll\_wind\_fw})} = \frac{1}{2mgS_h} \quad (5)$$

Using typical values from the measurements ($\rho_A = 1.2\frac{kg}{m^3}, A_f C_D = 5m^2, S = 2060m, v_{v\_aver} = \frac{18m}{s}, g = 9.81\frac{m^3}{kg\ s^2}$, $m = 10000kg, S_h = 2059m$) gives:

$$\frac{\partial V_w}{\partial (J_{roll\_wind\_bw} - J_{roll\_wind\_fw})} = 2.2 * 10^{-6}\frac{m}{sJ} \quad (6)$$

$$\frac{\partial C_r}{\partial (J_{roll\_wind\_bw} + J_{roll\_wind\_fw})} = 2.5 * 10^{-9}\frac{m}{sJ} \quad (7)$$

Apart from the effects in error in J_{roll_wind} estimation, there are also direct effects from errors in parameters on v_w and c_r estimates. The sensitivity in for example ρ_A can be calculated as:

$$\frac{\partial V_w}{\partial \rho_A} = -\frac{J_{roll\_wind\_bw} - J_{roll\_wind\_fw}}{2A_f C_d S v_{v_{aver}} \rho_A^2} \quad (8)$$

$$\frac{\partial C_r}{\partial \rho_A} = \frac{-A_f C_d S_h\,({v_{v_{aver}}}^2 + {v_w}^2)}{2mgS_h} \quad (9)$$

The sensitivities for the other parameters can be calculated in similar fashion. Table (2) summarizes how large error in each parameter that gives an error in the estimate v_w of 1m/s. Once again using the same example parameters values as before and with $J_{roll_wind_fw} = 4.0 * 10^6$J and $J_{roll\_wind\_bw} = 5.0 * 10^6 J$ and v_w=-1m/s.

Table 2 Wind Speed Estimation Sensitivity

Parameter	Sensitivity
$J_{roll\_wind\_bw} - J_{roll\_wind\_fw}$	$440kJ$
ρ_A	0.53 $\frac{kg}{m^3}$
$A_f C_d$	$2.2m^2$
S	$920\ m$
v_{v_aver}	$8\frac{m}{s}$

Table (3) summarizes how large error in each parameter that gives an error in the estimate c_r of 0.001. Looking at the results in the tables, the estimations seem to be quite robust to most parameter errors. The only exception is errors in the estimated rolling resistance and air resistance energy consumption $J_{roll\_wind\_fw}$ and $J_{roll\_wind\_bw}$.

Table 3 Roll. Resist. Coeff. Estimation Sensitivity

Parameter	Sensitivity
$J_{roll\_wind\_bw} + J_{roll\_wind\_fw}$	$404kJ$
ρ_A	0.12 $\frac{kg}{m^3}$
$A_f C_d$	$0.5m^2$
S_h	$210\ m$
${v_{v_{aver}}}^2 + {v_w}^2$	$33\frac{m^2}{s^2}$
m	810 kg

Inaccurate parameters will also influence the accuracy of these estimations. The effects of this can be analyzed by calculating how sensitive the calculations of the sum of rolling resistance and air resistance energy consumption are to errors in different parameters. This consumption is calculated from:

$$J_{roll\_wind} = J_{wheel} - m\frac{v(end)^2 - v(0)^2}{2} - mg\big(h(end) - h(0)\big) \quad (10)$$

That is, the sum of the rolling resistance energy and the air resistance energy is the energy consumed at the wheels minus the increase in kinetic energy and potential energy. The sensitivity to errors in the estimation of J_{roll_wind} with respect to measurements error in the different parameters can now be calculated through:

$$\frac{\partial J_{roll\_wind}}{\partial (J_{wheel})} = 1 \quad (11)$$

$$\frac{\partial J_{roll\_wind}}{\partial m} = -\frac{v(end)^2 - v(0)^2}{2} - g\big(h(end) - h(0)\big) \quad (12)$$

$$\frac{\partial J_{roll\_wind}}{\partial (v^2(end) - v^2(0))} = -\frac{m}{2} \quad (13)$$

$$\frac{\partial J_{roll\_wind}}{\partial (h(end) - h(0)} = -mg \quad (14)$$

Looking at equation (12), to limit the sensitivity to errors in vehicle mass, the altitude and the vehicle speed at the start of the segment should be close to the vehicle speed and altitude at the end of segment. For the test road segment, the altitude difference between starting point and end point is around 0.5 m, the speed at the starting point around 11 m/s and around 12 m/s at the end point. Using these numbers, the sensitives are calculated and presented table 4:

Table 4 Roll and Wind Resistance Energy Sensitivity

Parameter	Sensitivity
$\frac{\partial J_{roll\_wind}}{\partial (J_{wheel})}$	$1[-]$
$\frac{\partial J_{roll\_wind}}{\partial m}$	-16 $\frac{J}{kg}$
$\frac{\partial J_{roll\_wind}}{\partial (v^2(end) - v^2(0))}$	$-5000\ \frac{J}{m^2/s^2}$
$\frac{\partial J_{roll\_wind}}{\partial (h(end) - h(0)}$	$-98100\ \frac{J}{m}$

Worth noting is that some of the errors are likely to affect the estimate of J_{roll_wind} with a perturbation with the same sign in both directions and some of them are likely to have opposites signs. For example, a model error resulting in too high estimated wheel torque in one direction is likely to result in a too high estimate in the other direction also. The same goes for the vehicle mass estimate. When it comes to altitude, it is reasonable to assume that errors will come for poor map data and in that case affect J_{roll_wind} with different signs in the two directions. The significance of this is that the errors that are likely to produce errors with the same sign in both directions will not affect the wind speed estimation very much since this estimate is based on the difference in energy consumption. While as the rolling resistance coefficient is based on the sum it will be doubly affected by these kinds of errors but not so much by errors with different signs. The opposite goes for errors with difference signs in the two directions, rolling resistance estimate will not be so much affected but the wind speed estimate will be doubled affected.

In our example, the precision of the altitude at the starting point and at the end point is the most sensitive factor to the precision of the wind speed estimate. An altitude difference between the starting point and the end point that is 3 meters wrong will result in a wind estimate that is more than 1 m/s wrong. For the precision of the rolling resistance coefficient, the ability to estimate the wheel power accurately seems to be most critical. The error in this estimation will be directly propagated as an error in the estimation of the sum of air resistance and rolling resistance energy. If the same error is propagated in both direction, the error will turn up in the estimated rolling resistance coefficient. In our example, around 10 percent error in wheel power estimation results in an error in the estimation of the rolling resistance coefficient of 0.001.

4.2 Differences in road surface or vehicle collective

The method presented in [7] builds on two assumptions:

1. The road surface is equal in both directions
2. The vehicle collective is equal with regards to rolling resistance in both directions

If either of these conditions are violated an error in the estimates will occur. The wind speed estimate is assuming that the average rolling resistance is equal in both directions. If it's not, either because of different road surface or because of a different vehicle collective in the two directions, the difference in rolling resistance energy will be added as an offset in the wind speed estimate. The rolling resistance coefficient that is estimated will in this case be the average rolling resistance for the two directions. The magnitude of the error in wind speed estimate depend on how sensitive the energy consumption for the vehicles running on the road segment are to changes in road surface conditions compare to wind changes. In general, it depends a lot on the vehicle speed. In higher vehicle speeds, wind is more important and the error discussed here will not influence the wind speed estimate so much while in low speed conditions it will have a significant impact. In the example we used in the previous section, a difference in average rolling resistance coefficient of 0.001 corresponds roughly to a wind speed estimate offset of 0.5 m/s.

5. DISCUSSION

5.1 Application

Estimates of road resistance can be used for predicting the vehicle energy consumption. This can in turn be used for several things such as:

1) Range estimation of battery electric vehicles
2) Route planning (especially for battery electric vehicles)
3) Energy management

The idea for using the road resistance estimates for improved vehicle energy consumption is quite straight forward. If you have knowledge of the traffic situation and the driver behavior you can make a prediction of the speed profile on the upcoming speed segment. Using this speed profile and vehicle information together with the road resistance estimates a good prediction of the vehicle energy consumption at the wheels can be done using equation (1) for example, where v now is the predicted relative air speed rather than the predicted vehicle speed and c_r a function of prevailing road surface conditions. To be able to do a good range estimation of battery electric vehicles, the energy consumption prediction need to be complemented with knowledge of the remaining battery energy as well as good powertrain efficiency information.

For route planning, accurate vehicle energy consumption prediction in combination with charging opportunities are vital to route battery electric vehicles energy and cost efficiently without risking running out of battery energy.

The main foreseen use for energy management is to be able to accurately calculate the optimal speed profile in hilly terrain. Without knowledge of the road resistance, the vehicle might roll faster or slower than predicted, wasting either energy in form of braking, or time when going slower than expected.

5.2 Vehicle parameter's estimation

Another more indirect usage of road resistance estimates is to improve estimation of vehicle parameters such as vehicle mass, air drag coefficient and rolling resistance coefficient. One possibility to improve the rolling resistance coefficient is that if the vehicle is passing a number of road segments on which the average rolling resistance coefficient is available, the vehicle could learn its relation to the vehicle average. If it always been around x % lower in the past it is likely to be x % lower in the near future as well.

Vehicle mass estimation is still a challenge. Kalman filters have been suggested for example by [6]. One of the challenges is the disturbances from changing road conditions and inaccuracies in road slope information. GPS positioning have improved during the last decay and by using a precise positioning system in combination with accurate altitude data, the road slope information should be accurate. Combining this with road surface and wind information should enable improved accuracy of the mass estimation.

Another problem area that can be improved using estimates of vehicle independent road resistance parameters is detecting changes in the air drag coefficient of the ego vehicle. The air drag coefficient of a vehicle is traditionally measured in a wind tunnel and is well known by the vehicle. However, if something changes, for example if you add a roof box, the aerodynamic properties change a lot. Without knowledge of the prevailing road conditions, it is difficult to distinguish head wind from aerodynamics making it difficult to predict energy consumption after a turn. If the wind conditions are known, the vehicle has a good chance to quickly detect the new air drag conditions and adapt its energy consumption prediction accordingly.

5.3 Road weather information

Finally, road weather information can be improved from using information from connected vehicles. Today, most road weather information source rely on measurement from equipment at the roads. The main problems with this are that it is impossible to measure the road everywhere and that it might be difficult to measure how the vehicles are affected by the prevailing conditions. For example, when collecting the measurement data used in this paper, the wind speed reported in the area from the SMHI was between 4 m/s and 9 m/s. But when looking at the measured wind speed, the wind speed was much lower. A possible reason for this is that the reported wind speeds in the area is on locations where there is nothing limiting the wind. The selected road segment is in a small valley and is somewhat protected from wind. This shows that relying on more general data might not be such a good idea. The actual conditions are very local and therefore, the information need to be local as well. However, combining more general weather information with vehicle data might actually also improve the general weather predictions.

6. CONCLUSIONS

The results show that the estimation method is able to estimate the wind speed with reasonable good accuracy, especially when there is more or less no side wind. The side wind contributes to additional energy consumption when going in both directions. The analytical method is determining wind speed from the difference in energy consumption in each direction and hence, the contribution from side wind will contribute to higher rolling resistance coefficient estimate rather than higher wind speed. To be of any real use, the analytical method must be extended to be able to also deal with side wind. This should be possible by adding knowledge to the estimation of how sensitive each vehicle is to side wind. Large trucks with large trailers are likely to be much more sensitive than small cars.

When it comes to the rolling resistance coefficient the true value is not known and it is difficult to assess the result. In general, the estimated rolling resistance was higher than expected. However, in reality the method is estimating all resistance that is equal in both direction (grade resistance excluded). Apart from the effect from side wind already mentioned, model errors will also turn up as an extra addition to the rolling resistance estimate which could be considerable. Interesting though is that the measurements that was done when the road surface was moist show higher rolling resistance than the measurements on dry surface, suggesting that the method might at least work to detect changes in rolling resistance on a road segment.

REFERENCES

[1] Pandazis J. C., Winder A., "Study of Intelligent Transport Systems for reducing CO2 emissions for passenger cars", ERTICO Study of ITS measures to reduce CO2 emissions for cars, 2015

[2] Polack P., d'Andrea-Novel B., Fliess M., de La Fortelle A., Menhour L., "Finite-time stabilization of longitudinal control for autonomous vehicles via a model-free approach", IFAC World Congress, Toulouse, 2017

[3] Lefèvre S., Carvalho A., Borrelli F., "A Learning-Based Framework for Velocity Control in Autonomous Driving", IEEE Transactions on Automation Science and Engineering, Volume 13 issue 1, 2016

[4] Sadigh D., Driggs-Campbell K., Puggelli A., Li W., Shia V., Bajcsy R., Sangiovanni-Vincentelli A.L., Sastry S.S., Seshia S.A., "Data-Driven Probabilistic Modeling and Verification of Human Driver Behavior", Formal Verification and Modeling in Human-Machine Systems, 2014

[5] Driggs-Campbell K., Shia V., Bajcsy R., "Improved driver modeling for human-in-the-loop vehicular control", IEEE International Conference on Robotics and Automation (ICRA), 2015

[6] Lingman P., Schmidtbauer B., "Road slope and vehicle mass estimation using Kalman filtering", Vehicle System Dynamics, 2002

[7] Askerdal, M., Fredriksson J. "Vehicle Independent Road Segment Resistance Estimation", Proceedings from EVS30, 2017

[8] Sahlholm P., Johansson K. H., "Road grade estimation for look-ahead vehicle control using multiple measurement runs", Control Engineering Practice, Volume 18, Issue 11, 2010