

# **Vehicle Independent Road Section Resistance Estimation**

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## **Abstract**

Road resistance is commonly divided into three different components; rolling resistance, wind resistance and resistance from road gradient (hills). The total sum of road resistance is the force that must be delivered by the powertrain to the wheels of the vehicle in order to maintain speed. The idea pursued in this paper is that it is possible to find models for each of the different components of the road resistance where the input parameters used are separated into purely vehicle dependent and purely vehicle independent parameters and that it is possible to estimate vehicle independent parameters from log data from a large population of vehicles (big data). The advantages with this approach is that data from any vehicle can be used to improve the estimation and that all vehicles can benefit from the estimated data. In the long run, this can lead to a system that dynamically calculates the surrounding parameters of the road resistances and that adapts rapidly to changing conditions such as wind and wet road surface. The main benefit from using the results is improved range estimation of battery electric vehicles but it can also be used for less computational route planning and improved vehicle energy management.

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## **1 Background**

Battery electric vehicles (BEV) have many advantages compared to vehicles with conventional powertrains. However, the range of a BEV is much shorter than the range of a comparable diesel engine powered vehicle. Moreover if the vehicle user does not fully trust the vehicle's range estimation, the actual vehicle range of a BEV might shrink even further and hence, there is a need for more reliable range estimation.

Range estimation suffers from a number of difficulties. Some of them are related to uncertainties in vehicle parameters and properties such as vehicle mass and auxiliary load, while as other are more related to the environment such as traffic situation and road resistance. The work described in this paper is focusing on improving the latter.

Road resistance is defined as 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 different components of the road resistance have been studied in a number of different projects ([1], [2], [3]) and a lot is well known. However, in most studies the model parameters used are often dependent on both the vehicle, the road and the surroundings. Some exceptions exist though,

especially when it comes to the rolling resistance [4]. In this work, the focus is on finding and estimating the vehicle independent parameters of the rolling resistance and air resistance. The vehicle independent parameter of the gravitational force is the road slope and how to estimate it from vehicle log data has been studied by others [5].

Today, range estimation is done by the assumption that the vehicle will run on dry asphalt in zero wind. If the vehicle independent parameters were known, the range estimation algorithm would be able to adapt to changing conditions and more accurately calculate the range on different roads and in different conditions. Typically, the range estimation would be able to adapt to changes in wind conditions and to water and snow on the road surface as well as point out the difference in range on a dirt road compared to an asphalt road.

## 2 Problem formulation

The problem investigated in this work is how to split road resistance parameters into two groups, vehicle dependent and vehicle independent parameters and how to estimate the vehicle independent parameters from vehicle log data. To solve this problem, a simple vehicle dynamic model is 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,  $\rho_{air}$  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  $\alpha$  the road slope. Notice that  $v$  is the relative air speed, that is the vehicle speed  $v_v$ , minus the wind speed  $v_w$ .

Wind speed can be very fluctuating and change quite rapidly and measurements of parameters like  $a$  and  $\alpha$  can be quite noisy. It is therefore motivated to estimate the average value of the parameters over a road section rather than a continuous estimation.

Equation (1) can then be reformulated for a section starting at 0 and ending at  $S$ :

$$\frac{m(v_v^2(S) - v_v^2(0))}{2} = J_{prop} - \frac{\rho_{air} A_f c_d}{2} \int_0^S (v_v - v_w)^2 ds - mgc_r S_h - mg(h(S) - h(0)) \quad (2)$$

where  $v_v(S)$  is the vehicle speed at point  $S$ ,  $v_v(0)$  the vehicle speed at point 0,  $J_{prop}$  the total amount of net propulsion energy at the wheels over the section  $S$ ,  $h(S)$  the altitude at point  $S$ ,  $h$  the altitude at point 0 and  $S_h$  the horizontal length of section  $S$ . The problem investigated in this paper is to find estimates of the unknown parameters  $v_w$  and  $c_r$ .

## 3 Parameter estimation

The problem with estimating these parameters is that there are more unknowns than equations. In this particular case there are two unknowns,  $v_w$  and  $c_r$ , and one equation, formulated either as (1) or (2). The idea utilized in this work is that there are several road users, vehicles, traveling on the same road segment. If these road users share information the problem of estimating the unknowns becomes solvable. The estimation is based on the following assumptions:

### 3.1 Assumptions

1. There is no effect from side wind
2. The vehicles have good knowledge of its own parameters such as vehicle mass and frontal area.
3. The vehicles can accurately measure its propulsion/braking energy,  $J_{prop}$  and its vehicle speed  $v_v$ .
4. The road segment is well known, i.e. the vehicle knows the start and the end point.
5. The altitudes at the starting point and the end point are well known.
6. The rolling resistance coefficient is constant for the road section  $S$  and is equal in both directions
7. The wind speed and wind direction is constant for the road section  $S$
8. The vehicle distribution in terms of average and variance in speed, air resistance properties and rolling resistance properties are equal in both directions.

The first five assumptions make sure the only unknowns in equation (2) are the parameters to be estimated. Assumption 1 and 7 are the least realistic assumption. Side wind will have an effect on the overall road resistance and will be considered in future work and wind speed will not be constant on a road segment. However, the estimated wind speed should be regarded as an average over the segment.

### 3.2 Vehicle independent parameters

The wind speed is for sure a vehicle independent parameter but the rolling resistance coefficient is not. It depend both on the tires of the vehicle and on the road surface. To be able to split the rolling resistance into vehicle independent parameters and parameters depending only on the vehicle (and the tires), a lot of information of the tires is needed. Today, normal tires cannot provide this information themselves and the tires can be changed, hence the information cannot entirely be programmed into a control unit of the vehicle. Instead of digging deep into the tire modelling, the hypothesis in this paper is that the average vehicle rolling resistance coefficient of a road segment can serve as a vehicle independent coefficient. It is of course not independent of the vehicle collective, but if the conditions on a road segment are changing slowly, the traffic flow is high and the vehicles running on the segment are randomly distributed in terms of mass, air resistance properties and rolling resistance properties, the influence from one single vehicle will be insignificant and hence it will be independent, or at least close to independent, of each individual vehicle. How the average rolling resistance of a road segment can be used by a single vehicle will be included in future research and is outside the scope of this paper.

### 3.3 Estimation methods

#### 3.3.1 Estimation using a single vehicle

For a particular road segment stretching from point a to point b, the sum of the rolling resistance and the air resistance is calculated by withdrawing the vehicle's kinetic and potential energy difference when running from point a and point b from the total amount of energy delivered from the powertrain and the brakes to the wheels:

$$\frac{\rho_{air} A_f C_d}{2} \int_0^S (v_v - v_w)^2 ds + mgc_r S_h = J_{prop} - \frac{m(v_v^2(S) - v_v^2(0))}{2} - mg(h(S) - h(0)) \quad (3)$$

In equation (3), the powertrain dynamics has been neglected. For unloaded heavy duty vehicles, this dynamics could be of considerable size relative the kinetic energy of the complete vehicle. In the simulation environment used, this dynamics is modelled as a compensation term on the vehicle mass when calculating the vehicle acceleration. To improve the accuracy of the estimations in this paper, the integral of the compensated and varying mass,  $m_c(s)$  times the vehicle acceleration is used to calculate the kinetic energy change over the road segment:

$$\frac{\rho_{air} A_f C_d}{2} \int_0^S (v_v - v_w)^2 ds + mgc_r S_h = J_{prop} - \int_0^S m_c(s) a(s) ds - mg(h(S) - h(0)) \quad (4)$$

Using assumptions (2), (3) and (5) the right hand side of (3) can easily be calculated and is noted  $J_{roll\_wind\_fw}$ , that is:

$$J_{roll\_wind\_fw} = \frac{\rho_{air} A_f C_d}{2} \int_0^S (v_v - v_w)^2 ds + mgc_r S_h \quad (5)$$

where the subscript fw stands for forward direction.

The underlying problem remaining is that we have two unknowns,  $v_w$  and  $c_r$  and only one equation, i.e. it is possible to determine the sum of wind and rolling resistance but unless the vehicle speed has been varying a lot of the segment, it is impossible to determine how much each component contributes. Without knowing this, the wind speed and the rolling resistance coefficient cannot be determined and the knowledge is not vehicle independent and therefore of limited use for other vehicles. One solution to this is to let the vehicle run the same road segment in the opposite direction. Noting the sum of rolling resistance and wind resistance  $J_{roll\_wind\_bw}$  we get:

$$J_{roll\_wind\_bw} = \frac{\rho_{air} A_f C_d}{2} \int_0^S (v_{v\_bw} + v_w)^2 ds + mgc_r S_h \quad (6)$$

where the subscript bw stands for backward direction.

Now we have two equations and the wind speed and rolling resistance coefficient can be calculated. By subtracting (5) from (6) we get:

$$\frac{\rho_{air}A_fC_d}{2} \int_0^S (v_{v,bw} + v_w)^2 ds - \frac{\rho_{air}A_fC_d}{2} \int_0^S (v_v - v_w)^2 ds = J_{roll\_wind\_bw} - J_{roll\_wind\_fw} \quad (7)$$

Equation (7) is solvable but unfortunately it requires full knowledge of the vehicle speed trajectory over the road segment to get an exact answer. However, due to the rough estimates already done, it doesn't make sense to require such detailed information which makes the calculations more complicated and computational. Instead by approximating the speed trajectories in both directions with the average vehicle speed,  $v_{v\_aver}$ , over the road segment ran in both directions we can approximate (7) with:

$$\frac{\rho_{air}A_fC_d}{2} \int_0^S ((v_{v\_aver} + v_w)^2 - (v_{v\_aver} - v_w)^2) ds = J_{roll\_wind\_bw} - J_{roll\_wind\_fw} \quad (8)$$

Since the function to be integrated now is constant, by completing the squares equation (8) can be rewritten:

$$2\rho_{air}A_fC_dSv_{v\_aver}v_w = J_{roll\_wind\_bw} - J_{roll\_wind\_fw} \quad (9)$$

And the wind speed can be calculated as:

$$v_w = \frac{J_{roll\_wind\_bw} - J_{roll\_wind\_fw}}{2\rho_{air}A_fC_dSv_{v\_aver}} \quad (10)$$

The rolling resistance coefficient  $c_r$  can now be calculated using the estimated wind speed and either data from only one direction (equation (5) or (6)) or data from both directions (by using both (5) and (6)). If the latter is used one can use the sum of equation (5) and (6), rearrange and once again use a constant average speed  $v_w$  instead of the real speed profile to form:

$$c_r = \frac{J_{roll\_wind\_fw} + J_{roll\_wind\_bw} - \rho_{air}A_fC_dS(v_{v\_aver}^2 + v_w^2)}{2mgS_h} \quad (11)$$

Note that this is an estimate of the rolling resistance coefficient for that particular vehicle running on the chosen road segment. It is not the average rolling resistance coefficient we are looking for and is not vehicle independent. For that we need to use data from multiple vehicles.

### 3.3.2 Estimation using multiple vehicles

In real conditions, the single vehicle estimation is of little use. Partly since it is rare that a vehicle travels the same route segment in both directions with very little time in between and partly because there is no use of the estimated parameters if they are not given before the vehicle starts to travel on the road segment. Therefore it is vital to find vehicle independent parameters so that when a vehicle reaches a particular road segment, it can use road resistance parameters estimated from data from other vehicles that have travelled the same road segment.

In this work, the wind speed, wind direction (head or tail wind) and average vehicle rolling resistance have been chosen as the vehicle independent parameters to be estimated. By rearranging equation (5), still using the assumptions of constant vehicle speed over the segment and normalize with vehicle mass, the normalized rolling resistance can be written as:

$$g c_r S_h = \frac{J_{roll\_wind\_fw}}{m} - \frac{\rho_{air}A_fC_dSv_v^2}{2m} + \frac{\rho_{air}A_fC_dSv_v}{m} v_w - \frac{\rho_{air}A_fC_dS}{2m} v_w^2 \quad (12)$$

The normalized rolling resistance is in other words described by second order polynomial in wind speed and could be rewritten as:

$$g c_r S_h = \alpha + \beta * v_w - \gamma * v_w^2 \quad (13)$$

where  $\alpha = \frac{J_{roll\_wind\_fw}}{m} - \frac{\rho_{air}A_fC_dSv_v^2}{2m}$ ,  $\beta = \frac{\rho_{air}A_fC_dSv_v}{m}$  and  $\gamma = \frac{\rho_{air}A_fC_dS}{2m}$ .

Now consider the case where  $N_1$  vehicles are passing the same road segment in the same direction in a reasonable short time so that the wind and road surface can be considered to be constant over this period. If

each of the vehicles contributes with the  $\alpha, \beta$  and  $\gamma$  coefficients after running on the selected road segment, the collective sum of normalized rolling resistance becomes:

$$gS_h \sum_{i=1}^{N_1} c_{r,i} = \sum_{i=1}^{N_1} \alpha_i + v_w \sum_{i=1}^{N_1} \beta_i - v_w^2 \sum_{i=1}^{N_1} \gamma_i \quad (14)$$

where the index indicates data from vehicle number  $i$ .

Now let  $\hat{c}_r$  be the average rolling resistance. Then we can rewrite (13) into:

$$gS_h N_1 \hat{c}_r = \sum_{i=1}^{N_1} \alpha_i + v_w \sum_{i=1}^{N_1} \beta_i - v_w^2 \sum_{i=1}^{N_1} \gamma_i \quad (15)$$

Assuming that the vehicles on average are similar in both directions so that they on average have the same rolling resistance coefficient, and that the wind conditions are the same in both directions, the collective sum of the normalized rolling resistance for  $N_2$  vehicles going in the other direction becomes:

$$gS_h N_2 \hat{c}_r = \sum_{j=1}^{N_2} \alpha_j - v_w \sum_{j=1}^{N_2} \beta_j - v_w^2 \sum_{j=1}^{N_2} \gamma_j \quad (16)$$

where the index indicates data from vehicle number  $j$ .

Now normalizing equation (15) and (16) with  $N_1$  and  $N_2$  respectively, the left sides becomes equal and they can be merged into:

$$\frac{\sum_{i=1}^{N_1} \alpha_i + v_w \sum_{i=1}^{N_1} \beta_i - v_w^2 \sum_{i=1}^{N_1} \gamma_i}{N_1} = \frac{\sum_{j=1}^{N_2} \alpha_j - v_w \sum_{j=1}^{N_2} \beta_j - v_w^2 \sum_{j=1}^{N_2} \gamma_j}{N_2} \quad (17)$$

or:

$$v_w^2 \left( \frac{\sum_{i=1}^{N_1} \gamma_i}{N_1} - \frac{\sum_{j=1}^{N_2} \gamma_j}{N_2} \right) - v_w \left( \frac{\sum_{i=1}^{N_1} \beta_i}{N_1} + \frac{\sum_{j=1}^{N_2} \beta_j}{N_2} \right) + \left( \frac{\sum_{j=1}^{N_2} \alpha_j}{N_2} - \frac{\sum_{i=1}^{N_1} \alpha_i}{N_1} \right) = 0 \quad (18)$$

This is clearly an ordinary second order equation in wind speed and can easily be solved analytically.

What is left is to estimate  $\hat{c}_r$ . Once the wind speed is found,  $\hat{c}_r$  can be calculated using either equation (15), (16) or the sum of both. The latter holds information from all vehicles and is therefore used in this paper and  $\hat{c}_r$  is calculated from:

$$\hat{c}_r = \frac{1}{2gS_h} \left( \frac{\sum_{i=1}^{N_1} \alpha_i + v_w \sum_{i=1}^{N_1} \beta_i - v_w^2 \sum_{i=1}^{N_1} \gamma_i}{N_1} + \frac{\sum_{j=1}^{N_2} \alpha_j - v_w \sum_{j=1}^{N_2} \beta_j - v_w^2 \sum_{j=1}^{N_2} \gamma_j}{N_2} \right) \quad (19)$$

## 4 Results

The methods described in section 3.3 has been tested through complete vehicle simulations using three different types of vehicles, each with three different vehicle masses and each combination (vehicle mass/vehicle type) with three different tires on a selected 372 meters long road segment. The reference speed and altitude profile of the chosen segment is plotted in Figure 1. More information of the different vehicle configurations used can be found in table 1 in appendix.

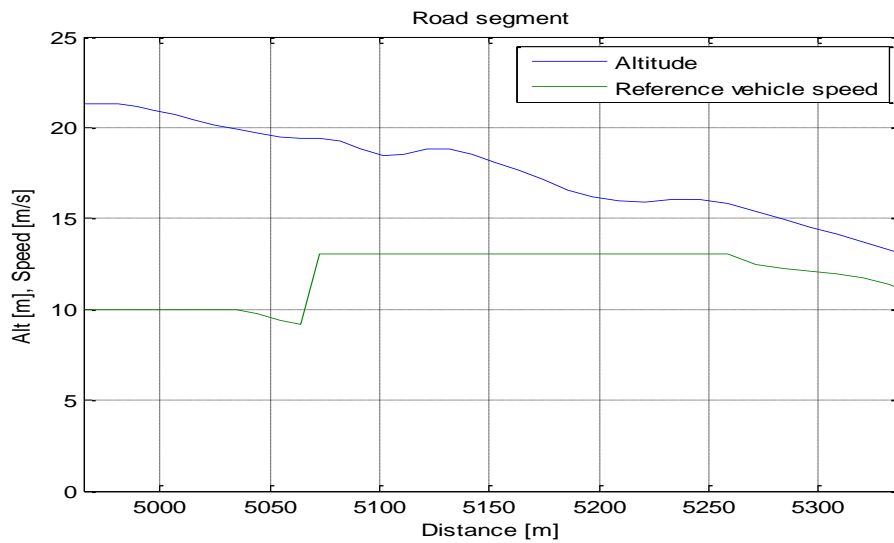


Figure 1. Selected road segment.

The simulation environment includes a driver model that tries to follow the reference speed as good as possible. The simulated vehicle speed for different vehicles will therefore differ a bit between different vehicle configurations since parameters as vehicle mass and engine power will determine how close to the reference speed the actual speed can be kept.

Section 4.1 presents results from estimates using data from a single vehicle running on a road segment in both directions. Section 4.2 presents results from a more realistic approach where different vehicles are running in both directions on the selected road segment.

#### 4.1 Results from estimates using a single vehicle

Figure 2 shows the estimated wind speed for all tested vehicle configurations when the simulated wind speeds were +5 m/s and +10m/s. The results show that the wind speeds are estimated with a relative error < 30% for all simulated combinations except two which have relative errors that are much higher, especially when the wind speed is 5 m/s. The two outliers are a 40 tons long-haul truck with the tire specification '305/70R19.5 78.5N/ton' and a 25 tons distribution truck with the tire specification '315/80R22.5 56.6N/ton'. The outliers are the same for both 5 m/s and 10 m/s wind speed.

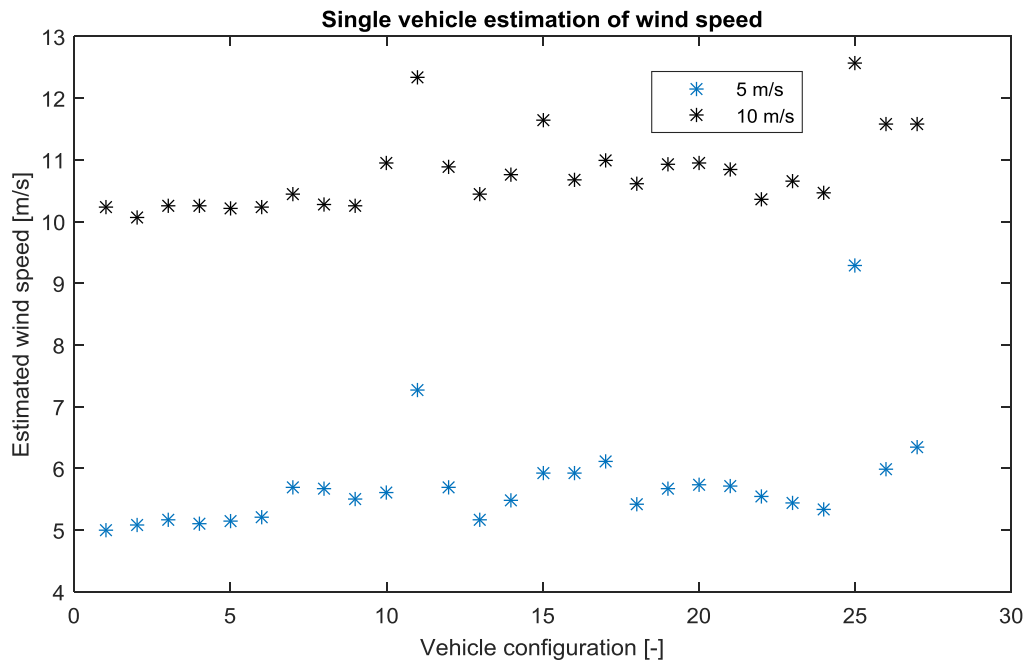


Figure 2. Wind speed estimation.

In Figure 3, the estimated road resistance coefficient is plotted together with the actual value of the coefficient for the different vehicle set-ups with simulated wind speeds of 5 m/s and 10 m/s. The estimation is accurate with a relative error < 10 % for all vehicle configurations. The precision of the estimation does not seem to depend strongly on the wind speed.

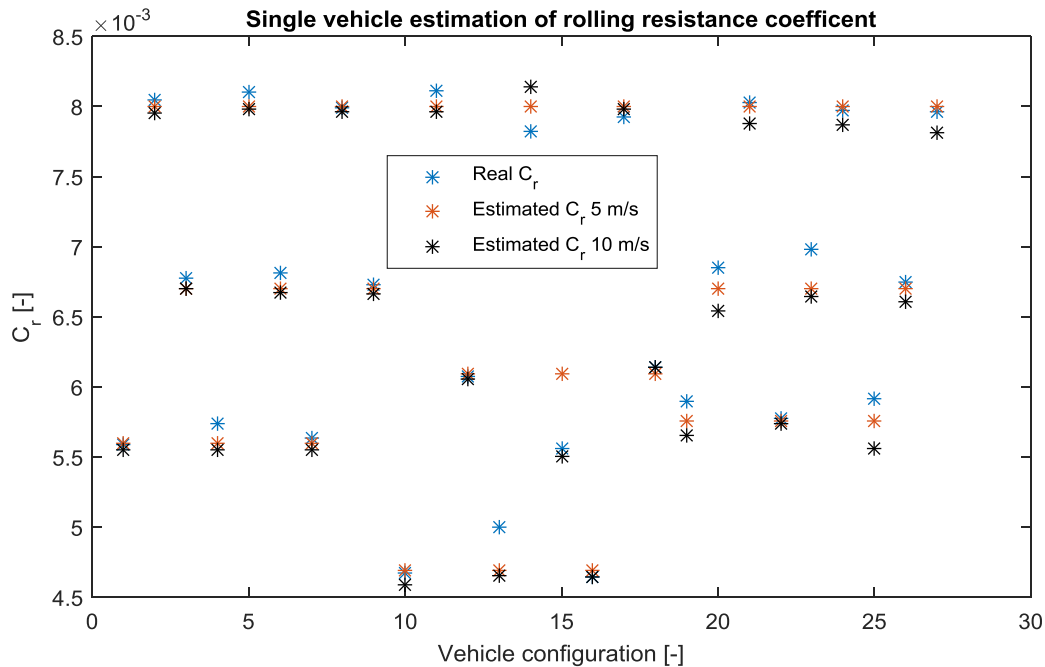


Figure 3. Road resistance coefficient estimation when wind speeds are 5 m/s and 10m/s.

Figure 2-3 show that the rolling resistance coefficient can be estimated with good accuracy and the wind speed with reasonable accuracy using the presented method where a single vehicle is driven on a road segment in both directions. The selection of a whole segment reduces the influence of numeric noise and

the use of data from vehicles running in both directions enables separation of rolling resistance and air resistance. The main reason for the remaining errors is that the average vehicle speed over the section is used rather than using the exact vehicle speed profile.

## 4.2 Results from estimates using multiple vehicles

In this section, results from estimations using the multiple vehicles approach describe in chapter 3.3.2 are presented. Simulations from the same 27 vehicle configurations that were used in the single vehicle estimation were used once again. Instead of letting the same vehicle running the same road segment in each direction and then calculate the wind speed and road resistance for each vehicle, vehicles were chosen in a random order to run in one of the directions (also randomly chosen) and then the wind speed and average road resistance were calculated from data from all vehicles that had already run the segment. Figure 4 plots the estimated wind speed against the total number of vehicles driven during constant conditions in both directions. The estimated wind speed converges to a somewhat higher wind speed than the actual wind speed. The reason is the same as for single vehicle estimation, namely that this is the error from the assumption of constant vehicle speed over the road segment. Note also that the wind speed is estimated to be zero until at least one vehicle have ran in each direction. That is required from the estimation algorithm used.

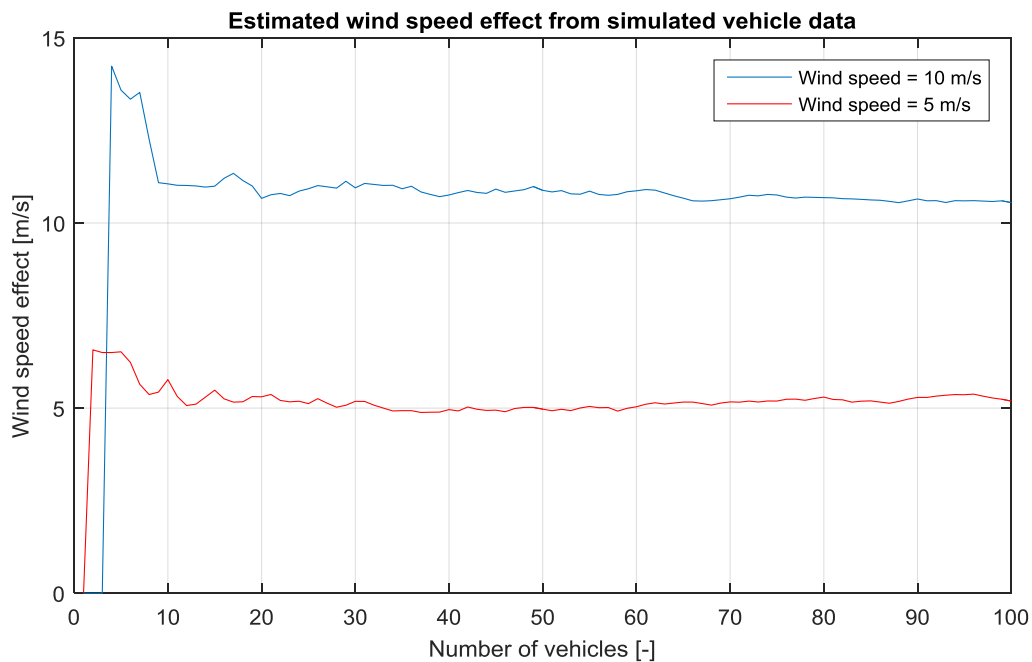


Figure 4. Wind speed estimation from multiple vehicles.

Figure 5 plots the corresponding estimated rolling resistance using the wind speeds plotted in Figure 4. Note that the estimation seem to converge to a value close to the actual average rolling resistance. The wind speed estimation is more sensitive to the errors in the constant speed assumption than the rolling resistance coefficient. Note also that as soon as at least one vehicle has been driven in each direction, the estimated average rolling resistance coefficient will be equal in both directions. This follows directly from the assumption that the average rolling resistance is equal in both directions.

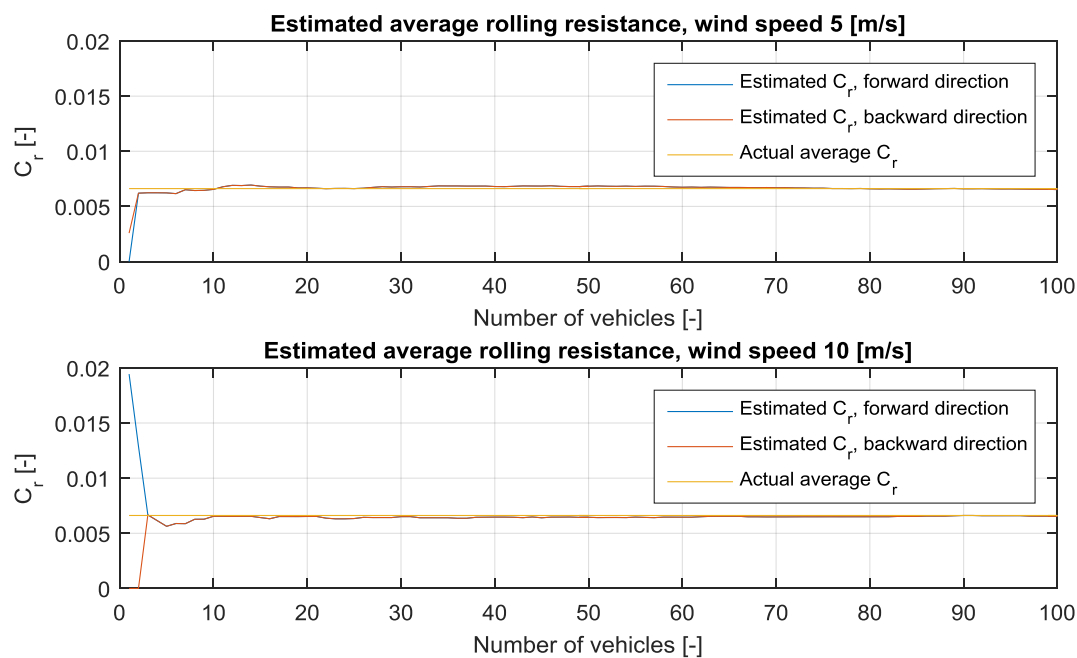


Figure 5. Estimated average rolling resistance coefficient using multiple vehicles.

## 5 Discussion and conclusions

The assumptions made in this work are quite severe. When looking into data from real vehicles running on real roads in traffic environment and in real weather conditions, all of the assumptions will not hold. The vehicles cannot measure their wheel torque, their mass estimations are not perfect, the wind speed and direction will not be constant and there will be an effect from side wind, to mention some of the disturbances that need to be handle before going to a real application. The work done so far have been focusing on if it is possible to separate road resistance parameters into vehicle independent parameters and parameters depending merely on the vehicle and if it is possible to estimate the vehicle independent parameters from vehicle log data and under what circumstance. This paper shows that if wind speed, wind direction and average rolling resistance are chosen as the vehicle independent parameters, they can indeed be estimated from vehicle log data with pretty good accuracy if all the given assumptions hold.

Another important finding, is that if the rolling resistance is equal in both directions, the air resistance and the rolling resistance can be separated from each other. This is extra important on road segments with more or less constant vehicle speed. On those segments, the individual vehicles will have difficulties to separate the air and rolling resistance from each other. And since different vehicles have different aerodynamic properties and rolling resistance properties, the total road resistance data from one vehicle will be useless for another.

A remark is that even though there will be errors in the wheel torque estimation in real vehicles, the estimation process presented here could still work. The important thing is that estimated wheel torque is unbiased. If that is true, than the estimation error should decrease as the number of vehicles used in the estimation process increases.

A second remark is that the estimation algorithms assume static conditions in wind speed, wind direction and rolling resistance. It is however easy to adapt the method to changing conditions by applying a moving average estimation approach instead. How well this will work depend on if the rate of vehicles passing the segment is high enough compared to change rate of the conditions.

Future work will focus on validating the assumptions and investigating the side-wind effect. Apart from the lack of side wind assumption (3), the vehicles can accurately measure its propulsion/braking energy,  $J_{prop}$ , is presumed to be the least realistic. The predominating vehicles of today has no wheel torque sensor and

the wheel torque is estimated from the combustion engine torque. There are several different sources of errors that make this estimation difficult. The engine itself is very complex and it might be difficult to estimate its exact output torque, mechanical auxiliaries connected to the engine via a belt gives parasitic losses and the rest of the drive-train, including the transmission also add losses. However, the accuracy of the wheel torque estimation is likely to be more precise using electrified vehicles with no combustion engine (or engine used merely as range extender) and the effect of errors in this estimation decreases when the amount of log data increases as long as the estimation is unbiased.

## References

- [1] R. Karlsson, *Parameter Estimation for a Vehicle Longitudinal Model*, Master thesis vehicle system LiU, 2015
- [2] B. Koo, K. Han., *Estimate the Road Resistance Coefficient of Light Weight Vehicle*, SAE Technical paper, 2013
- [3] P. Baldiserra, *Proposal of a coast-down model including speed-dependent coefficients for the retarding forces*, SAGE publications, 2016
- [4] K Yoshimura, MM Davari, L Drugge, J Jerrelind, A Stensson Trigell, *Studying road surfaces roughness effect on rolling resistance using brush tyre model and self-affine fractal*, The Dynamics of Vehicles on Roads and Tracks: Proceedings of the 24th International Symposium on Dynamics of Vehicles on Roads and Tracks, 2015
- [5] P Sahlholm, K H Johansson, *Road grade estimation for look-ahead vehicle control using multiple measurement runs*, Control Engineering Practice, Volume 18, Issue 11, 2010

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## Appendix 1, vehicle configurations

Three types of vehicles have been used in the simulations, namely a city bus, a long haul truck and a distribution truck. Each vehicle have been simulated with three different masses and each combination of vehicle type and vehicle mass have been simulated with three different type of tires with different rolling resistance coefficient on dry asphalt. The vehicle type, mass and tire combinations can be found in Table 1. The vehicle number correspond to the vehicle configuration number used in the text.

Table 1. Vehicle configurations used in estimation process

Vehicle configuration id	Vehicle type	Vehicle mass (kg)	Tyre dimension
1	City bus	13400	275/70R225 54.9N/ton
2	City bus	13400	235/75R175 78.5N/ton
3	City bus	13400	295/80R225 65.7N/ton
4	City bus	10000	275/70R225 54.9N/ton
5	City bus	10000	235/75R175 78.5N/ton
6	City bus	10000	295/80R225 65.7N/ton
7	City bus	20000	275/70R225 54.9N/ton
8	City bus	20000	235/75R175 78.5N/ton
9	City bus	20000	295/80R225 65.7N/ton
10	Long haul truck	40000	315/70R22.5 46N/ton
11	Long haul truck	40000	305/70R19.5 78.5N/ton
12	Long haul truck	40000	295/60R24 59.8N/ton
13	Long haul truck	20000	315/70R22.5 46N/ton
14	Long haul truck	20000	305/70R19.5 78.5N/ton
15	Long haul truck	20000	295/60R24 59.8N/ton
16	Long haul truck	60000	315/70R22.5 46N/ton
17	Long haul truck	60000	305/70R19.5 78.5N/ton
18	Long haul truck	60000	295/60R24 59.8N/ton
19	Distribution truck	14000	315/80R22.5 56.6N/ton
20	Distribution truck	14000	295/60R22.5 65.7N/ton
21	Distribution truck	14000	235/75R17.5 78.5N/ton

22	Distribution truck	9000	315/80R22.5 56.6N/ton
23	Distribution truck	9000	295/60R22.5 65.7N/ton
24	Distribution truck	9000	235/75R17.5 78.5N/ton
25	Distribution truck	25000	315/80R22.5 56.6N/ton
26	Distribution truck	25000	295/60R22.5 65.7N/ton
27	Distribution truck	25000	235/75R17.5 78.5N/ton