

Model-Based Estimation of Vehicle Aerodynamic Drag and Rolling Resistance

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ABSTRACT

Commercial vehicles transport the majority of the inland freight in US and a significant number of passengers. They are large fuel consumers as they operate a large number of hours per day, pulling heavy loads. The increasing fuel price and the Green House Gas emission regulation have provided a strong impetus for new technologies capable of improving the commercial vehicle fuel economy. Among others, optimized powertrain control can improve the vehicle fuel economy, particularly if it is based on accurate information about the instantaneous load demand. Furthermore, model-based online vehicle parameter estimator is critical for implementation of an adaptive vehicle controller.

While vehicle mass estimation has been successfully demonstrated, rolling resistance and aerodynamic drag estimation has not been fully explored yet. This paper examines this problem using model-based approach with a supervisory data extraction scheme. The estimator uses signals from the standard vehicle CAN bus and accelerometer sensor to determine vehicle rolling resistance and aerodynamic drag coefficient on-the-fly. A supervisor monitors vehicle motion and extracts data only during events with high signal to noise ratio. The algorithm was tested using experimental data acquired from real-world driving cycles. The estimator is validated with a coast-down test and shows a sufficient accuracy in predicting the road load.

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INTRODUCTION

Commercial vehicles -buses, dump trucks, semi-tractors, etc. -provide various services to the society and account for the majority of inland freight transportation in US [1]. However, they are also large fuel consumers. The Green House Gas emission of heavy vehicles has been regulated by the first-ever fuel economy standards [2]. And the second phase of the regulation has also been proposed, aiming at further reducing the carbon emission by estimated 1 billion metric tons over the lifetime of the vehicles sold under the program [3]. In order to meet the standards, manufacturers are looking forward to using more efficient powertrains [4] and more sophisticated powertrain control schemes. One of the examples of the latter one is the transmission control unit which can improve the engine efficiency by selecting higher gear and down speeding the engine, for a given wheel-torque demand [5,6]. However, in the domain of commercial vehicles, the load demand can change suddenly depending on vehicle parameters in situations like connecting or off-loading a trailer. Both the weight and shape/size of the trailer will affect the overall load demand. If the transmission control is not adapted properly, it can affect the engine operation points and even compromise the vehicle drivability. Therefore, the knowledge of the vehicle load demand is essential for transmission shift strategy. And its accurate estimation is the goal of this paper.

Estimating the load demand requires the knowledge of several vehicle parameters: vehicle mass, rolling resistance and aerodynamic

drag coefficient. Calibrating these parameters in advance for each type of vehicle can be a challenging task for commercial vehicles due to the wide variety of engine-transmission-body combinations. In addition, the parameters of commercial vehicles in a large fleet are often subject to change. For example, the rolling resistance coefficient can vary depending on tires and road pavement. Vehicle mass and aerodynamic drag coefficient can significantly change when a different trailer is attached to the tractor. Therefore, estimating the parameters online is necessary for commercial vehicles, as it reduces the initial calibration effort, and allows fast adaption of the powertrain controller to different vehicle configurations leading to overall better fuel economy.

Online vehicle parameter estimation has been an active research area in the recent decades. The model-based approach-using the vehicle longitudinal dynamic model and the signals from the Control Area Network (CAN) bus-is the preeminent method in estimating vehicle mass [7,8,9], due to the minimal requirements of additional sensors. Road grade estimation has also received attentions, since it is a major contributor to external load. The information from sensors -such as, GPS [7], accelerometer [10] and barometer [11] - are usually noisy, and thus model-based filters are often combined with the sensor measurement to enhance the estimation accuracy [12]. Simultaneous estimation of mass and road grade is a more challenging problem due to the time-varying nature of the road grade. However, several model-based methods have been proposed to address this problem [13,14,15].

While the vehicle mass and road grade estimation has been successfully implemented, the online estimation of rolling resistance and aerodynamic drag coefficient requires further attention. The parameters are usually estimated off-line [16], using coast-down test [17], and sometime using additional measuring devices [18]. An online estimation of the two parameters using the standard CAN bus signal has been attempted in [7]. Although the estimates have the right order of magnitude, they did not reach a sufficient accuracy. An alternative approach has been proposed to estimate one parameter (rolling resistance or aerodynamic drag coefficient) at a time using the Extended Kalman Filter [19]. The result achieved higher accuracy. However, one of the drawbacks of the method is that, since only one parameter is estimated at a time, the error in one parameter will affect the accuracy of the other parameter.

This paper presents a method to continuously estimate rolling resistance and aerodynamic drag coefficient on the fly. The approach is based on the model-based recursive estimator, combined with a supervisor controlling the data extraction events. The paper is organized as follows. The vehicle model and the proposed estimation scheme will be described in detail in the subsequent sections. Experimental data of real-world city and highway driving was acquired and used to test the online estimator in a simulation. The accuracy of the estimator is validated by the results from coast-down tests, which serves as the reference.

Estimator Design

The design of the estimator, as shown in Figure 1, consists of two parts: a supervisor and an online estimation algorithm itself. The supervisor continuously monitors vehicle motion, identifies situations that are suitable for estimating the parameter of interest and enables the recursive estimation during such events. The recursive estimator applies a model-based approach, which has been widely used in vehicle parameter estimation, due to the advantage of minimal instrumentation requirement. Although rolling resistance and aerodynamic drag coefficient cannot be directly measured by sensors, they can be estimated from the vehicle longitudinal dynamic model.

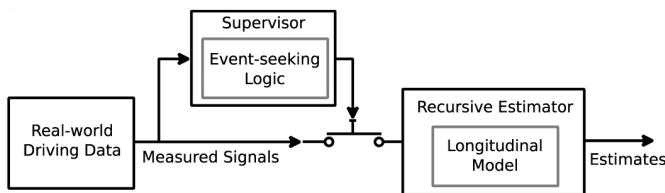


Figure 1. Schematic illustrating the estimation process

Vehicle Longitudinal Dynamic Model

An illustration of the vehicle longitudinal forces on grade are shown in Figure 2.

The longitudinal dynamic is described in Eq. (1). The following assumptions have been made. First, the vehicle motion is dominantly longitudinal, and therefore, the lateral forces are not considered. Second, no slip presents between wheels and road surface. Third, brakes are not activated, since the actual brake force cannot be known accurately. And last, the effects of lateral wind and intermittent wind gusts are not considered.

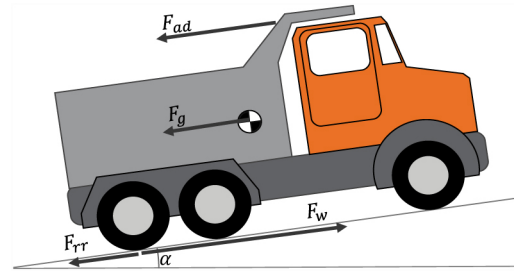


Figure 2. Vehicle longitudinal forces on grade. Road grade is denoted by α .

$$ma = F_w - F_{rr} - F_{ad} - F_g \quad (1)$$

The traction force at wheel F_w can be calculated as shown in Eq. (2)

$$F_w = \frac{T_e \omega_e \eta}{v} \quad (2)$$

Where T_e , ω_e , v , η are the engine torque, engine speed, vehicle speed and overall driveline efficiency respectively. This relationship is based on the assumption that the wheel slip does not occur.

Aerodynamic drag can be calculated from Eq. (3). The coefficients, which are associated with vehicle frontal area A , air density ρ and aerodynamic drag coefficient C_d , can be lumped together as a single term C_{dl} , since we are only interested in their combined value.

$$F_{ad} = \frac{1}{2} \rho A C_d v^2 \triangleq C_{dl} v^2 \quad (3)$$

Rolling resistance can be calculated from Eq. (4). Although studies have shown that the rolling resistance coefficient C_r increases nonlinearly with vehicle speed [20], a constant value is often adequate to the purpose of load estimation.

$$F_{rr} = mg C_r \cos(\alpha) \approx mg C_r \quad (4)$$

Road grade force can be calculated as in Eq. (5), as on a small grade, $\sin(\alpha)$ is approximately equal to α .

$$F_g = mg \sin(\alpha) \approx mg \alpha \quad (5)$$

Signals for Estimation

The signals needed for the estimation include vehicle speed, longitudinal acceleration, engine torque, engine speed, road grade and vehicle mass. Among them, all but the last two are available from the CAN Bus under the SAE J1939 [21] standard for commercial vehicles. The engine speed is measured through sensors and has high accuracy. However, the engine torque signal is less reliable. The torque sensor is not available on most of the vehicle, due to its high cost. Most commonly, the engine torque is estimated as a percentage load through the engine speed and the maximum engine torque [22]. The percentage estimation error is the greatest at low load condition and asymptotical decreases to a minima at full load. Other accessories such as the load of fan, alternator and compressor, are also considered

when calculating the net output torque. Road grade is measured by an accelerometer with internal filtering. Vehicle mass can usually be estimated online using techniques referenced in introduction. In this study, we use the actual vehicle mass in order to exclude the error that could be brought in by the mass estimation.

Brake signal and lateral acceleration are also recorded. Although these signals are not used for calculation, they are used by the supervisor to identify estimation events. The estimator will be stopped if the brake is activated, because the braking force is usually not available. The estimator will also be halted if cornering motion is detected through the lateral acceleration, because the model used for estimation considers only the longitudinal motion.

Supervisor Design

Online estimators can be classified based on whether they are event-seeking or averaging [8]. The former employs a supervisor to monitor the vehicle motion to identify events suited for estimation.

Depending on what parameters are being estimated, the best situation for data extraction varies. The two common driving situations suitable for estimation are acceleration and constant-speed. During a sharp acceleration event, mass-related inertia force dominates the load demand; rolling resistance and aerodynamic drag, on the other hand, only accounts for a small portion of the total load demand. This explains in the previous study [7], mass estimation achieved adequate accuracy, but rolling resistance and aerodynamic drag estimation did not. A different composition of load demand is during the constant speed. The acceleration is small and therefore, the inertia force is approximately zero. The engine torque is solely used to counteract the aerodynamic drag and rolling resistance. The engine torque estimation is also more reliable during this steady-state condition. Therefore, estimating rolling resistance and aerodynamic drag coefficient during constant speed can achieve a high signal to noise ratio, which is essential for an accurate measurements.

Estimation Algorithm

Recursive estimation algorithm is preferred for online applications, due to the limitation of memory and computing power of the onboard controllers. Several commonly used algorithms are Recursive Least Square (RLS) [7], RLS with forgetting factor [13] and (Extended) Kalman Filter [19]. RLS is suitable for estimating constant parameters. If the parameters can change, the estimator requires periodic resetting. RLS with forgetting factor is a variation of the original algorithm which can be used for measuring parameters that changing slowly but continuously [13]. The influence of old measurements gradually decreases, allowing the estimator to adapt to the new measurements. Kalman Filter can be used, if the dynamics of the parameters are known. Kalman filter and RLS are closely related. Both algorithms obtain the optimal estimation in the least-square sense [23].

Both rolling resistance and aerodynamic drag coefficient are treated as constant values in the model. Therefore, RLS algorithm is well suited for this task. A linear model can be written in the form of Eq. (6):

$$y = \phi \theta \quad (6)$$

Where y , ϕ and θ are often referred as the output variable, the input variable and the parameter to be estimated, respectively. The least square method bases on finding the parameter value that minimizes the cost function of the sum of squared error as shown in Eq. (7):

$$V(\hat{\theta}, n) = \frac{1}{2} \sum_{i=1}^n (y_i - \phi_i \hat{\theta}_k)^2 \quad (7)$$

The analytical solution is shown in Eq. (8):

$$\hat{\theta} = (\sum_{i=1}^n \phi_i \phi_i^T)^{-1} (\sum_{i=1}^n \phi_i y_i) \quad (8)$$

Directly solving this equation is computational intense and requires memory to store all the previous data. In online estimation, it is often solved in a recursive method, as described in Eq. (9), (10), (11) [24].

$$K_k = P_{k-1} \phi_k^T (\phi_k P_{k-1} \phi_k^T + R)^{-1} \quad (9)$$

$$\hat{\theta}_k = \hat{\theta}_{k-1} + K_k (y_k - \phi_k \hat{\theta}_{k-1}) \quad (10)$$

$$P_k = (I - K_k \phi_k) P_{k-1} \quad (11)$$

Where $\hat{\theta}_k$, ϕ_k , y_k , P_k are the parameters, input variables, output variables and error covariance at the k th steps respectively. R is the covariance of error; K is the gain which determines how much the estimated need to be adjusted based on the error between measured output and predicted output. The algorithm only needs the memory to store the previous estimate and error covariance $\hat{\theta}_{k-1}$ and P_{k-1} , and updates the new estimates $\hat{\theta}_k$ after acquiring each new measurements ϕ_k and y_k .

For rolling resistance and aerodynamic drag estimation, the combined drag force of can be written as in Eq. (12).

$$\frac{T_e \omega_e \eta}{v} - ma - mg\alpha = \hat{C}_{dL} v^2 + \hat{F}_{rr} \quad (12)$$

It is linear in parameter in terms of $\hat{F}_{rr}$ and $\hat{C}_{dL}$, and can be written in the form of Eq. (6) where:

$$y = \left[\frac{T_e \omega_e \eta}{v} - ma - mg\alpha \right] \quad (13)$$

$$\phi = [v^2 \quad 1] \quad (14)$$

$$\hat{\theta} = [\hat{C}_{dL} \quad \hat{F}_{rr}]^T$$