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Towards Data Driven Method for Quantifying Performance of Truck Drivers

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Abstract

Understanding factors that influence fuel consumption is a very important task both for the OEMs in the automotive industry and for their customers. There is a lot of knowledge already available concerning this topic, but it is poorly organized and often more anecdotal than rigorously verified. Nowadays, however, rich datasets from actual vehicle usage are available and a data-mining approach can be used to not only validate earlier hypotheses, but also to discover unexpected influencing factors.

In this paper we particularly focus on analyzing how behavior of drivers affects fuel consumption. To this end we introduce a concept of “Base Value”, a number that incorporates many constant, unmeasured factors. We show our initial results on how it allows us to categorize driver’s performance more accurately than previously used methods. We present a detailed analysis of 32 trips by Volvo trucks that we have selected from a larger database. Those trips have a large overlap in the route traveled, of over 100 km, and at the same time exhibit different driver and fuel consumption characteristics.

1 Introduction

In Sweden, as in the rest of Europe, road vehicles are the most commonly used method to transport both cargo and people. Approximately 520 billion ton-kilometers was moved in 2011 in Europe using trucks, which is close to 75% of all the cargo, as reported by [7]. This makes fuel efficiency very important, for both environmental and financial reasons. For example, the fuel burned by vehicles accounts for around 20% of the CO₂ emissions in Europe. In addition, fuel expense is one of the most important cost factors, accounting for approximately 30% of the total operating expenses of a heavy duty truck.

This shows how important it is, both for the manufacturers of vehicles as well as for their users, to understand factors that influence fuel consumption. A lot of effort has been spent on obtaining such knowledge, but it is mostly poorly organized and often more anecdotal than rigorously verified. One of the biggest reasons for that is the difficulty in reproducing realistic road conditions. Many different forms of analysis were performed, but their scope was limited to carefully designed and well-controlled testing environments. This puts into question how applicable the results actually are and whether the documented findings will also be relevant in other settings. For some aspects, such as engine design, those lab tests work quite well, but for evaluating drivers, they have been found insufficient.

Therefore we base our approach on data that comes directly from real life driving. The missions we analyze occur during any time of the day, in different countries around Europe, transporting diverse cargo, at various seasons of the year and so on. Such rich datasets from actual vehicle usage are only becoming available recently, and data-mining methods provide an enticing way of analyzing them. Those results can be used to not only validate earlier hypotheses, but also to discover unexpected relationships.

On the other hand, this variability of external circumstances makes driver performance classification significantly harder. It is not possible to obtain any form of ground truth about individual drivers, much less their specific actions and driving decisions. Therefore, even though we have found a number of cases that we can
argue are interesting and capture new knowledge, we are still working on more systematic and quantitative way to evaluate our results. In particular, the influence of various external factors cannot be measured directly nor estimated with confidence in individual cases, and therefore we need to rely on statistical results across large number of samples to draw conclusions.

Moreover, there are many different points of view from which to evaluate drivers, but we are interested not so much in the performance itself, but mainly in how various behaviors translate into fuel usage. More specifically, we investigate whether it is possible to identify conditions which correspond to specific driving actions, in particular ones that we can label as good or bad. Significant number of factors and high complexity of the driving task, together with the inability to do controlled experiments prevent us from being able to fully assess driver performance. On the other hand, we can draw statistically valid conclusions from the large dataset we have access to, in order to overcome those difficulties.

On a vehicle scale, fuel consumption is affected by many factors, only some of which vehicle manufacturers have control over, e.g. planned route, aerodynamics or tires. At least equally many, however, are outside their control, such as weather or road topology. When evaluating drivers, it is very important to compensate for as many of those factors as possible, in order to achieve fair comparisons.

This paper is organized as follows. In the next section we review related literature, followed by description of the data we are working with in section 2. After that we introduce the concept of Base Value in section 3 and discuss in section 4 how can it be used to evaluate and rank drivers. We close with conclusions and ideas for future work.

1.1 Related Work

Fuel consumption for heavy duty vehicles is an issue that affects our daily lives. The recently adopted Euro VI standard exemplifies the importance of fuel consumption reduction, as it directly affects particle emissions. The Euro VI standard enforces, among other aspects, reduction of noxious emissions by 66% and of nitrogen oxide emissions (NOx) by 80%, compared to Euro V.

Liimatainen [4] has demonstrated how to use fuel consumption as an incentive for drivers to increase their fuel efficiency. He also points out that it is difficult to take external factors into account when assessing driver’s performance. Ting et al [6] have, in a simulation study, shown the importance of drivers and address the issue of driver fatigue and its effects on driving capabilities. Irmscher et al [3] investigate driver psychology, in particular aggressive drivers, and its influence on steering and speed. Related efforts for reducing fuel consumption include e.g. platooning, which Alam et al [1] shows to reduce amount of fuel consumption and noxious emissions, as well as the usage of brakes.

Rafael-Morales and de Gortar [5] conducted an extensive field study to determine the effects of so called “technical driving” for reducing fuel consumption. They evaluate several means of using vehicle in an efficient manner, looking from various perspectives, including analysis of relation between torque and engine speed. Fröberg et al [2] employ a similar approach, however focusing more on optimising speed profile for different road conditions.

2 Data

We use two large datasets that have been collected in research and development projects within Volvo Group Trucks Technology (VGTT). The first dataset comes from European Field Operational Test (Euro-FOT) project [8], in which VGTT was a partner with the role of testing Fuel Efficiency Advisor functionality. The other is an internal Volvo project called Customer Fuel Follow-up (CuFF). In both projects, data from multiple trucks have been collected, covering a wide area in Europe and also spanning over a long period of time, offering a variety of both geographic and ambient conditions.

For analysis in this paper we have selected a subset of data consisting of 32 trips belonging to the CuFF database. They were selected because they all contain the same road segment, of approximately 100 km in length. This allows us to do comparisons of how different drivers behave on the same road, but under different conditions. Figure 1 illustrates part of the chosen segment, highlighting with green line each of the trip’s GPS location.

All vehicles have similar characteristics, being the same truck model, including a gearbox with 12 gears and a cruise control system. On each trip we have collected over one hundred signals. They were logged from the vehicle’s internal Controller Area Network (CAN), as well as from a number of additional sensors,
at 10 Hz sampling frequency.

Together, the databases amount to approximately 100 TB of data. However, it is important to note that even with this large amount of information, we do not have complete knowledge of all the relevant circumstances. Among the most important factors that we are missing are traffic and weather conditions. There are also a number of problems with various sensors, for example the cargo weight sensors are not entirely reliable.

3 Base Value

Current methods for assessing driver performance typically rely on using well-known, easy to measure parameters such as fuel consumption, distance traveled, trip time, etc. Those are used to calculate a number of performance indicators, defined based on existing expertise. Common performance indicators include brake usage, wheel steering and accelerator pedal position, acceleration patterns, and so on. In short, those are all model-based approaches that fundamentally originate from existing knowledge about what kinds of actions are generally good or bad. The problem with them is their generality and the fact that they cannot take into account specific driving conditions.

Instead, we propose an approach that incorporates knowledge about many such circumstances into an intuitive number. This allows us to take trip-specific conditions into account when comparing and evaluating drivers. While we have access to hundreds of sensor and control signals that are being processed by on-board ECUs, they still do not provide a complete picture of all the events that are happening at any given time.

Therefore, we make use of the data collected during real operation of vehicles in order to abstract away impact of various factors. We calculate a so-called Base Value (BV) parameter, describing vehicle operation under specific, fixed set of conditions — and we use this parameter to capture and quantify a number of unknown factors.

In particular, our Base Value corresponds to the fuel consumption of a vehicle driving at constant speed on a flat road. Such a definition captures a large number of factors that influence fuel consumption, for example the weather influence (including temperature, air pressure, humidity) or individual characteristics of the given truck (including total weight, engine type, aerodynamics, type and air pressure in tires). At the same time, this measure is independent of individual drivers, since it is based on situations were no human decisions are made.

This is clearly an idealized requirement, and for practical reasons, we need to relax out conditions. For example, in order to have control over speed, we only consider segments where the driver has decided to engage cruise control. It does not result in perfectly constant speed, of course, but it is the best possible approximation. We chose to require cruise control being on as to eliminate driver’s influence over the selected segment.

Another specific condition is for the vehicle to be
in top gear. This is because our recorded data shows that 90% of the travel takes place on highway, and therefore we focus on that scenario. For lower gears there are no segments with constant speed, and usage of cruise control in lower gears is also much less common. Sometimes such situations occur when using maximum torque to climb a steep hill. However, depending on vehicle load, different trips will have different speed and gear, which makes them very difficult to compare, due to for example discrepancy in efficiency for the powertrain and gear ratio.

Next requirement is the minimum length of the segment, i.e. the amount of consecutive recorded samples that fulfill the previously explained conditions. Without having all the information it is very hard to get instantaneous fuel consumption that BV ideally represents. We would have to abstract away all factors that can influence it momentarily (e.g. another vehicle overtaking our vehicle or a turn maneuver which increases lateral acceleration can both increase fuel consumption).

Overal, such an increase is typically small, but if used as a reference measure, it will have large negative impact. Also, speed, when recorded at high frequency, is not a constant number and it behaves more like a sinusoid alternating around the desired value. That means that for some fractions of a second the vehicle will accelerate while for others it will not — leading to high-low fuel consumption pattern. By selecting a longer segment, we can average all those factors for fuel consumption and get a good estimate of the amount of fuel that should be used.

All segments that fit those conditions are BV Segments, since for each of these we can calculate its specific BV. We can obtain multiple BVs for a given trip, as long as we can find multiple BV segments. This is very important as it allows us to compare BVs belonging to the same trip in different ways. Intuitively, close BV segments should yield similar values as many of the factors influencing fuel consumption should remain the same. There are some factors that can change, like switching type of road from highway to urban or following another vehicle, i.e. platooning, but they are not very common. On the other hand, we are more willing to accept larger differences in BVs originating from segments far away, as the number of factors that change can be significantly larger (e.g. weather or technical condition of the truck itself).

Figure 2 shows segments in which we can calculate BV for a given trip. Such segments can either be far apart or close to each other, even consecutive in nature. Each dashed vertical line represents the starting point of one BV segment. BV is essentially the average of the corresponding segment in Figure 2, bottom plot.

Analysis of close BV segments for same trip can increase the confidence in the calculated values. Encountering significantly different values is also valuable, as we can flag such situations when they happen and present them to the user or investigate possible causes. Analysis of BV segments located far apart can also be used to provide information on how conditions have changed.

Ideally we want to find BV segments on actual flat road. However, long segments with flat road are very few, and the number of trips passing through such segments is even fewer. For this reason we have decided that we needed to relax that requirement. We created a linear prediction model for fuel consumption based
on road gradient and vehicle weight. Such a simple regression model is sufficient, as evident from Figure 3. It shows a very clear linear relation between fuel consumption and the combination of road gradient and vehicle weight. Equation 1 defines the linear regression model for road gradient as the term being subtracted from the measured fuel consumption:

$$FC_{\text{flat}} = FC - RG \times W \times rmc,$$

where $FC$ is fuel consumption, $RG$ is road gradient, $W$ is vehicle weight and $rmc$ is road model constant.

Equation 2 defines BV as the mean fuel consumption for a given segment after we have removed the road influence:

$$BV = \text{mean}(FC_{\text{flat}})$$

An active database regarding various environmental factors can help with identification of bad data. Figure 4 shows one example of an error in road gradient data that is hard to identify automatically. It can be clearly seen that it negatively affects the calculation of our BV — the fuel consumption was expected to be lower in that area.

To summarize, we define Base Value as a number representing fuel consumption for a given vehicle at constant speed on a flat road, given the current vehicle and environmental characteristics. By calculating BV we have a number representing fuel consumption as it is affected by factors that are unknown and cannot be measured. This can help “level the field” when we do cross-trip comparisons. For example, higher cargo weight, bad weather conditions or under-inflated tires will increase fuel consumption but that increase will be captured by BV. Therefore, we can minimize the impact of those factors over driver performance ranking.

In our efforts to improve BV accuracy we have come across a lag in when fuel consumption is recorded. Such a lag occurs most commonly when a change in gradient happens and the magnitude of the lag is correlated with that change. This lag affects not only the calculation of BV but also the ability to have good instantaneous fuel consumption predictions. An example can be seen in Figure 4, in the bottom plot, which represents fuel consumption equivalent for flat road (i.e. using Eq 1). In this example, the lag can be observed in the middle, where there are sharp changes in values.

4 Driver performance rankings

In the data exploration process of the complete dataset we have come across an area to which we will refer as Hannover East. It is the highway road passing east of Hannover E45 which also intersects with E30 road. We found this region to be interesting to analyze as it contains several distinct scenarios. Based on the length of the road we want to analyze, we have access to between 30 and over 200 trips passing through same road segment. Those trips take place over a two year period, covering all weekdays as well as all of year’s seasons, both day and night time. Vehicles driving on this road have all cargo ranges, from light load, 15-20 tons, to heavier loads, in the range of 40 tons. Considering the variety of conditions present, the number of trips available seems low. We do have to stress that all data comes from real operations of commercial vehicles, which poses a number of an extra challenges.

Fleet operators are always interested in the performance of their drivers. The most common way to quantify driver performance is to look at measured fuel consumption. This method, however, is heavily biased based on factors such as cargo weight, as well as type of terrain and weather. It strongly favors drivers assigned to vehicles with low load. Figure 6 illustrates relation
between rankings based on measured fuel consumption and the weight of the vehicle. All vehicles were driven on same road but at different times of day and year.

As can be seen in Figure 6, low load vehicles generally have a very good rank. On the other hand, for vehicles with similar load, a number of other factors can have a more significant impact upon their rank. We assume that such a default ranking system, especially as it is known by the drivers, has a detrimental effect on their performance. They will generally not try to optimize their fuel consumption if driving a heavy vehicle, as they already know that their ranking will be lower. The same goes for light vehicles, as they already know they will have good fuel consumption.

An improvement to this system can easily be done by taking into account weight when ranking drivers. Based on our road influence model, we can easily estimate how much fuel is used due to weight and road gradient. Figure 7 illustrates how ranks change when we take vehicle weight into account.

Each color represents relative weight between trips, from light colors corresponding to low vehicle loads to darker colors corresponding to higher vehicle loads. We have previously shown in Figure 6 that there are few trips with really low load, while the majority of trips...
have similar, relatively high load. Figure 7 shows that most of the trips change their rankings when taking into account weight and the road they drive on. We can observe various types of changes after equalizing weight. Specifically, there are trips at all load levels that maintain similar ranking, moderate changes are the most common, but at same time there is a number of drastic changes that also occurs (for example, a shift from rank 8 to rank 32). However, this method does not capture other factors that are also independent of the driver and that affect fuel consumption, such as traffic or weather. Selecting the same road stretch can only guarantee that static conditions remain similar, such as road topology or pavement, and to some degree similar traffic.

Therefore, we can look at how ranks change when normalizing fuel consumption using the Base Value introduced in the previous section. This can be seen in Figure 8. The benefits of using BV as a normalization factor are clearly superior to just equalizing weight. We can confidently select trips happening in different days of year as well as on different roads as we can capture both static and dynamic factors in BV, such as weather condition, environment and vehicle characteristics. Differences between the rankings can be seen in Figure 9 as well as in Figure 10.

One of the major disadvantages of using BV is that in some cases significant changes may occur between the place where it has been calculated and the place where it is being used. This is likely to introduce large errors. In general, however, it is not likely to happen very often.

Nowadays, we have route planners that provide operators with important information even before the vehicle begins a mission. Such information comes in many forms, e.g. maps of road gradient, weather forecast, traffic information and others. We can use this knowledge to compute, off-line, some of the data we require to classify and rank driver performance.

Past experiences can help us create a driver profile. A driver profile would include overall performance and rankings for various factors, e.g. vehicle load, distance, season, time of day, as well specific performance, for a specific set of conditions, such as steep hills, urban area or similar. This information can give us indication of what needs to be calculated beforehand for the next trip, leading to a decrease in online computation requirements. It can also provide data about which upcoming road segments have a high probability of being interesting. Likewise, we can identify segments that are suited for BV calculation before the vehicle starts its mission, which leaves us with only two signals that needs to be monitored, specifically vehicle speed and cruise control state for the desired duration.

Automatic detection of performance can be achieved online with minimal computation provided we do not require real time feedback to driver or transmission of data. Such detection can be useful in many ways. In cases where a deviation from normal performance is detected we can identify key factors for that specific case and assess which of the factors are responsible.

Based on past experiences we can we have information regarding static factors, e.g. road gradient, before we even start driving. By using a priori knowledge we can reduce the amount of computation required to work with high frequency signals.
As a test case we have chosen a segment east of Hanover, Germany. From our CuFF database we have identified 32 trips passing through this 100 km segment, trips that also have BV segments, which was one of the requirements. Figure 11 shows three plots for this segment. We have chosen to go with three plots that include the most important information. Top plot shows the measured fuel consumption relative to BV, middle plot show each vehicle’s speed while bottom plot shows altitude profile for this particular segment. We can easily distinguish 2 areas of interest. First area is in the beginning of the shown segment while second is towards the end of the segment.

For the first interesting area, in Figure 11, we can exclude road topology as being the responsible factor for decrease in speed for various trips. As these trips happen over a period of two years we have excluded road works as a possible explanation as well. For the same reason weather can not be the factor determining drivers to lower their speed, which leads us to another major factor that influences speed, i.e. traffic. Closer inspection of that specific region indicates that the speed reduction starts happening roughly 2 kms before the intersection of afore mentioned roads, E30 and E45, two major highways in Germany, and ending at about 1 km after that. The total length of this area is about 12 km.

The next interesting area in this segment is towards the end of this. For this area we have found that road gradient is the main cause for reduction in speed as this reduction has high correlation with the load of the vehicle. Close examination revealed that different drivers slow down at different times. This can prove valuable in learning timing for reducing speed based on weight and road gradient as well as for other conditions. Such knowledge is not so easily obtained as we need good accuracy for instantaneous fuel consumption signal which, as discussed in BV section is subject of future work.

Figure 12 shows a subset of our 32 trips, consisting of lower vehicle loads and higher vehicle loads. It can easily be seen that the reduction in speed is similar for the vehicles with similar load, especially the heavier ones, and at same time that there is some different point at which drivers start reducing their speed.

Figure 13 shows another subset, consisting of mixed loads. In both figures, 12 and 13, we can notice that light vehicles can maintain cruising speed while heavier vehicles are forced to slow down.

5 Conclusions and future work

In this paper we have discussed one way to approach driver performance ranking. We incorporate unknown factors into one number, Base Value. We have presented results of using the method, as well as discussed its advantages and disadvantages.

Future work is directed towards a way to better calculate BV, in particular by eliminating the lag effects, compensating for different gear and eventually being able to calculate BV for any speed profile. Those improvements will increase the number of trips for which we can calculate BV. By increasing the accuracy of BV
we can unlock more opportunities for long term evolution of assessment of drivers and vehicles alike. At the same time, it will offer the possibility to classify driver’s performance based on various conditions and create a driver profile that will give fleet operators the ability to maximize their driver’s efficiency.

References


