ISSN 2176-5480

22nd International Congress of Mechanical Engineering (COBEM 2013)
November 3-7, 2013, Ribeirão Preto, SP, Brazil

PREDICTIVE FUEL ECO DRIVER COACHING SYSTEM BASED ON ROAD EVENTS PROCESSING

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Abstract: *Nowadays, improvement of fuel economy is one of the most important areas in the automotive industry. Regarding environmental aspects, it has become critical to develop methods to protect it as well as to reduce running costs, like with advanced driver assistance systems (ADAS). In this work, an ADAS system based on fuel economy strategies for road topography and events was developed and evaluated. The software includes fuel eco functionalities to control the vehicle speed and acceleration automatically based on vehicle positioning and incoming road data. The combined map-based and self-learning platform receives real-time GPS data to perform map-matching and expand the road attributes (downhill, uphill, slope, curvature, intersection, speed limit, etc.) database of a mapped road segment - look-ahead methodology. Based on this road map data the software modulates the drive according to the vehicle parameters (weight, engine configuration, transmission, aerodynamics, etc.) and calculates an ideal speed and acceleration for optimal fuel consumption. The displayed ideal speed and upcoming events establish an Eco-support for the driver, allowing him to reduce his fuel consumption by up to 20 % (considering the boundary case), thus reducing the overall costs and improving the environmental behavior of the vehicle. Furthermore a change of the driver`s mindset towards more awareness of economical driving is highly assumed.*
Keywords: *Look-ahead method, fuel economy, environment care, map-matching.*

1. INTRODUCTION

Due to the increase of environmental care aspects and standardization of technologies, it has become critical for the modern automotive industry to focus on the development of systems that enhance the performance of tomorrow's vehicles in order to minimize the environmental effects and running costs (Capiello, *et al.*, 2002).

Considering commercial vehicles, fuel expenses can take up to 60% of the overall freight costs during a truck's life, showing the potential for development of advanced tools that can allow truck drivers to save fuel. One of the main alternatives in this concern are the Advanced Driver Assistance Systems (ADAS) (Delehaye *et al.*, 2007), which are basically electronic solutions that can reduce (up to 20% in some cases) fuel consumption, as shown in Fig 1. Increasing the awareness for economical behavior, the driver of tomorrow has the chance to shape a better future.

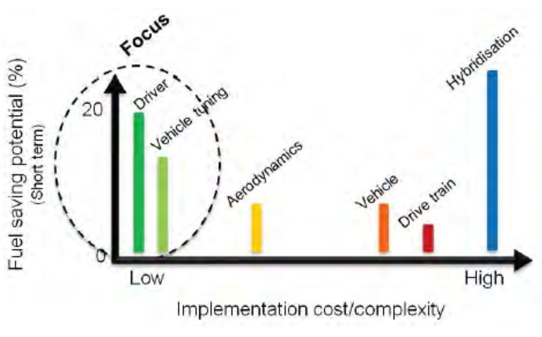

Figure 1. Comparison of potential fuel saving technologies against implementation cost/complexity.

This paper describes the development of a system that coaches the driver how to drive in a fuel economy way based on an optimized algorithm that calculates the optimal speed taking into account ahead road events by means of topography reading and processing. This method is called Predictive Fuel Eco Driver Coaching (PFEDC) and focuses on the driver's "fine adjustment".

The core code of the PFEDC system, which has been developed since 2006 within Volvo Technology department (parts of it already equips other ADAS system), is connected to the eHorizon self-learning platform (SLP eHorizon) and to a corresponding database (SLP database) - also developed by Volvo. The software was evaluated for map-matching functionality as well as for speed limit calculation.

Using this combined map-based and feed-forward self-learning scheme, the system is able to target an ideal speed for optimal fuel economy. Moreover, connected to a map-matching function, a fast positioning of the vehicle on the driven road is provided.

2. METHODOLOGY

The methodology of the PFEDC is based on the look-ahead approach (Takeda *et al*, 2012). The track to be driven will be defined into different areas of events and together with a map-matching function the vehicle position can be determined.

Based on these events, existing speed limits and the optional maximum speed (which can be set by the driver), the software calculates an ideal speed for optimal fuel consumption, ensuring an environmental way of driving and reducing running costs while comparing the actual and ideal speed as a driver support. The block diagram of the system is shown in Fig. 2.

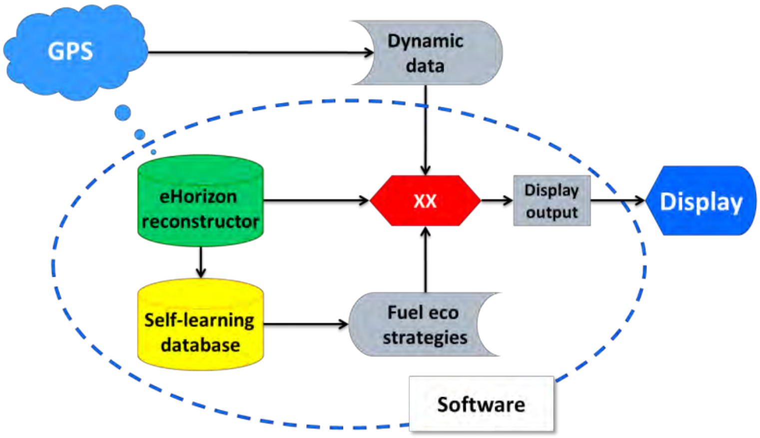

Figure 2. Block diagram of the PFEDC system. The dynamic data is received directly through the vehicle Controller Area Network (CAN).

2.1 Data Receiving

The road map data which is needed for the analysis of the track can be provided in two ways, map-based and/or self-learnt (both solutions have the eHorizon reconstruction and the database – see Fig. 2), whereas each option indicates that a GPS connection is available to include data regarding the roads' speed limits and to initiate the map-matching function while the software is running. The self-learning system can be feed forwarded in order to enhance the data quality and events position accuracy, turning into a hybrid map-based system.

The SLP eHorizon receives the 3D GPS data via the vehicle's communication network (CAN) with a rate of 1 Hz from the corresponding sensors and converts it from [NMEA] to [KLM] format. This process stores the coordinates of altitude, *alt*, longitude, *long*, and latitude, *lat*, as well as the time, *t*, between each of the received sets of data. Before submitting, the SLP eHorizon transforms the coordinates into data sets (time step/distance, time step/curvature, time step/slope, time step/speed).

2.2 Data preparation

These data sets which are needed for the target speed and event calculation are stored inside the SLP database to be later accessed by the EcoDriverTester-Model. The transformation for each set of data is enlightened in the following statements:

2.2.1 Distance

The total distance, *kmt* [km], is calculated as function of the time step, *b*, of the GPS signal by transforming the given coordinates of latitude and longitude at each time step to a distance between the points and summing them up, as one can see in Eq. (1), Eq. (2) and Eq. (3).

$$kmt(b) = \sum_{1}^{b} \arccos(dvalue).r2d \tag{1}$$

ISSN 2176-5480

$$dvalue(b) = \sin(lat(b-1).d2r).\sin(lat(b).d2r) + \cos(lat(b-1).d2r).\cos(lat(b).d2r).c \quad (2)$$

where

$$c = \cos((long(b-1) - long(b)).d2r) \quad (3)$$

where for this set of equations, *r2d* = 57,2957795 and *d2r* = 0,01745329 are considered.

2.2.2 Curvature

The curvature radius, R [1/m], (as shown in Fig. 3) is calculated using the relative wheel speeds, V_{Rf}, V_{Rr} (right wheel front and rear axle) and V_{Lf}, V_{Lr} (left wheel front and rear axle) and the tread, L [m], as can be seen in Eq. (4) to (6). The needed truck parameters are received via the truck's CAN.

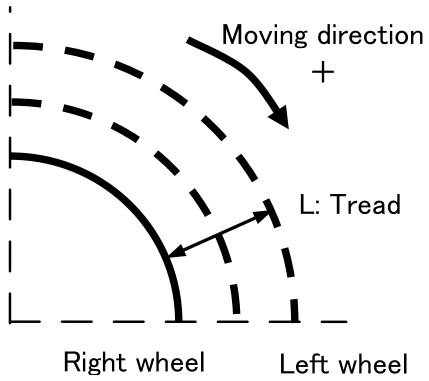

Figure 3. Curvature radius methodology.

$$R = \frac{Rf + Rr}{2} \quad (4)$$

$$Rf = \frac{L \cdot VRf}{VLf - VRf} + \frac{L}{2} \quad (5)$$

$$Rr = \frac{L \cdot VRr}{VLr - VRr} + \frac{L}{2} \quad (6)$$

2.2.3 Slope

The slope S [%] is calculated using the differences in altitude and distance between each of the time steps, as seen in Eq. (7).

$$S = \frac{alt(b) - alt(b-1)}{kmt(b) - kmt(b-1)} \cdot 1000 \quad (7)$$

2.2.4 Speed

The current velocity v *[km/h]* of the truck is calculated using the submitted time t [s] and the difference of the already calculated total distance *kmt* at each time step b as shown in Eq. (8).

$$v(b) = \frac{kmt(b) - kmt(b-1)}{\frac{t(b)}{3600}} \quad (8)$$

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2.2.5 Intersection

The intersections on the track can't be calculated, since for example a traffic signal does not always stop the vehicle every time the track is driven. Therefore the intersections can just be combined manually with pre-saved road map data.

2.3 EcoDriverTester- and ASL-Model: Target speed and event calculation

The core algorithm of the PFEDC is based on two models (EcoDriverTester and ASL). The EcoDriverTester-Model loads the prepared data sets from the SLP database, interpolates them to provide a smooth and uniform data distribution and inserts them into the ASL-Model. The intersections (seen section 2.2.5) and speed limit regulations as well as the optional maximum speed (which can be set by the driver) are also handled and inserted by the EcoDriverTester-Model.

Based on this input, the ASL-Model calculates the target (ideal) speed and the events which are needed for the look-ahead methodology to provide the interface with data for the map-matching and driver support functions.

The truck's parameters needed for the calculation are received via the truck's CAN.

2.3.1 Ecodrivertester and interpolation

The data sets of curvature, slope and speed as well as the speed limit regulations are interpolated including the calculated total distance, *kmt*, exchanging the base of 'time steps' to a base of 'distance'.

The interpolation is provided by the embedded function which linearly interpolates the values of y with old base x to the new base x_i. The function for the concept of this interpolation can be seen in Fig. 4.

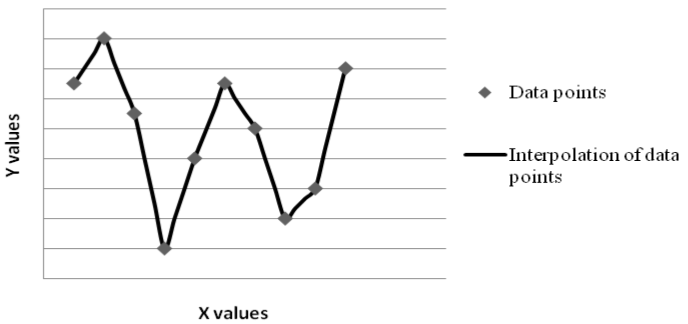

Figure 4. Concept of interpolation for embedded function 'interp1(x,y,x_i)'

Each interpolation takes the total distance *kmt* as the old base x and the new base x_i is a vector containing the distance in steps of 10 m. Following, the special adjustments for each interpolation and the output which will be inserted into the ASL-Model will be shown.

2.3.2 Interpolation of curvature, slope, speed and speed limit

The interpolation inside the EcoDriverTester-Model creates smooth arrays of 'distance/curvature', 'distance/slope', 'distance/speed' and distance/speed limit'. For the curvature radius, saturation for absolute values higher than 1000 1/m and for the slope for higher values than 20% is implemented to avoid loops inside the software. The interpolations can be seen in Fig. 5, Fig. 6, Fig. 7 and Fig. 8.

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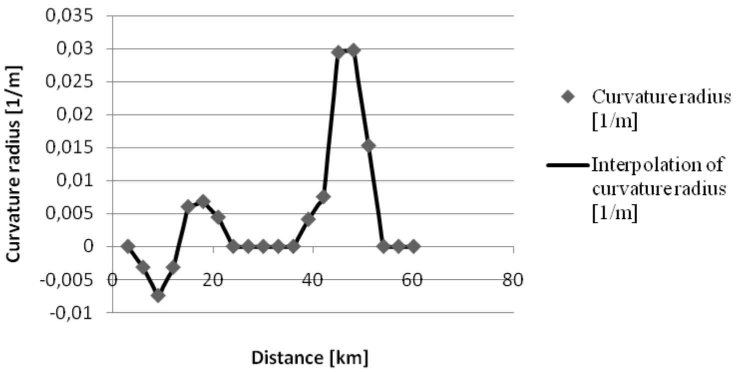

Figure 5. Interpolation of curvature radius.

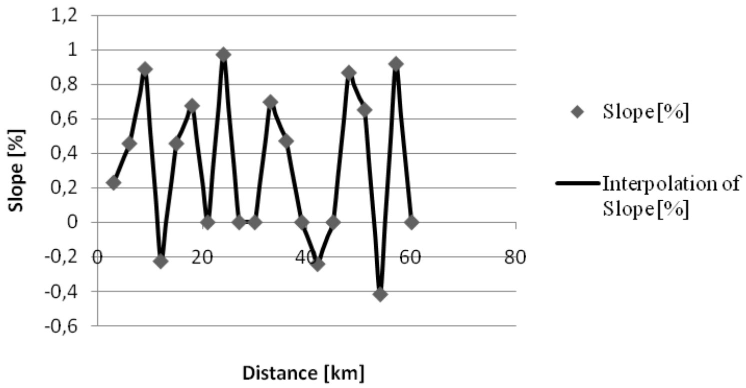

Figure 6. Interpolation of slope.

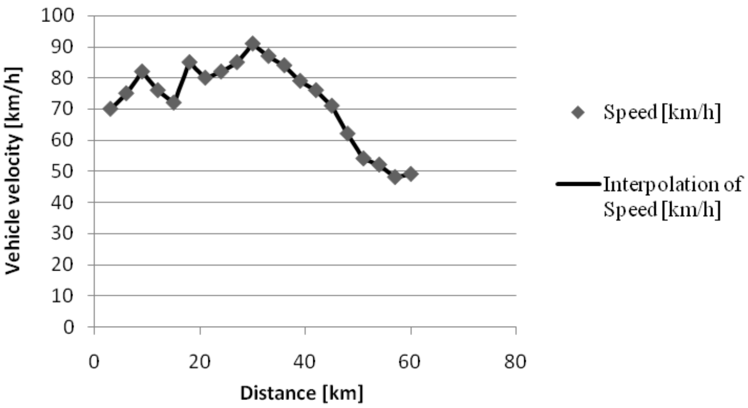

Figure 7. Interpolation of speed.

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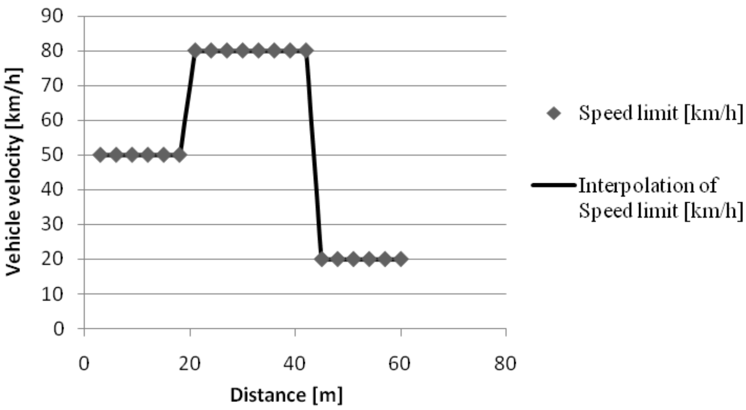

Figure 8. Interpolation of speed limit.

2.3.3 ASL-Model and speed limit

The target speed is based on the inputs which have been created by the EcoDriverTester-Model and the truck's parameters. The target speed decision is based on a combination of five speed limit factors: Speed limit by GPS provider s_{l1}, an internal fix minimum speed limit s_{l2}, a maximum speed limit, manually inserted by the driver s_{l3}, a speed limit based on curvature s_{l4} and the slope conditions s_{lcon}. These five limitations create the combined speed limit S_L.

The speed limit s_{l1}, provided through the GPS, has already been interpolated for the whole track and is therefore the first base for comparison. The first part to be included, are the minimum speed limit s_{l2} and the maximum speed limit s_{l3} which provide a 'top' and 'bottom' gap for the limitation for the combined speed limit S_L.

The speed limit for curvature s_{l4}, is calculated from the absolute values of the curvature interpolation with Eq. (9).

$$sl4 = \sqrt{\frac{g}{|R|}} - \frac{crv.decspd}{3,6} \tag{9}$$

The parameter *crv.decspd* has a default value of 2 km/h and is used as an offset under the optimal curve speed for security reasons. After comparing the so far combined speed limits with s_{l4} for the minimum, the fix minimum s_{l2} is taken into account one more time to ensure that no curvature limitations are below this value.

The last factor s_{lcon} is based on seven different slope conditions: Not a slope (0), down to flat (1), down to up (2), flat to up (3), up to down (4), up to flat (5) and flat to up (6). These conditions are calculated from the interpolation of slopes, comparing each of the next values and therefore dividing the track into areas of different slope conditions.

Based on these conditions it is decided which speed limit will be seen as relevant for the combined speed limit S_L:

- If the slope condition is (0), the so far calculated combined speed limit of s_{l1} to s_{l4} is taken as S_L.

- If the slope condition is (1) or (2), the combined speed limit of s_{l1} to s_{l3} is taken and increased by 0,5 km/h.

- If the slope condition is (3), (4) or (5), the combined speed limit s_{l1} to s_{l3} is taken and decreased by 0,5 km/h.

- If the slope condition is (6), the combined speed limit s_{l1} to s_{l3} is used without any changes.

Fig. 9 shows the combined speed limit S_L for condition (0).

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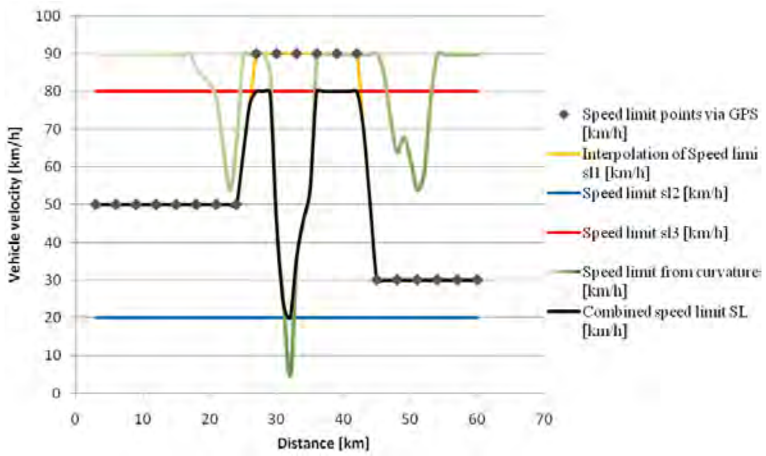

Figure 9. Combination of speed limits for slope condition (0).

2.3.4 ASL-Model and event decisions

The ASL-Model decides based on the calculated interpolations and an offset in distance whether an upcoming curve or slope can be regarded as an event which needs a speed limit regulation. In the following the events of curvature and downhill are explained.

2.3.4.1 Curvature event decision

To regard an upcoming curve as an event which needs a speed limit regulation, out of the following requirements, either Eq. (10), (11) and (12) or (10), (11) and (13) need to be fulfilled.

$$R_{min} \leq |Rc| \leq R_{max} \tag{10}$$

$$D_c \leq P_{out} - P_{in} \tag{11}$$

$$s_{l3} \leq V_c \tag{12}$$

$$D_{1C} \leq D_{cur}\,(Vc \div 3.6 \cdot \beta + D_{Offset\_C}) \tag{13}$$

Where R_{min} and R_{max} are the set borders for a curvature radius of relevance [1/m], D_c is the set lower limit for an unchanged condition [m], P_{in} and P_{out} are the start and the end positions in the offset database [m], s_{l3} is the maximum speed limit given by the driver [km/h], $D_{1C} = P_{in} - P_c$ [m], P_c is the current position of the vehicle as offset in the database [m], D_{Cur} is the section before the corner [m], D_{offset_C} is the offset of D_{Cur} in the database [m] and β is the factor defining D_{Cur} based on the truck's parameters. An overview for the parameters can be seen in Fig. 10.

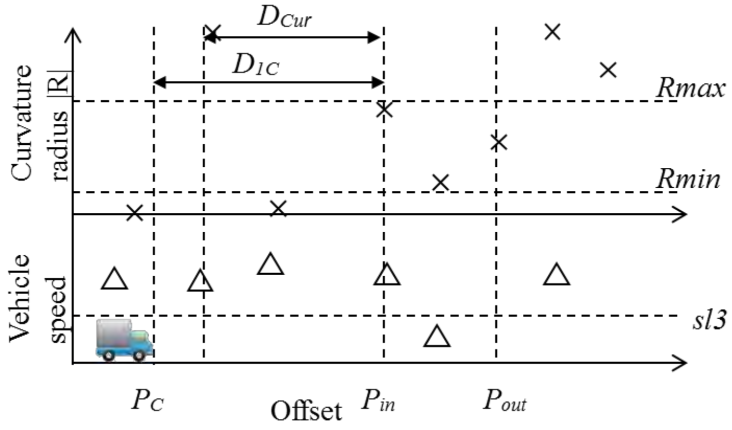

Figure 10. Overview of curvature event parameters

If these requirements are met, the ASL-Model calculates the value of $V_{target\_C} = y$ as shown in Fig 11.

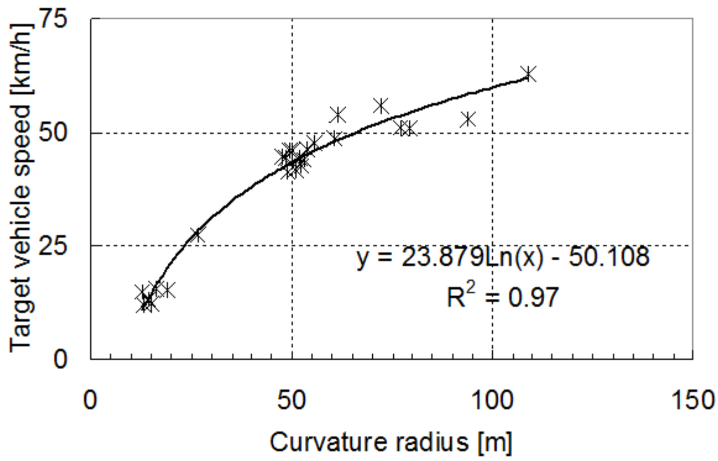

Figure 11. Evaluation of $V_{\text{target\_C}}$ with the above shown ratio

The calculated value will be inserted into Eq. (14) to get the ideal speed S_{LCur} for the upcoming curvature event.

$$SL_{Cur} = \frac{V_{\text{target\_C}} - Vst\_c}{P_{in} - Pst\_c} \cdot (Pc - Pst\_c) + Vst\_c \tag{14}$$

2.3.4.2 Downhill event decision

To regard an upcoming downhill as an event which needs a speed limit regulation, the following requirements, shown in Eq. (15) and (16), need to be fulfilled.

$$D_1 \leq D_{DH} (= Vc \div 3.6 \cdot \alpha + D_{offset\_H}) \tag{15}$$

$$Vc \geq V_{lwr} \tag{16}$$

Whereas $D_1 = P_{in}$ - Pc [m], D_{DH} defines the section before downhill [m], α is the factor defining D_{DH} based on the truck's parameters, D_{offset_H} is the offset of D_{DH} in the database [m], V_c is the current vehicle speed [km/h] and V_{lwr} is the fix lower speed limit to start speed [km/h].
An overview for the parameters of the downhill event can be seen in Fig. 12.

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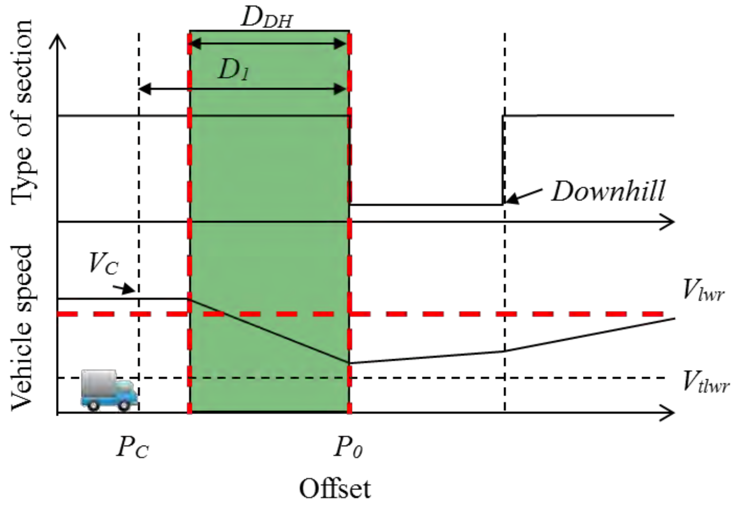

Figure 12. Overview of downhill parameters.

If these requirements are met, the ASL-Model calculates the value of V_{tlwr} as shown in Eq. (17):

$$V_{tlwr} = Vc \cdot k + V_{offset} \tag{17}$$

where k is the factor defining V_{tlwr} regarding the truck's parameters and V_{tlwr} the target lower speed limit [km/h]. The calculated value will be inserted in Eq. (18) to get the ideal speed for the upcoming downhill event.

$$SL_{Slope} = \frac{V_{tlwr} - Vst}{P_0 - Pst} \cdot (Pc - Pst) + Vst \tag{18}$$

2.3.5 Ideal speed

Based on the speed limit S_L, from 2.3.3, and with the through look-ahead methodology calculated ideal speeds for curvature and slope events, a last combination creates the final ideal speed I_S. In this combination the calculated events have a higher priority and just for track parts without upcoming events the combined speed limit S_L is used.

This final velocity I_S needs to be targeted by the driver to gain the best fuel economy. The influence of curvature and downhill event can be seen in Fig. 13, showing the resulting areas of fuel saving.

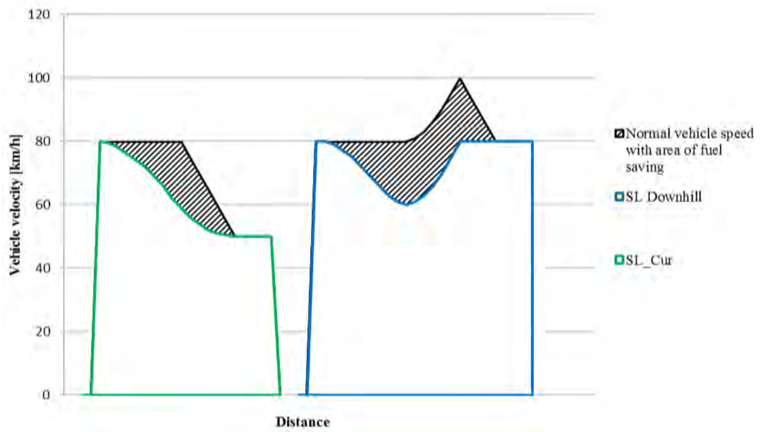

Figure 13. Influence of curvature and slope events on fuel saving.

3. SECURITY APPICABILITY

Other variables can be added to the driver coaching software especially ones related to driver security, for example, information on how safe that road segment is and roll-over risk. By installing for example a strain-gauge, vibration

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intensity and frequency data can also be collected, given the possibility of feeding the data base with road conditions, which can also be used as input for the speed calculation for driver coaching (Mayhew and Simpson, 2002).

Based on the calculated events of curvature and downhill, as well as on the different slope conditions and pre-saved intersections, it would be possible to notify the driver about the upcoming event, giving him the opportunity to drive more carefully in places of higher accident rate (Kuroyanagi, *et al*, 2010).

4. INTERFACE & SPEED PROFILE OPTIMIZATION

With the ideal speed calculation, as well as the smothering for optimize and minimized fuel consumption, a Human Machine Interface (HMI) for the application can be developed. In this project, the moving bars method was applied. In this case, the driver has the task to follow the coaching by keeping the current speed bar as closer as possible (or below) the optimal speed bar. Figure 14 shows the HMI graphics used to evaluate this feature.

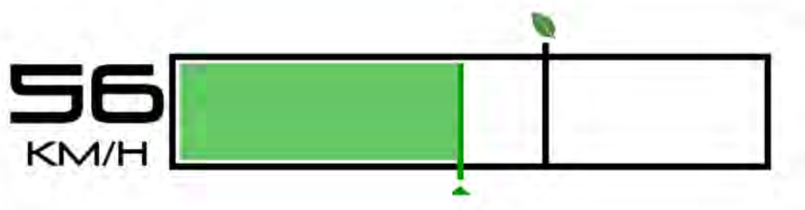

Figure 14. Graphics layout.

5. FUEL ECONOMY SIMULATION AND DRIVER'S MINDSET

The usage of the PFEDC software creates, assuming the worst case of driver mindset, a reduction of fuel consumption by nearly 20% (estimated figures based on previous research – see Fig. 1) and additionally, a mindset change for the driver is highly assumed since he is actively noticing in which situations the software calls for a reduced or increased velocity. This way an improvement in overall 'standard of drivers' mindsets and fuel economy can be reached, reducing running costs as well as increasing the security on our roads by increasing the driver's attention.

Simulations, using the Volvo Global Simulation Platform (GSP), were performed and the results are shown in Fig. 15. For this route (Curitiba – Paranaguá – Curitiba) a fuel economy potential of 4.5% was noticed, showing the feasibility of this feature and its capability of save fuel. Of course, the driver has to follow the tips in order to achieve this saving, but, as it increases security as well, it can be tracked and supervised.

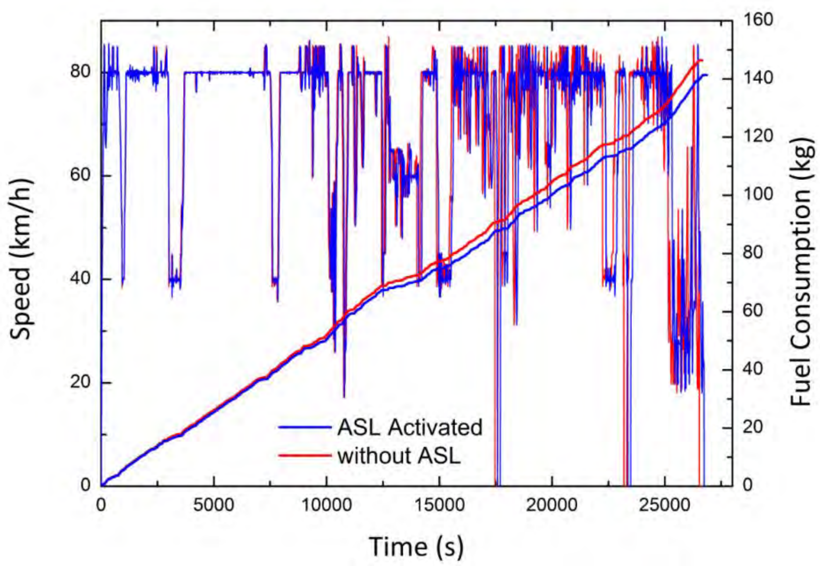

Figure. 15. Speed profile optimization over 28000 s of truck driving considering the route Curitiba – Paranaguá – Curitiba.

As it was shown, this system can save fuel and through simulations tools, it has been proved that it can, indeed, enhance vehicle efficiency by means of driver coaching.

ISSN 2176-5480

6. ACKNOWLEDGEMENTS

The authors thank Volvo do Brasil for providing infrastructure and documentation necessary to develop this project. Danny Thelen-Loss, also would like to thank Volvo for the opportunity of accompanying this project during his internship at Volvo do Brasil.

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