

# Dual Stage Multilevel Control for Heavy Duty Vehicles under Different Traffic Conditions

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**Abstract:** The present paper details a performance analysis made through model-based simulation of a dual stage multi-level control algorithm applied to heavy duty vehicles that accounts for traffic information. Such work exploits a control algorithm at different level of traffic congestion. In the two stages control, the first level entails a supervisory optimizer, which evaluates the optimal speed and gear shifting profile according to road and vehicle information to minimize fuel consumption; the second level is an actuator control that computes the powertrain signals to be applied to the engine actuators to comply with the indications given by the supervisory control. The advancement brought by the present work resides in the introduction of speed constraints related to different traffic levels: i) free flow, ii) free flow/conditioned, iii) conditioned and iv) congested. To each state, a maximum limiting speed is associated and several scenarios are investigated in simulated environment. All the results are compared to a conventional Cruise Controller to assess the achievements in terms of fuel consumption reduction, assessing that the proposed control strategy ensures an average reduction of about 3.5% over all the investigated conditions.

*Keywords:* Fuel Economy, Optimal Control, Dynamic Programming, Traffic, Heavy Duty Vehicles, Energy Management.

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## 1. INTRODUCTION

The seeking for fuel consumption and harmful emissions reduction is driving the efforts of researched and industries towards the development of advanced control algorithms and innovative solutions that can provide on-board driver support in achieving such targets.

Among the available solutions, the Advanced Driver Assistant Systems (ADAS) can take advantage of the Electronic Horizon (EH) to predict which could be the optimal speed and driving behaviour to be adopted according to the information gathered through installed sensors on path length, road conditions, elevation, slope, traffic state, etc. Several ADAS solutions are currently available, such as the Adaptive Cruise Control (ACC) that modulates the vehicle speed according to that of the preceding one.

Several studies have also remarked the advantage in the use of look-ahead controls that exploit optimal control strategies to compute the best speed for a defined path. For instance, the application of Dynamic Programming (DP) method is widely used to solve such kind of optimization problems, considering also the information on the best gear shifting schedules.

In a previous work of the authors (Donatantonio et al., 2018), the implementation of a dual stage multilevel optimal control algorithm has been investigated on a heavy duty truck to verify the improvement on fuel consumption reduction with respect to a fixed point Cruise Controller (CC).

A further advancement proposed by this work is the introduction of traffic state modelling to investigate which are the differences in the achieved fuel consumption reduction under variable vehicle speed limitations. In the following sections, the multilevel control algorithm used for the computation of the optimal speed and gear shifting profile is briefly presented, followed by the description of the considered traffic model. Afterwards, the results achieved for single and multiple traffic state conditions are illustrated and discussed.

## 2. MULTILEVEL CONTROLLER

The multilevel control strategy here adopted, and extensively discussed in the work of Donatantonio et al., (2018), is made of two stages: (i) an offline optimal control and (ii) an online powertrain control.

### 2.1 Offline optimal control

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The high level of the optimal control algorithm (i.e., supervisory control) relates to the offline evaluation of the optimal velocity profile and gear-shifting schedule by minimizing the fuel energy consumption over the target road mission. The travel time minimization is also accounted, but on an indirect base.

This algorithm is launched by the driver once the truck mission is known and the path is available from, e.g., the navigation system. Among the features of the algorithm, the limited computational time might allow the evaluation of new control strategies on-board and during the update of traffic flow, road works and weather conditions, for instance.

The minimization problem is formulated according to the indications given by Hellstrom et al. (2010) in terms of vehicle kinetic energy  $K$  expressed in the space domain  $s$ :

$$\arg \min_{\dot{m}_f, \lambda, F_{br}} J(\dot{m}_f, \lambda, K) = \int_0^S \dot{m}_f \sqrt{\frac{m}{2K(s)}} ds \quad (1)$$

where  $\dot{m}_f$  is the fuel mass flow rate,  $\lambda$  is the oxygen excess ratio at the engine exhaust,  $F_{br}$  is the brake force,  $S$  is the assigned path length and  $m$  is the vehicle mass.

The kinetic energy variation is subject to the vehicle dynamics equation:

$$\frac{dK}{ds} = F_{dr}(\dot{m}_f, \gamma, K, F_{br}) - F_{aero}(K) - F_{slope}(\alpha(s)) - F_{roll}(K, \alpha(s)) \quad (2)$$

In eq. (2), the terms  $F_{dr}$ ,  $F_{aero}$ ,  $F_{slope}$  and  $F_{roll}$  are the driving, aerodynamics, slope and rolling forces, respectively. They depend on the instantaneous kinetic energy level, fuel mass flow rate and braking force as well as on gear ratio  $\gamma$  and local road slope  $\alpha$ .

The energy minimization problem is solved by means of Dynamic Programming (DP) algorithm (Sundstrom and Guzzella, 2009), with direct constraints on minimum and maximum allowed speed (i.e., kinetic energy) and gear ratio as well as maximum braking force, fuel flow and travel time. The problem discretization is approached by finite difference (forward Euler method), dividing the path length  $S$  through step sizes of about 200 m each (Donatantonio et al., 2018).

The cost function  $J$  in eq. (1) is mainly formulated as:

$$J = F_{dr}^2 + \mu \left| \frac{1}{v_{req}} - \frac{1}{v} \right| \quad (2)$$

which accounts for two terms, one related to the driving force, squared to avoid negative effect due to braking actions, and the other to the deviation of the vehicle speed from the target one, to implicitly handle travel time. The parameter  $\mu = 1.1 \cdot 10^5$  m is a constant weight, heuristically determined, needed to equalize and balance the two terms in equation (2) (Donatantonio et al., 2018).

Once obtained the optimal speed the vehicle should travel at, the optimal gear-shifting schedule is then identified through a second minimization problem formulation (Donatantonio et al., 2018). Such problem involves two main issues, one related to a specific fuel amount, used to recover from the speed decrease during shifting process, and another connected to the time lost due to shifting torque gap.

## 2.2 Online powertrain control

The low level of the optimal controller deals with the online computation of the engine actuators control signals, to cope with the outcomes of the offline supervisory control in terms of optimal vehicle speed and gear-shifting schedule.

The accounted approach combines map-based and dynamic models, derived from the heavy duty truck models of Wahlstrom and Eriksson (2011), Eriksson (2001) and Ivarsson et al. (2010). The truck is equipped with a 300 kW, 12.7 l, inline-6 Diesel engine with EGR and VGT, with an overall weight of 40 t.

The main inputs of the model are: (i) engine speed, (ii) fuel injection, (iii) EGR valve opening and (iv) VGT opening. The main outputs are: (i) engine torque, (ii) total fuel mass, (iii) air fuel ratio, (iv) intake manifold pressure, (v) realized EGR fraction, (vi) compressor mass flow and (vii) turbocharger speed.

As engine operation constraints, the oxygen excess at the exhaust must be high, to keep soot at admissible levels, and the turbocharger speed should not exceed its maximum admissible value, to avoid mechanical damage. More details on the online optimization can be found in the work of Donatantonio et al. (2018).

## 3. TRAFFIC MODEL

As main advancement with the previous paper of Donatantonio et al. (2018), this work focuses on the understanding of how traffic conditions may influence the optimization results achieved with the control algorithm depicted in section 2.

It is well recognized that travel time increases according to the number of vehicles moving on the same road section. This delay could be mainly related to the difficulties in performing manoeuvres, traffic lights and road intersection priorities.

In the last decades, great attention has been devoted to the field of traffic flow theory. Generally, two points of view can be considered: a microscopic one, which focuses on one single vehicle/driver in relation to the other units, and a macroscopic one, where the vehicle flux is considered as a whole and characterized in space and time over the entire road. In this work, only the macroscopic point of view is accounted.

To represent traffic average features, three main variables can be introduced, being traffic speed, flux intensity and vehicle density (Cantarella, 2008). The traffic speed  $v$  is generally

assumed as the average speed of all the vehicles involved in the traffic flow. Flux intensity  $q$  can be expressed as the number of vehicles  $n$  that travel through a specific road section within a time interval  $T$ :

$$q = \frac{n}{T} \quad (4)$$

and vehicle density  $k$  can be instead expressed as the number of vehicles  $m$  located on a specific road length  $L$ :

$$k = \frac{m}{L} \quad (5)$$

If the hypothesis of steady-state traffic flux in time and space is made, a state equation among the aforementioned variables can be applied:

$$q = k \cdot v \quad (6)$$

As extensively discussed in the work of Jabeena (2013), several papers present a mathematical correlation between speed  $v$  and density  $k$ , such as the simple linear Greenshield model:

$$v = v_f \left( 1 - \frac{k}{k_j} \right) \quad (7)$$

the generalized Pipe model:

$$v = v_f \left[ 1 - \left( \frac{k}{k_j} \right)^n \right] \quad (8)$$

or the bell-shape Drake model:

$$v = v_f \cdot \exp \left[ -\frac{1}{2} \left( \frac{k}{k_{cri}} \right)^2 \right] \quad (9)$$

In equations (7), (8) and (9), the term  $v_f$  represents the free flow speed, whereas the terms  $k_j$  and  $k_{cri}$  are the jam and critical densities, respectively.

If the state equation (6) is represented on the  $v$ - $q$  plane, four main areas can be identified:

- *free flow*: the vehicles are free to move at their desired speed, with low interactions (i.e., without traffic);
- *conditioned flow*: vehicles interaction start to be significant, influencing their average speed;
- *congested flow*: the interactions among vehicles become critical, further reducing the average speed and achieving the maximum flow;
- *unstable flow*: vehicles movements are affected by frequently start-stop manoeuvres.

According to the Highway Capacity Manual (Transportation Research Board, 2000), a further classification of the

highway infrastructure service level can be done on vehicle density bases:

- *free flow*:  $k \leq 23$  vehicles/km;
- *free/conditioned flow*:  $23 < k \leq 35$  vehicles/km;
- *conditioned flow*:  $35 < k \leq 48$  vehicles/km;
- *congested flow*:  $k > 48$  vehicles/km.

In the present work, the former vehicle density values are applied to the Drake model (eq. (9)) to define a specific speed range for each traffic condition. The speed limits are reported in Table 1.

**Table 1. Speed limits for each traffic condition.**

Traffic state	Lower limit [km/h]	Upper limit [km/h]
Free	110	130
Free/conditioned	89	110
Conditioned	63	89
Congested	40	63

The speed limits related to the free flow, the conditioned flow and the congested flow are accounted in the optimal control algorithm presented in section 2. Such values will represent the limits on the optimal speed that can be achieved, according to the different traffic states. It is worth noting that such limits are here assumed as the range within which any vehicle can travel according to the traffic state, and its speed can freely vary within such range.

#### 4. RESULTS AND DISCUSSION

The effects of traffic conditions on optimal energy management are investigated in simulated environment by taking into account the same real path already considered in the work of Donatantonio et al. (2018). Such path is the Swedish E4 highway from Södertälje to Norrköping, with an overall length of about 120 km. The results are compared to those related to the use of a fixed point Cruise Controller (CC).

According to the speed limits reported in Table 1, the reference values for each simulation are reported in Table 2. The maximum speed value  $v_{max}$  is achieved as average between the lower and upper limits in Table 1. The required speed  $v_{req}$  is instead considered as the average speed to be kept over the whole path to achieve a desirable travel time. Such value is also considered as initial speed value for the simulation, also associated to the initial gear  $\gamma_0$ . It is worth remarking that the minimum allowed speed is set equal to 40 km/h.

A first analysis is performed by applying one traffic condition at a time to the whole path. The results are resumed in Table 3, where the overall fuel consumption (expressed in litres per 100 km) is reported for the proposed optimal control *Optimal* and the Cruise Controller *CC*, with its percentage variation on the last column.

**Table 2. Reference values for the simulation analysis**

Traffic state	$v_{max}$ [km/h]	$v_{req}$ [km/h]	$\gamma_0$
Free	120	80	14
Conditioned	76	70	14
Congested	51.5	50	12

It can be observed that, in all the investigated traffic scenarios, the optimal controller allows achieving a lower fuel consumption with respect to the CC, with a maximum decrease of -4.51% under conditioned traffic.

**Table 3. Results for single traffic condition scenarios.**

Traffic state	Optimal [l/100 km]	CC [l/100 km]	Variation [%]
Free	34.03	34.82	-2.27
Conditioned	31.75	33.25	-4.51
Congested	29.25	30.40	-3.78

The decrease in fuel consumption is nevertheless associated to an increase in the travel time, which however do not exceed in any case +0.5%. This proves that, for each traffic state, the travel time of both Optimal and CC approaches are equal. The average percentage variation of the fuel consumption reduction, evaluated on the values reported in Table 4, is thus -3.52% with a variance of 0.87.

A further analysis is performed by combining different traffic states during the whole path and evaluating the related fuel consumption variation. The following cases are investigated:

- Case 1: free flow (1st half) + conditioned (2nd half);
- Case 2: free flow (1st half) + congested (2nd half);
- Case 3: free flow (1st third) + congested (2nd third) + free flow (3rd third);
- Case 4: free flow (1st quarter) + conditioned (2nd quarter) + congested (3rd quarter) + conditioned (4th quarter).

The results for this analysis are reported in Table 4, where the variation with respect to the CC is again remarked. As for the previous investigation, the proposed optimal controller achieves a fuel consumption reduction in all the investigated cases.

**Table 4. Results for multiple traffic condition scenarios.**

Cases	Optimal [l/100 km]	CC [l/100 km]	Variation [%]
Case 1	32.53	33.66	-3.36
Case 2	31.04	32.23	-3.69
Case 3	32.63	33.71	-3.20
Case 4	31.76	32.99	-3.73

However, differently from the single traffic state scenarios, the percentage variation of fuel consumption with respect to the CC presents a small variance, since all the values ranges between a minimum of -3.20% and a maximum of -3.73%.

Indeed, the average reduction is -3.50% and the variance is 0.05%. This remarks that, although the average value is almost the same one achieved for the single traffic state analysis, the variance is reduced by one order of magnitude.

These results suggest that, under more realistic (and miscellaneous) traffic conditions, the fuel consumption reduction seems not to change much with respect to traffic variation. Conversely, the average fuel economy appears to be stable and repeatable over all the investigated cases.

## 5. CONCLUSIONS

The presented work describes a model-based analysis of the fuel consumption reduction that can be achieved with the implementation of a dual stage multilevel controller on a heavy duty truck under different traffic conditions. The achieved results prove that the optimal controller can reach a maximum fuel consumption reduction of -4.51% compared to a single point Cruise Controller, with comparable travel time. Nevertheless, if considering multiple traffic state over the same travel path, the achieved fuel consumption reduction seems stabilize independently from the type of traffic state and the frequency change, with an average value of -3.50% and a variance of 0.05. As future work, the investigation of the effect of different truck weights and a random change in the traffic conditions will be performed to evaluate the robustness and the consistency of the proposed analysis.

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