FUEL EFFICIENT INTELLIGENT CONTROL OF HEAVY TRUCKS

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ABSTRACT

This work answers the need for improvement in fuel economy in heavy duty vehicles (HDV's), in a manner simple enough to be used in open road missions. A lookahead anticipatory control (LA) method is designed to adjust longitudinal motion (signified by velocity of the vehicle system) using knowledge of fluctuations in road grade. The prediction of driving behaviour is done using a fuzzy logic function based on a predefined rule-base. Control action of the brake and throttle positions are implemented by taking the state-dependent riccati equation approach. The results of the proposed controller are compared against those of a standard PI cruise controller. Moreover, results of simulations on a 40 ton vehicle show the proposed method capable of increasing fuel economy.

Keywords: fuzzy forecasting, dynamic programming, state dependent riccati equation.

INTRODUCTION

The regulation of vehicle speed is a major contributor to fuel economy. In [1] fuel economy was showed to be specifically a result of the application of intelligent energy management systems. These systems are complex algorithms able to fulfill the task of learning the behavior of the driver, environment and vehicle conditions. Then modify the propulsion and operation of the hybrid electric vehicle accordingly. The same can be said of conventional and electric powertains with appropriate modifications.

Systems of predictive driving, that makes choices according to a set of assumption and criteria for the maximization of a defined objective, in this case fuel economy were used in [2] and [3]. As a solution to the fuel economy problem, full vehicle speed trajectories were generated by the use of future road information as part of a Lookahead control strategy. The constructed conceptual vision of the road ahead was the basis for decision-making, done using topographical maps combined with GPS and three dimensional road maps, which were used to increase or decrease velocity of the vehicle before significant changes in road slope. Optimization was achieved using a Dynamic Programming algorithm which generated an efficient velocity profile for the vehicle to follow in response to changes in uphill or downhill road travel. A fuel economy of 3.5% was achieved in [2] and 3.53% in [3]. However, the computational complexity within the system due to DP implementation is a major limitation to the system. In [4] the optimal speed trajectories were also produced using Dynamic Programming (DP), however, within an advisory system which gives a warning to the driver in real time on the optimal speed appropriate to a certain road condition. The speed profile was generated and applied in this case to a conventional powertain vehicle. The results varied between 3.8%-3.9% improvements in fuel economy while maintaining time constraints. While [5] assumed the vehicle operates in a stochastic environment due to the uncertain nature of traffic. Then, generated speed trajectory using a stochastic dynamic programming (SDP) algorithm to reduce consumed fuel. This SDP policy algorithm describes the optimal vehicle speed as a function of current values of road grade and speed (reference speed).

Intelligent optimization and data based methods were another approach to solve the problem. In [6] a neural network works as the trajectory generator of the entire vehicle speed profile. The optimizer used instantaneous road grade, limited history of previous vehicle speeds, vehicle fuel consumption and road grade which were all used to calculate the appropriate cruise speed. The results from simulations showed 8-10% over constant road segments, out of which 3.7 to 10.6% were a direct result of the use of road information.

In the same context, [7] used a Quadratic Programming (QP) in the design of an online velocity planner as part of an advisory system (ADAS) for the driver. The velocity trajectory was designed with the objective of fuel efficiency and the results showed an average reduction of 11.4%, with a prediction horizon of 1.8 millisecond in real world driving. The paper [8] studied the performance of predictive energy management in terms of computational complexity and accuracy. The problem solved in this study was fuel efficiency in traffic driving and fuel efficient lead vehicle following. Furthermore, several solutions to the predictive optimality problem were examined: exponential varying velocity prediction, Markov chain velocity prediction and Neural network prediction with three respective types back propagation (BP-NN), layer recurrent (LR-NN) and radial basis function(RBP-NN). While as mentioned above the control action was done in NMPC. The comparison between velocity profile generators techniques was done with respect to sensitivity to tuning parameters, prediction precision and computational cost and resultant vehicle fuel economy. The results showed that the neural predictors showed the best overall

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performance across a range of real-world drive cycles although no future driving profiles is assumed known and no telemetry on-board sensor information is available for the controller. In this study three velocity prediction strategies applied in the MPC framework. However, no exact number for fuel reduction was given in the paper.

In the model predictive control context, [9] developed two prediction algorithms with low system requirements for speed prediction, all within a V2V initial stage framework. The preceding vehicle used an MPC algorithm and the leading vehicle speed prediction algorithm used a Markov chain to extend the prediction horizon. The focus was on the ego vehicle, and results in the car-following scenario on a highway showed a significant 15% reduction in fuel consumption while ensuring ride comfort. As did [10] by developing a Predictive Cruise Control (PCC). This cruise controller used prior knowledge of the road condition as an input to vary the speed and achieved a reduction of 4.8% as a result. In [11]future road information (curve and slope) were utilized in another control strategy that combined both Pontrygin's minimum principle (PMP) and linear quadratic regulator (LQR) to solve optimal control problem. A switching control strategy was suggested to be used to handle speed limitation due to curvature; this then reacts to the speed resulting from previously mentioned controllers which would implement in anticipatory driving.

The focus of this paper is on attaining fuel economy by adjusting cruise speeds in intelligent control methodologies. Applied mainly as forecasted cruise control where vehicle properties and road grade are used as inputs to regulate upcoming vehicle speed by small increments. In addition, reducing the complexity of the problem the prediction inputs to only road grade to the intelligent optimizer. Then the vehicle nonlinear equations were reformulated to enable implementation of a state dependent riccati equation (SDRE) to ensure fuel economy.

The paper is organized as follows: Section 1 was the introduction and related work to this study. In Section 2 the system equations are discussed. Next the Forecast function is explained followed by the action control strategy in Section 3. Then, Section 4 and 5 contains the simulation across different scenarios with the discussion then the conclusion respectively.

VEHICLE MODEL

The dynamic model of the vehicle in this section is based on the analysis of longitudinal dynamics in [12]. The torque output from the engine is assumed in this study as an equation of fuelling u_f, and engine speed w_e,

$$T_e = f(u_f, w_e) \tag{1}$$

The engine map was thus generated relating the values of u_f and w_e in the following function:

$$T_e = a_e w_e + b_e u_f + c_e \tag{2}$$

The engine is modeled without taking into consideration the internal friction torque as an expression of driving torque and torque from the clutch, as follows:

$$J_e \dot{w}_e = T_e - T_c \tag{3}$$

The engine mass moment of inertia is J_e, and the value of engine speed is w_e is kept between the range of operation [500, 2400] rpm. The maximum fueling function is dependent on engine speed:

$$u_{f,\max} = a_n w_e^2 + b_n w_e + c_n \tag{4}$$

$\delta_f \in$ [0, c] is normalized fuelling signal i.e. where the value of c is determined from the simulation.

In this study, for simplicity reasons the clutch is assumed stiff.

$$T_c = T_e \tag{5}$$

$$w_e = w_c \tag{6}$$

To further simplification the transmission is constant with no gear shifting occurs. Thus the gear is kept constant at G=12 is always engaged and the gear ratio i and the input speed w_i and the output speed w_o , are related as follows:

$$w_i = i \quad w_o \tag{7}$$

Transmission ratio i_t and the efficiency of that gear n_t show the energy losses, i_t denotes the current gear's conversion ratio.

$$T_p = i_t T_t n_t = T_c i_t n_t = T_f \tag{8}$$

$$w_t = i_t w_t = w_e \tag{9}$$

Similarly the final drive inertia are neglected and modeled by the efficiency n_f this brings thus:

$$T_d = T_f i_f n_f = T_w \tag{10}$$

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where the value of i_f is the conversion ratio in the final drive.

As noted before the drive shafts are neglected and the driveline is inflexible thus:

$$J_w \dot{w}_w = T_w - T_b - r_d F_w \tag{11}$$

the wheel (driveline) inertia J_w and the wheel radius is r_d. While F_w represents wheel's friction force. The brake torque T_b is simply obtained from the following equation

$$T_b = \delta_b \cdot k_b \tag{12}$$

where $\delta_b \in [0, 1]$, is the brake control signal and k_b is a constant.

The aerodynamic resistance force is expressed by:

$$F_a = \frac{1}{2} c_w A_a \rho_a v^2 \tag{13}$$

ρ_a is the air density, v is the velocity of the vehicle, A_a is the cross sectional area of the vehicle and c_w is the air drag coefficient.

The resistance force F_r is modeled proportionally to the rolling resistance coefficient C_r, to the normal force of the vehicle on the tires F_N

$$F_r = c_r F_N \tag{14}$$

$$F_r = mg \cdot \cos \theta \tag{15}$$

the road slope is θ and the m is the mass of the truck.

The resistance force due to gravity is F_g and represents the gravitational force. It is dependent on the road slope θ and the mass of the vehicle m and is expressed as:

$$F_g = mg \cdot \sin \theta \tag{16}$$

The traction force is dependent on the longitudinal slip. Longitudinal slip (s) can be simplified by assuming it is at low values, and can be defined as:

$$s = \frac{r_d w_w - v}{r_d w_w} \quad or\, s = \frac{r_d w_w - v}{v} \tag{17}$$

The above equation connects tire rotation w_w and vehicle speed v using the wheel radius r_d. Using Equation. (12), it is seen that this corresponds to a situation of a constant slip level.

The vehicle motion in the longitudinal direction is modelled here taking all the previous equations. The governing dynamics for the velocity v is

$$m\dot{v} = F_w - F_a - F_r - F_g \tag{18}$$

where F_w is the resulting friction force at the wheel. Table-1 shows the model parameters.

Table-1. Vehicle Parameters.

J_e	**Engine inertia**	**A_a**	**Cross section area**
J_w	**Lumped inertia**	**c_w**	**Air drag coefficient**
r_d	Wheel radius	g	Gravity constant
C_r	Roll resistance	d_1	$\left(\frac{b_e k_p v_1 n_1 i^2}{r_d^2}\right)$
d_2	$\left(\frac{b_e k_p n_1 i^2}{r_d^2}\right)$	d_3	$\left(\frac{I_p b_e n_1 i^2}{r_d^2}\right)$
d_4	$\left(\frac{b_e k_p v_1 n_2}{r_d}\right)$	d_5	$\left(\frac{b_e k_p v_1 n_1 i^2}{r_d}\right)$
d_6	$\left(\frac{I_p b_e n_2}{r_d}\right)$	d_7	$\left(\frac{I_p b_e n_2 i}{r_d}\right)$
d_8	$\left(\frac{I_p b_e n_2 i}{r_d}\right)$	d_9	$b_e k_p n_3$

The fuel flow is expressed as integral of the function of engine speed expressed by w_e [rad/s] and fueling function u_f [g/cycle], this is shown in the following equation:

$$\dot{m}_f(w_e, u_f) = \frac{n_{cyl}}{2\pi n_r} w_e u_f \tag{19}$$

The value of n_{cyl} represents the number of cylinders and n_r is the number of crankshaft revolutions per cycle. The value of fuel consumed is the integral of fuel flow Equation. (19).

From all of the above, the longitudinal system dynamic results:

$$m\dot{v} = T_w - T_b - F_a - F_r - F_g \tag{20}$$

$$m\dot{v} = i_f i_t T_e - T_b - F_a - F_r - F_g \tag{21}$$

ARPN Journal of Engineering and Applied Sciences

$$\dot{v} = \frac{r_d}{J_w + mr^2{}_w + n_f i_t^2 n_t i^2{}_t J_e}(n_f i_t n_t i_t T_e - k_b \delta_b - r_d(F_a + F_r + F_g)) \quad (22)$$

The driver model is modeled as the throttle signal δ_f, and controller is represented as:

$$\delta_f = k_p e_1 + I_p \dot{e}_1 \quad (23)$$

The brake signal is shown as the following equation:

$$\delta_b = k_b e_2 + I_b \dot{e}_2 \quad (24)$$

The brake and throttle are engaged at different instances according to the predefined velocity limits. Two reference velocities are highlighted for the brake and the throttle where e_1 shows the error as a result of the throttle set-point and e_2 is the brake error signal as a result of the difference between actual velocity and the brake set-point.

Substituting Equation. (23) and (24) into the torque function in Equation. (2):

$$T_e = -d_3 v^3 + (d_1 - d_6 - d_2 \dot{v})v^2 + (d_4 - d_6 \dot{v} - d_7)v - d_8 \dot{v} + d_9 \quad (25)$$

Where the values of d1-d9 are constants shown in Table-1 and v is the speed of the vehicle. Then Assuming that the input throttle and brake signals are disengaged the system equation becomes:

$$\frac{d}{dt}f(v) = \frac{r_d}{J_w + mr_d^2 + i_f^2 \eta_f i_t^2 \eta_t} \times \left(a_1(c_1 v + c_2) - 0.5A_a v^2 - mgr_d(c_r \cos\theta + \sin\theta)\right)$$

$$\frac{d}{dt}f(v) = m_t\left(a_1(c_1 v + c_2) - 0.5A_a v^2 - mgr_d(c_r \cos\theta + \sin\theta)\right) \quad (26)$$

Where the values are as follows:

$$c_1 = \frac{a_e i_t}{r_d}, \quad c_2 = c_e, \quad a_1 = i_t \eta_t i_f \eta_f,$$

$$m_t = \frac{r_d}{J_w + mr_d^2 + i_f^2 \eta_f i_t^2 \eta_t}$$

To reformulate the system it is assumed to have two states:

$$\dot{x}_1 = \dot{v} = f(v, u, \theta) \quad (27)$$

$$\dot{x}_2 = v = x_1 \quad (28)$$

The nonlinear state matrix becomes:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} f(v,u,\theta) & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u \quad (29)$$

CONTROLLER STRUCTURE

The control structure is based on a two loop control configuration. The outer loop contains forecasting decision function that builds an initial guess velocity (V_{ref}) based on road grade and is implemented by a fuzzy logic controller. The inner loop employs the reference velocity tracking by translating it into fueling and braking level, representing the cruise controller and is done using a state dependent riccati equation SDRE controller. The schematic of the control strategy is depicted in Figure-1:

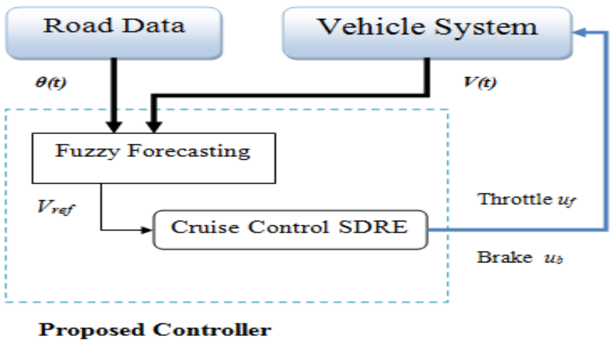

Figure-1. Schematic block diagram of the (LA) controller.

Fuzzy logic forecasting

The vehicle behaviour is forecasted by a fuzzy decision function. The inputs to the decision function were chosen as future road slope θ(t) and current velocity v. The fuzzy logic decision function would use these inputs to generate a preliminary forecast of what the future velocity of the system should be. The rules are based on expert knowledge, which was developed in this study. These rules are adaptable to the system requirements as well as the driver ability which makes it easy in terms of application. Thus, fuzzy logic is preferred because of the black-box input output relationship.

The main objective is to find the velocity trajectory that would be appropriate for each road condition and would give the best fuel economy. It must be restated that the environment is represented by the road grade, which is known in this study. The engine provides the propulsive force for the vehicle's motion, and the road grade represents a significant influence on the resistance

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forces as seen in Equation. (15) and (16), due in part to the large mass of the vehicle.

The expert knowledge shows that fuel reduction occurs during transitions between positive and negative road grades. Therefore, during positive road grades it is advised to slightly increase speed to counter the loss in speed in that situation. And in the case of negative road slopes naturally the speed of the heavy vehicle in this case increases due to the gravitational forces, thus the driver decelerates before the negative slope. Therefore, the driving conditions mapped in the fuzzy decision space are: level road, negative road (downhill driving) and positive road (uphill driving).

The membership functions used are triangular symmetrical distribution function for each of the inputs (current velocity and future road slope). And the linguistic interpretation of road slope ranges from a positive (-5%) to a negative (-5%). The input velocity also ranges between the two limits of $80 < V < 90$ Km/h. The If-Then-part of the rules of the controller refers to the values of the output variables. In this study the method used is generally known as the Mamdani's minimum inference operation, which is the most popular method. The inputs are fuzzy singletons, $A' = \theta_0$ and $B' = v_0$, the results C' can be obtained from the following relation:

$$\mu_c(t) = \vee_{i=1}^{n} [\mu_{Ai}(\theta_0) \Lambda \mu_{Bi}(v_0)] \Lambda \mu_{Ci}(w) \qquad (30)$$

To obtain the crisp control output from an inferred fuzzy inference engine, the centroid area method was used in this study as follows:

$$Z_{coa} = \frac{\int_z \mu_C(z) Z dz}{\int_z \mu_C(z) dz} \qquad (31)$$

The value Z is output from the given inputs and their fuzzy relation, and $\mu_C(z)$ is the aggregated output membership function. The output is the reduction or increase, which must occur to the average velocity within range of -5 to 5 km/h. Therefore, crisp output of the fuzzy forecast controller to the cruise controller increases or decreases the speed before uphill's or downhill's.

Cruise control

The cruise controller (SDRE) tracks the velocity trajectory supplied by the fuzzy forecasting function. Therefore, control action is taken by the SDRE controller which provides both the throttle and braking signal to the vehicle system. SDRE is a nonlinear control method and can be thought of as a variation of the LQR control concept, possessing its simplicity. It uses a semi-global linearization method as opposed to linearization around a certain set-point as is the case in other nonlinear control algorithms [13]. This conciliates complexity with applicability. The SDRE approach requires the nonlinear state equations to be reformulated into a pseudo-linear state-dependent coefficient (SDC) form in which the system matrices become functions of the current state:

$$\dot{x} = A(x)x + B(x)u \qquad (32)$$

From the system dynamics in Equation. (26), (27), (28) and (29) the nonlinear vehicle system is factorized to generate:

$$\dot{x}_1 = m_{tr}(a_1 c_1 - 0.5 A_a x_1) x_1 \qquad (33)$$

Thus, the coefficient of the *A* matrix becomes:

$$a_{11} = m_{tr}(a_1 c_1 - 0.5 A_a x_1) \qquad (34)$$

then the system equation becomes:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} a_{11} & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u \qquad (35)$$

After obtaining the quasi-linearized system matrices in Equation. (35), a standard Riccati equation can be then solved at each time step to design the state feedback control law on-line. For implementation, the equations could be approximately discretized at each time step.

The SDRE controller is then specified similar to LQR by:

$$u = -R^{-1} B^T P(x) x = -K(x) x \qquad (36)$$

where the value of *P(x)* is calculated from the Riccati equation [14]:

$$A^T \left[P - PB(R + B^T PB)^{-1} B^T \right] A - P + Q = 0 \qquad (37)$$

the approach is an extension of the LQR for tracking of a reference signal, in our case, the reference signal is the generated V_{ref}, and input is added to the control input vector:

$$u_k = -R^{-1} B^T(x) P(x)(x - V_{ref}) = -K(x)(x - V_{ref}) \qquad (38)$$

The next task lies in the choice of the values of *Q* and *R* which have a crucial role in the stabilization and tracking ability of the system. In the spirit of simplicity

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only constant values are considered in the choice of the two values, where:

$$Q = C' \cdot C = [1 \quad 0]^{-1} \cdot [1 \quad 0] \tag{39}$$

In tuning the above values the following considerations were taken: large values of Q would contribute to the increase in the gain matrix and thus more control input and faster the time it takes to reduce disturbances. In addition, an increase in the value of R would produce a decrease in values of feedback gain. This would increase sluggishness, however, that could be advantageous for the control of overshoot.

In this particular application the values of tuned Q were:

$Q = \begin{bmatrix} 200 & 0 \\ 0 & 0 \end{bmatrix}$ while R is chosen as $R = [1]$.

SIMULATION

The described system in this study and the designed controller were implemented in Matlab and Simulink. The road data used were constant uphill road and a road profile that mimics real road segments according to [15] and [16]. All road profiles spanned over a distance of 3.5 Km, while the simulation parameters are detailed in Table-2.

From Figure-1 the general structure of the designed control system is depicted. The system is the heavy vehicle model while road data is taken from the previously defined road profile. The calculated road slope data and current vehicle velocity are both inputs to the fuzzy inference system discussed in the previous section. The fuzzy forecasting function alters the velocity set-point in order to increase fuel economy. Then the second level controller, SDRE controller translates the reference velocity to vehicle parameters (throttle and brake signals) which are fed into the vehicle system. The vehicle is assumed moving without stoppage all throughout the simulation i.e. $V = 0$ never occurs.

The assessment of the designed system performance is carried out with respect to fuel economy. The difference in fuel consumption is defined as follows:

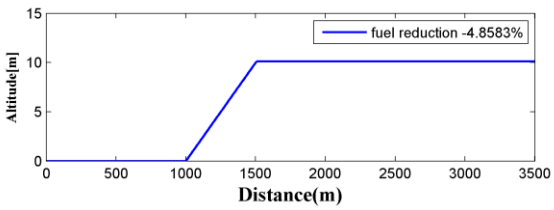
$$\Delta fuel = \frac{fuel_1 - fuel_2}{fuel_1} \times 100\% \tag{40}$$

The values of $fuel_1$ and $fuel_2$ are the fuel consumption resulting from the standard PI controller and the designed (LA) controller respectively. The results of the proposed controller with the different road conditions are summarized in Table-3.

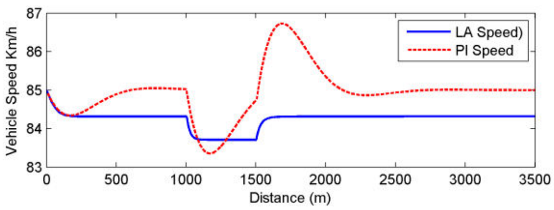
The first studied scenario is a constant uphill road depicted in Figure-2-(a) with a 2% slope. The slope of this segment road is pre-calculated by a preprocessing algorithm which outputs the position and the slope of the individual point on the road. The velocity response is shown in Figure-2-(b) while the fuel consumption of the controller is shown in Figure-2(c). From Table-3 and Figure-2-(d) a reduction of -4.8583 % in the consumed fuel is shown between the standard PI cruise controller and the developed Lookahead Anticipatory controller.

The second segment is also a constant uphill profile of 3% shown in Figure-3(a), over a distance of 3.5 Km which is slightly steeper than the previous segment. With the increase in steepness of the road profile the fuel consumption is reduced further as shown in Table-3, by the use of the designed controller. As accelerations appropriate to the road segment increase are chosen by the controller then implemented by the second level controller. The vehicle speed response is shown in Figure-3(b) while the fuel consumed and normalized fueling are both shown in Figure-3(c) and Figure-3(d) respectively. The fuel economy was increased by a percentage of 8.0576% with the use of the proposed controller over the standard PI controller.

The final scenario was a generated road profile also over a distance of 3.5 Km shown in Figure-4(a). The speed response and fuel consumption are shown in Figure-4(b) and Figure-4(c). The values of reduction in fuel consumption are shown in Table-3 showing enhancement in performance by a percentage of 15.2963 % in favour of the developed controller.



(a)



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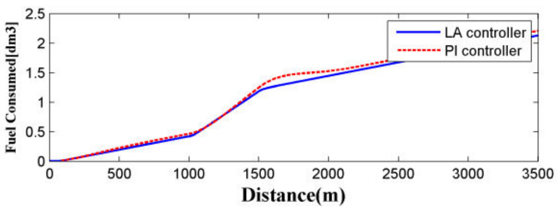

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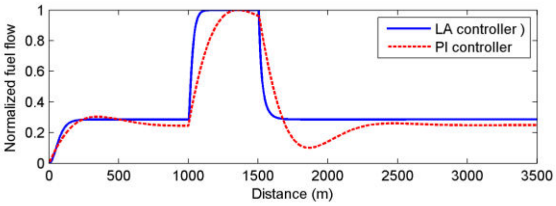
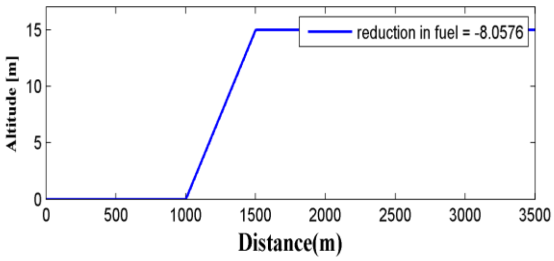
VOL. 11, NO. 6, MARCH 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



(d)

Figure-2. (a-b-c-d) Results in response to a 2% uphill slope.



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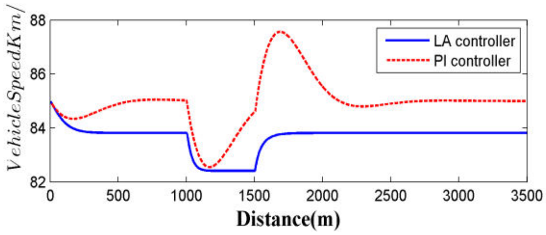
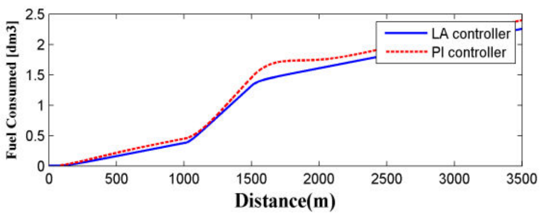


(b)

Figure-3. (a-b) Results in response to a 3% uphill slope.



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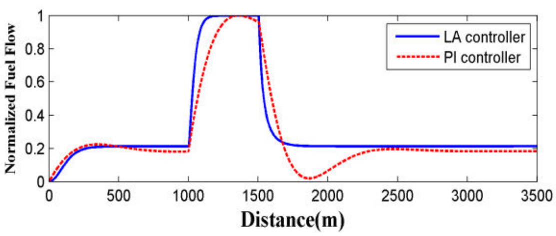

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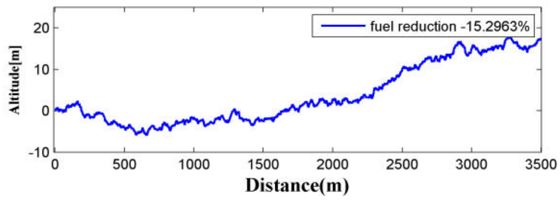
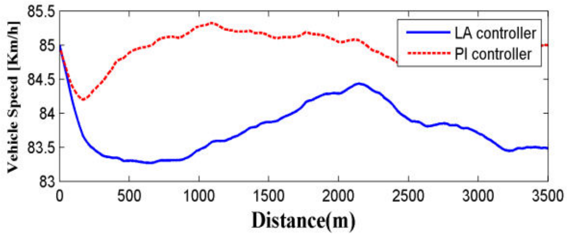
Figure-3. (c-d) Results in response to a 3% uphill slope.



(a)



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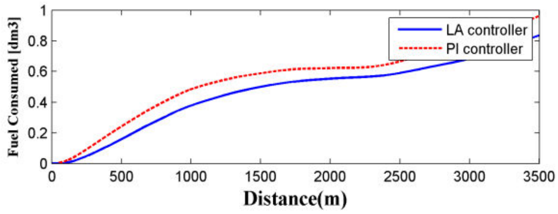

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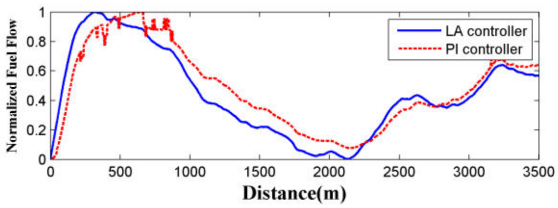

(d)

Figure-4. (a-b-c-d) Results in response to generated road.

CONCLUSIONS

This study offers a two loop control structure to adapt velocity of conventional heavy duty vehicles (HDV), in response to changes in road topography. The control strategy uses a combination of current velocity state and future and current slope to choose the speed of the vehicle (V_{ref}), while keeping the velocity of the vehicle within constraints determined by the driver or traffic regulations. A fuzzy forecasting function was used to apply the above prediction strategy by selecting the appropriate velocity for each road section. Then a nonlinear controller is used to implement the selected velocity (V_{ref}). The simulations were done and the results show that the reduction in fuel occurs during uphill fluctuations in road grade. In application, the uphill road of 2% and 3% inclination respectively, obtained a reduction of 4.8583% and 8.0576% in fuel consumption, in favor of the LA controller. The generated road gave a further reduction of 15.2963% which shows that the designed controller satisfies the objective. In addition, the need for braking was reduced as the velocities were kept within the constraints throughout the simulations.

It is worth noting, that although the value of fuel consumption is improved, however, the solution to the fuel optimization problem is only suboptimal. Therefore, in future the forecasting in the LA controller would be replaced by a fuzzy linear programming optimization algorithm which would also increase the optimality of the solution.

Table-2. Simulation parameters.

Description	*Values*	*symbol*
Mass	40 tons	m
Number of cylinders	6	n_{cyl}
Ratio final drive	3.27	i_f
Efficiency final drive	0.97	n_f
Wheel inertia	32.9	J_w
Engine inertia	3.5kgm^2	J_e
Rolling resistance	7x10^{-3}	C_r
Gravity coefficient	9.81	G
Cross section area	10	A_a
Air density	1.29	p_a
Wheel radius	0.52	r_d
Gear ratio (G=12)	1	i_t
Gear efficiency (G=12)	0.99	n_t

Table-3. Controller performance.

Road segement	LA controller performance
2% uphill slope	4.8583%
3%uphill slope	8.0576%
Generated road	15.2963%

REFERENCES

[1] H. K. A. N. S. M. V. and R. G. Khayyam, Intelligent energy management in hybrid electric vehicles, 2010.

[2] E. Hellstrom, Lookahead Control of Heavy Vehicles, 2010.

[3] M. Ivarsson, Fuel optimal powertrain control for heavy trucks utilizing lookahead, 2009.

[4] F. Jimenez and W. Cabrera-Montiel, "System for Road Vehicle Energy Optimization Using Real Time Road and Traffic Information," Energies, 2014.

[5] K. K. F. S. Y. M. McDonough, Stochastic Fuel Efficient Optimal Control of Vehicle Speed, 2014.

[6] M. M. J. F. Abou-Nasr, Exploiting Terrain Information for Enhancing Fuel Economy of Cruising Vehicles by Supervised Training of Recurrent Neural Optimizers, 2015.

[7] M. B. M., D. K. Henzler, "Online velocity trajectory planning for manual energy efficient driving of heavy duty vehicles using model predictive control," in Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on, Qingdao, 2014.

[8] C. H., M. S. Sun, "Velocity Predictors for Predictive Energy Management in Hybrid Electric Vehicles," IEEE Transactions on Control Systems Technology, 2015.

[9] J. Jing, Vehicle Fuel Consumption Optimization using Model Predictive Control based on V2V communication, 2014.

[10] T. Ivens, Predictive Cruise Control for Heavy Duty Vehicles, 2010.

[11] A. Al Alam, Optimally fuel efficient speed adaptation (Doctoral dissertation), 2008.

[12] U. Kiencke, Automotive Control Systems for Engine, Driveline, and Vehicle, 2005.

[13] S. Katsev, Streamlining of the State-Dependent Riccati Equation Controller Algorithm for an Embedded Implementation, 2006.

[14] N. M. D. J. and L. G. Singh, "Control of pendulum on a cart with state dependent riccati equations," International Journal of Computer, Information, and Systems Science, and Engineering. 2009.

[15] Q. Z. C. He, L., "Non-stationary Random Vibration Analysis of Vehicle with Fractional," in International Conference on Intelligent Computation Technology and Automation, 2008.

[16] P. R. Johannessona, "Laplace processes for describing road profiles," in 5th Fatigue Design Conference, Fatigue Design 2013, 2013.