

HEAVY VEHICLES FUEL CONSUMPTION OPTIMIZATION USING MACHINE LEARNING MODEL

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ABSTRACT: The average fuel consumption for vehicles is needed and crucial all over the phases of their life-cycle. This paper advocates a data summarization approach based on distance rather than the traditional time period when developing individualized machine learning models for fuel consumption. This paper presents Heavy Vehicles Fuel Consumption Optimization using Machine Learning Model. The performance of a method for reducing the fuel consumption of a heavy duty vehicle (HDV) is described and evaluated both in simulation and using a real HDV. The proposed model can easily be developed and deployed for each individual vehicle in a fleet in order to optimize fuel consumption over the entire fleet. The results also show that our simulations are sufficiently accurate to be transferred directly to a real HDV. In cases where the allowed range of speed variation was restricted, the proposed method outperformed standard predictive cruise control (PCC) by an average of around 3 percentage points as well, over the same road profiles.

KEYWORDS: Artificial Neural Networks (ANN), fuel consumption optimization, data summarization, Heavy Vehicles.

I. INTRODUCTION

The average fuel consumption for vehicles is needed and crucial all over the phases of their life-cycle. These models are important to the manufactures to build the parts of vehicles accordingly, regulators and consumers [1]. In order to deal with increasingly strict limitations on greenhouse gas emissions, and the likely increase in (fossil) fuel prices, heavy-duty vehicle (HDV) manufacturers are under pressure to reduce fuel consumption.

Moreover, the competitive nature of the HDV market also forces manufacturers to develop fuel-efficient vehicles [2]. On a flat road, driving with constant speed (standard cruise control) is the optimal solution to the problem of minimizing the fuel consumption with a constraint on travelling time. Speed profile optimization is an effective approach for reducing the fuel consumption of a single HDV. This approach can also be used in other applications such as in HDV platooning [3].

In general, every customer wants to use less fuel for the vehicles with more profit. In general, techniques used to develop models for fuel consumption fall under three main categories: • Physics-based models, which are derived from an indepth understanding of the physical system. These models describe the dynamics of the components of the vehicle at each time step using detailed mathematical equations.

• Machine learning models, which are data-driven and represent an abstract mapping from an input space consisting of a selected set of predictors to an output space that represents the target output, in this case average fuel consumption. • Statistical models, which are also data-driven and establish a mapping between the probability distribution of a selected set of predictors and the target outcome

It is common to formulate the speed profile optimization problem as an optimal control problem [4]. In this formulation, the optimization is carried out (during driving)

with respect to fuel consumption, and with constraints on travelling time, number of gearshifts, and the allowed speed range for the vehicle. These methods, which are usually referred to as predictive cruise control, allow the vehicle to deviate from the cruise control's set speed based on the slope angle of the road ahead.

Several previous models for both instantaneous and average fuel consumption have been proposed. Physics-based models are best suited for predicting instantaneous fuel consumption because they can capture the dynamics of the behavior of the system at different time steps [5]. Machine learning models are not able to predict instantaneous fuel consumption with a high level of accuracy because of the difficulty associated with identifying patterns in instantaneous data. However, these models are able to identify and learn trends in average fuel consumption with an adequate level of accuracy.

Previously proposed machine learning models for average fuel consumption use a set of predictors that are collected over a time period to predict the corresponding fuel consumption in terms of either gallons per mile or liters per kilometer. While still focusing on average fuel consumption, our proposed approach differs from that used in previous models because the input space of the predictors is quantized with respect to a fixed distance as opposed to a fixed time period. In the proposed model, all the predictors are aggregated with respect to a fixed window that represents the distance traveled by the vehicle thereby providing a better mapping from the input space to the output space of the model. In contrast, previous machine learning models must not only learn the patterns in the input data but also perform a conversion from the time based scale of the input domain to the

distance-based scale of the output domain (i.e., average fuel consumption).

II. LITERATURE SURVEY

S. Wickramanayake and H. D. Bandara, et. al. [6] arranged Fuel utilization forecast of armada vehicles exploitation AI. They trained an ability to display and anticipate the fuel utilization is significant in improving efficiency of vehicles and forestalling offensive exercises in armada the board. Fuel utilization of a vehicle relies upon a few interior components like distance, vehicle qualities, and driver conduct, conjointly as outside factors like street conditions, traffic, and climate.

L. Wang, A. Duran, J. Gonder, and K. Kelly, et. al. [7] created Displaying substantial/medium duty fuel utilization upheld drive cycle properties. They trained various ways for foreseeing weighty/medium duty vehicle fuel utilization upheld driving cycle data. A polynomial model, a recorder fake neural net model, a polynomial neural organization model, and a variable accommodative relapse sp lines (MARS) model were created and checked exploitation data gathered from skeleton testing performed on a package conveyance diesel truck operational over the extraordinary modern Diesel Truck (HHDDT), city territory genuine Vehicle Cycle (CSHVC), new work Composite Cycle (NYCC), and water powered half breed vehicle (HHV) drive cycles. H. Almer, et. al. [8], compares the accuracy of the proposed fuel consumption models with respect to input data collected at 1 minute and 10 minute intervals and concludes that the 10 minute interval yields more accurate models. Vehicle weight is not typically available as a standard sensor and the weight was estimated using the suspension. In this paper, we also use vehicle speed and road grade to derive the predictors of the proposed model. G. Fontaras, R. Luz, K.

Anagnostopoulos, D. Savvidis, S. Hausberger, and M. Rexeis, et. al. [9] utilized perception gas outflows from hdv in europe-a test confirmation of develop of the arranged methodological approach. As shown by them, the European Commission in joint coordinated effort with genuine Obligation Vehicle makes, the city College of Innovation and completely totally extraordinary counseling and investigation bodies has been setting up a beginner authoritative system for perception and news gas emanations from genuine Obligation Vehicles (HDVs) in Europe.

H. A. Rakha, K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck, et al. [10] proposed a method to calibrate the VT-CPFM model parameters for passenger cars by using US EPA city and highway cycles and fuel economy ratings. Unfortunately, there were no currently available public driving cycles and fuel economy ratings reported for HDT. The model parameters calibrated under one scenario might require recalibration for new scenarios, which is time-consuming.

III. METHODOLOGY

The architecture of Heavy Vehicles Fuel Consumption Optimization using Machine Learning Model is represented in below Fig. 1. The model is developed by using duty cycles collected from a single truck, with an approximate mass of 8, 700 kg exposed to a variety of transients including both urban and highway traffic in the Indianapolis area. Data was collected using the SAE J1939 standard for serial control and communications in heavy duty vehicle networks.

Several processing steps were needed in order to generate the predictors of the model. These predictors are derived from two measurements, namely, road grade and transmission output speed. The first processing step consisted of down sampling

the road grade and obtaining the vehicle speed from the transmission output speed. The road grade was measured using an on-board inclinometer and down-sampled to 1 Hz.

In order to reduce the noise in the variable, a moving average low pass filter was applied to the vehicle speed obtained and the variable was down-sampled from 50 Hz to 1 Hz. The purpose of the second processing step was to derive the synthetic duty cycles. Towards this objective, the duty cycles in the real data were split into segments defined by intervals between consecutive vehicle stops.

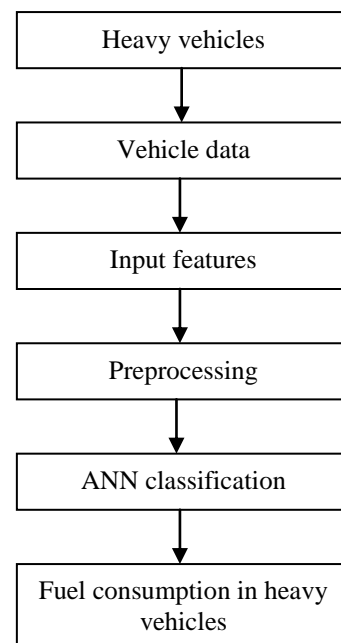


Fig. 1: SYSTEM ARCHITECTURE

Consider the problem of reducing the fuel consumption of an HDV, moving from a given start point to a given end point, in a case where the road profile (here represented as a composite Bezier curve) is known. In order to evaluate a speed profile in a real HDV, a similar procedure is used: The optimized speed profile is again used as a look-up table from which the HDV receives a desired speed based on its current position along the road.

The speed profile optimization is carried out in simulation using Artificial Neural Networks (ANN) with respect to fuel consumption only. Moreover, the optimized speed profile must fulfill certain constraints, namely (i) the instantaneous maximum speed must not exceed an upper limit (the speed limit), (ii) the instantaneous minimum speed should be above a user-defined limit to ensure that the vehicle does not affect the traffic negatively, and (iii) the average speed should not be below a certain threshold.

Dataset will be divided into 80% and 20% format, 80% will be used to train ANN model and 20% will be used to test ANN model. Using this model we can create ANN object and then feed train and test data to build ANN model. Predict Average Fuel Consumption:- Using this module we will upload new test data and then ANN will apply train model on that test data to predict average fuel consumption for that test records Fuel Consumption Graph: Using this module we will plot fuel consumption graph for each test record.

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IV. RESULT ANALYSIS

The model is developed by using duty cycles collected from a single truck, with an approximate mass of 8,700 kg exposed to a variety of transients including both urban and highway traffic in the Indianapolis area. Data was collected using the SAE J1939 standard for serial control and communications in heavy duty vehicle networks. Twelve drivers were asked to exhibit good or bad behavior over two different routes. Drivers exhibiting good behavior anticipated braking and allowed the

vehicle to coast when possible. Some drivers participated more than others and as a result the distribution of drivers and routes is not uniform across the data set.

When coupled with the difference in standard deviation of the average fuel consumption for the 1 km and the 5 km windows (Table II), this trend indicates that aggregating the input and output data over 5 km provides a stable profile for the fuel consumption of the vehicle over the routes and this profile does not necessitate extensive learning. It was found that the trip distance is an important indicator and that predicting fuel consumption over long route segments for small vehicles in urban areas has better accuracy. We believe that extending the data collection interval promotes a linear relationship between fuel consumption and distance traveled. While this approach yields good average fuel consumption prediction over long distances, point-wise predicted fuel consumption may not adequately track actual values.

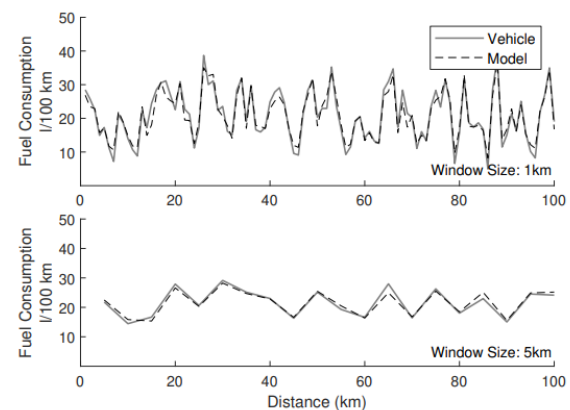


Fig. 2: PREDICTED VERSUS ACTUAL FUEL CONSUMPTION FROM FTS FOR A 1 KM WINDOW (TOP) AND 5 KM WINDOW (BOTTOM)

To illustrate this behavior, Fig. 2 shows the predicted and actual fuel consumption over the first 100 km of the test data set (Fts) for window sizes 1 km and 5 km. The 1 km model is able to better track fuel consumption on a per window-basis. These

standard deviations indicate that the models derived using the proposed approach are stable.

in order to generate the optimal speed profiles for the HDV. First, however, the HDV's fuel consumption was measured when driving with standard CC, with a set speed of 80 km/h, on all 10 road sections so as to generate the baseline case against which the optimized speed profiles were later compared. Next, the speed profile optimization was executed, constraining the minimum average speed of the HDV to be at or above 80 km/h, the maximum speed to be at most 90 km/h, and the minimum speed to be at least 60 km/h.

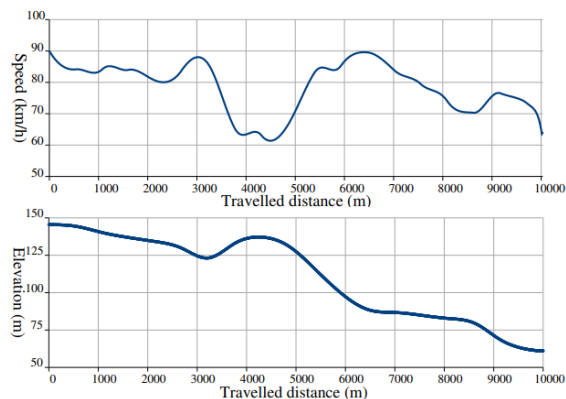


Fig. 3: SPEED OF VEHICLE AND ELEVATION OF ROAD WITH RESPECT TO TRAVELLED DISTANCE

An example of an optimized speed profile, with its corresponding road profile, is shown in Fig. 3. In this case, the HDV speeds up (at a travelled distance of around 3 km) right before an uphill climb which helps it to avoid excessive acceleration to reach the top. Conversely, when driving through the downhill parts of this road profile, the HDV starts (at travelled distances of around 4.5 km and 8.5 km, respectively) with a low speed in order to avoid unnecessary braking during the driving. The optimized speed profiles were then transferred to an HDV in order to measure its fuel consumption as it followed the speed profiles over the same 10

road profiles. The proposed speed profile optimization algorithm reduced the fuel consumption of the HDV substantially, by around 10.2% on average (over a total of 80 km of highway). This saving was achieved while the HDV was driving at 77.9 km/h (on average) over the 8 considered road profiles.

V. CONCLUSION

In this paper, Heavy Vehicles Fuel Consumption Optimization using Machine Learning Model is described. The amount of fuel consumed will be provided numeric value based on the vehicle the consumption of fuel differ. Machine learning in model that might make helpfully created for each overwhelming vehicle. The proposed model can easily be developed and deployed for each individual vehicle in a fleet in order to optimize fuel consumption over the entire fleet. Different model configurations with 1, 2, and 5 km window sizes were evaluated. The results show that the 1 km window has the highest accuracy. This model is able to predict the actual fuel consumption on a per 1 km-basis with a CD of 0.91. This performance is closer to that of physics-based models and the proposed model improves upon previous machine learning models that show comparable results only for entire long-distance trips. The proposed speed profile optimization algorithm reduced the fuel consumption of the HDV substantially, by around 10.2% on average (over a total of 80 km of highway). This saving was achieved while the HDV was driving at 77.9 km/h (on average) over the 8 considered road profiles.

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