A Machine Learning Model for Average Fuel Consumption in Heavy Vehicles

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ABSTRACT

This paper advocates an information summarization for every fleet, the methodology should apply and adapt to approach supported distance instead of the standard period of several completely different vehicle technologies (including time once developing personal machine learning models for fuel future ones) and configurations while not elaborated data of the consumption. This approach is employed in conjunction with some vehicles specific physical characteristics and measurements. predictors derived from speed and road grade to provide whole fleet. The predictors of the model square measure collective over mounted window sizes of distance traveled. completely different window sizes square measure evaluated and also the results show that a one-kilometer window is in a position to predict fuel consumption with a zero.91 constant of determination and mean absolute peak-to-peak % error but four-dimensional forroutes that embrace each town and main road duty cycle segments. [9].

Index Terms: vehicle modeling, neural networks, average fuel consumption, data summarization, fleet management.

I. INTRODUCTION

Fuel consumption models for vehicles are of interest to makers, regulators, and customers. they're required across all the phases of the vehicle life-cycle. In this paper, we tend to specialize in modeling average fuel consumption for significant vehicles throughout the operation and maintenance part. In general, techniques won't to develop models for fuel consumption make up 3 main categories:

Physics-based models, that are derived from AN in-depth understanding of the physical system. These models describe the dynamics of the elements of the vehicle at whenever step victimization careful mathematical equations [1], [2].

Machine learning models, that are data-driven And rep-resent AN abstract mapping from AN input house consisting ofa specific set of predictors to an output house that represents the target output, during this case average fuel consumption [3], [4].

Statistical models, that also are data-driven and estab-lish a mapping between the likelihood distribution of a specific set of predictors and also the target outcome [5], [6].

Trade-offs among the on top of techniques are primarily with relevance value and accuracy as per the necessities of the meant application.

In this paper, a model that may be simply developed for individual significant vehicles in a very massive fleet is projected. hoping on correct models of all of the vehicles in avery fleet, a fleet manager will optimize the route designing for all of the vehicles supported every distinctive vehicle foretold fuel consumption thereby guaranteeing the route assignments are aligned to attenuate overall fleet fuel consumption. These forms of fleets exist in numerous sectors together with, road transportation of products public transportation construction trucks and refuse trucks [7], [3], [8].

These necessities build machine learning the technique of an extremely prognosticative neural network model for average fuel selection once taking into thought the required accuracy consumption in significant vehicles. The projected versus model will the value of the event associated adaptation of an individualized an exceedingly fleet so as to optimize fuel consumption over the model for every vehicle within the fleet.

Several previous models for each fast and average fuel consumption are projected. Physics-based models are best fitted to predicting fast fuel consumption as a result of they will capture the dynamics of the behavior of the system at completely different time steps. Machine learning models aren't ready to predict fast fuel consumption with a high level of accuracy owing to the issue related to distinctive patterns in fast knowledge. However, these models are ready to establish associated learn trends in average fuel consumption with an adequate level of accuracy [4],[1],[2],[3].

Previously projected machine learning models for average fuel consumption use a group of predictors that are collected over a period of time to predict the corresponding fuel consumption in terms of either gallons per mile or liters per kilometer. whereas still specializing in average fuel consumption, our projected approach differs from that employed in previous models as a result of the input house of the predictors is quantal with relation to fastened a hard and fast a set} distance as against a fixed period of time. within theprojected model, all the predictors ar aggregate with relation toa hard and fast window that represents {the distance the house the gap} traveled by the vehicle thereby providing a stronger mapping from the input house to the output space of the model. In distinction, previous machine learning models should not solely learn the patterns within the input file however additionally perform a conversion from the time-primarily based scale of the input domain to the distance-based scale of the output domain (i.e., average fuel consumption).

Here we using the same scale for both the input and output spaces of the model offers several benefits:

The data is collected at a rate that is proportional to its impact on the outcome. When the input space is sampledwith respect to time, the amount of data collected from avehicle at a stop is the same as the amount of data collectedwhen the vehicle is moving.

The predictors within the model are able and ready to capture the impact of each the duty cycle and therefore the atmosphere on the common fuel consumption of the vehicle (e.g., the amount of stopsin Associate in Nursing urban traffic over a given distance).

New technologies such as V2I and dynamic traffic man- agreement can be leveraged for additional fuel efficiency optimization at the level of each specific vehicle, route and time of day. [10]–[12].

The remainder of the paper is organized as follows: Section II includes a review of previous connected work, Section III introduces the planned machine learning model, Section IV describes the method used for data collection and data summarization, Section V presents the results of applying the planned model underneath totally different configurations, and Section VI summarizes the principle findings of this study and offers direction for future work.

II. RELATED WORK

As mentioned on top of, physics-based, machine learning, and applied mathematics models have all beenwont to model average fuel consumption. The EPA and also the European Commission developed physics- based, full vehicle simulation models for significant dutyvehicles [1], [2].

These models area unit capable of predicting average fuel consumption with associate accuracy of±3% compared to real measurements obtained from a flowmeter [2]. This level of accuracy comes at the value of a considerable development effort.At the opposite finish of the modeling spectrum area unit applied mathematics procedures that area unit applied underneath strict testing conditions to make sure that the reportable results area unit standardized and repeatable. for instance, the model projected by the Code of Federal Regulation (CFR) estimates fuel consumption for brand spanking new vehicles by exploitation well outlined applied mathematics strategies for specific duty cycles created from segmentsof planet journeys. Similarly, the SAE J1321 normal isused to estimate fuel consumption when market modifications or underneath varied operative conditions for trucks and buses[5][6] . This normal com- pares similar vehicles following identical route underneath similar operative conditions exploitation real knowledge collected from the sector. for instance, the quality was utilized in to match the fuel consumption of animpression vehicle thereto of 2 take a look at vehicles when dynamical lubrication fluids within the engine, transmission and shaft. the quality was conjointly used in to live the performance of 3 fuel technologies in 2 vehicles operative in coal mines. The generalizable characteristics of machine learning mod- else to completely different completely different} vehicles and different operative conditions created this modeling methodology engaging for fuel consumption prediction in several studies. within the remainder of this section we have a tendency to discuss these models with regard to the underlying machine learning technique, the illustration of the input area and also the illustration of the output area[8].

Different types of machine learning techniques are used and compared for the aim of modeling fuel con- Sumption. as an example, gradient boosting, neural networks and random forest area unit compared in neural networks and variable regression splines area unit compared in and support vectormachine, neural networks and random forest area unit compared in [7][3][4]. supported the results, these studies determinea way of selection. but the variations between these techniquesarea unit principally marginal and as declared in [7] and [14], the techniques area unit comparable. we tend to believe that the variations area unit primarily because of completely different knowledge assortment and knowledge summarization methodologies. during this paper, we tend to opted to use neuralnetworks as a result of this system is best suited to models with continuous input and output variables. furthermore, neural networks area unit less vulnerable to shire knowledge.

The input of antecedently projected fuel consumption models conjointly varies significantly. A holistic model would possibly conceive to capture driver behavior, vehicle dynamics and also the impact of the surroundings on the vehicle. as an example, the models introduced in use mixtures of 1st, second, third and fourth orders of auto acceleration and speed as predictors[4]. In the predictors embrace vehicle speed, distance traveled, elevation, longitude, latitude and day of the week. Predictors associated with the road condition (e.g., grade, curvature and roughness) and also the vehicle's in operation conditions (e.g., vehicle speed, acceleration, gear, and a couple of torque) area unit employed in the foremost necessary predictors during this previous study were found to be acceleration, % torque, and gradient. Vehicle speed wasn't necessary as a result of it had been maintained nearly constant throughout knowledge assortment. In far more than thirty predictors were investigated in as well as wind speed, platooning, engine strength and breaking rate and also the most vital predictors were found tobe road grade, vehicle speed and vehicle weight. Vehicle weightisn't usually offered as a customary device and also the weight in was calculable mistreatment the suspension. during this paper, we tend to conjointly use vehicle speed and road grade to derive the predictors of the projected model. These variables are often directly obtained from non-invasive, reasonable and wide offered telematics devices[7][3].

Typically, the predictors of the models area unit derived from completely different device values that area unit sampled at mounted time intervals [3],[4].The author compares theaccuracy of the projected fuel consumption models with reference to computer file collected at one minute and ten minute intervals and concludes that the ten minute interval yields additional correct models. In [7], measurements area unitcollected every one minute or one mile, whichever is that the smallest. on condition that the vehicles were traveling at constant speed during this study, this amounts to aggregation computer file over a hard and fast a hard and fast mile. Each seem to hint that aggregation computer file over distance traveled is more suited to fuel consumption modeling.

III. DATACOLLECTION AND SUMMARIZATION

The model is developed by using duty cycles collected from a single truck, with an approximate mass of 8, 700kg exposed to a variety of transients including both urbanand highway traffic in the Indianapolis area. Data was collected using the SAE J1939 standard for serial controland 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 participatedmore than others and as a result the distribution of driversand routes is not uniform across the data set. This field test generated 3, 302, 890 data points sampled at 50 Hz from the vehicle CAN bus and a total distance of 778.89km over 56 trips with varying distances. Most of the tripscovered a distance of 10 km to 15 km.

In order to increase the number of data points, synthetic duty cycles over an extended distance were obtained by assembling segments from the field duty cycles selected at random. Moreover, a set of drivers are assigned to thetraining segments and a different set of drivers are assigned to the testing segments, thereby ensuring that the training (Ftr) and testing (Fts) data sets derived fromthe respective segments are completely separate.

A. Model Predictors

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. A review of the data also showed thatthere is a linear relationship between the vehicle speed and the transmission output speed given by the following equation:

Vehicle Speed ≈ 59.3 × Transmission Output Speed

In order to reduce the noise in the variable, a moving average low pass filter was applied to the vehicle speed obtained by using (15) and the variable was down-sampledfrom 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 vehiclestops (Figure 1). A total of 455 real data segments were obtained from all the twelve drivers in the study. Out of these, 358 segments from nine drivers were used to derive the training data set and the remaining 97 segments, obtained from the remaining three drivers in the study, wereused to derive the testing data set Fts.

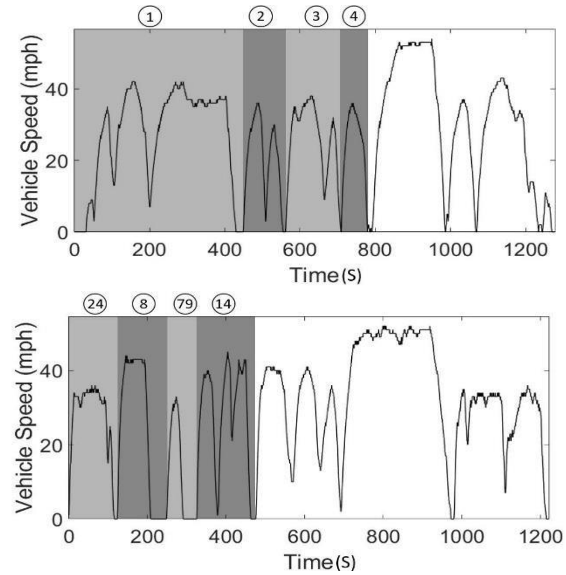

Fig. 1. The first four segments of a sample real duty cycle (top). A sample synthetic duty cycle created by concatenating segments 24, 8, 79, and 14 from the realdata (bottom)

One synthetic duty cycle is generated by sampling, without replacement, from the real data segments and concatenating the selected segments until a total distance of 15 km is reached. The total distance of 15 km was selected in order to mimic the real routes used for the fielddata collection. It was found that an average of five segments are needed to create 15 km of data. Figure 1 shows an example synthetic duty cycle generated using this process. Combining segments using the above approach resulted in a continuous vehicle speed. However, discontinuities were observed in road grade from one segment to the next as shown in the example of Figure 2. These duty cycles are then aggregated over a fixed distancetraveled based on the desired window (x). Table I shows the total number of data points (i.e., windows) as well as the total distance for each data set and for each window size being considered in this paper. The third step in the input data processing consists of generating the predictors for the proposed model. As previously mentioned, these predictors are calculated for each window and derived from vehicle speed and road grade. The selected predictorsconsist of:

- number of stops.
- time stopped.

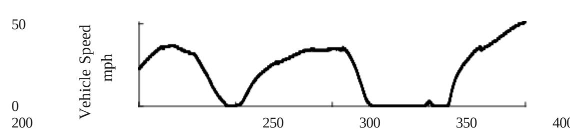

TABLE I

NUMBER OF DATA POINTS (I.E., WINDOWS) AND TOTAL DISTANCE FOR THE TRAINING (F(x)tr) AND THE TESTING (F(x)ts) DATA SETS WITH VARYING SIZE WINDOWS (I.E., 1, 2, AND 5 km.)

Windowsize	$F(x)_{tr}$		$F(x)_{ts}$	
	Number of Points	Distance (km)	Number of Points	Distance (km)
$x = 1\ km$	20,000	20,000	32,089	32,089
$x = 2\ km$	20,000	40,000	23,106	46,212
$x = 5\ km$	20,000	100,000	6,061	30,305

- average moving speed,
- characteristic acceleration,
- aerodynamic speed squared,
- change in kinetic energy and
- change in potential energy.

The on top of predictors were selected as a result of they're believed to capture the vehicle dynamics additionally because the driver's behavior and also the impact of the route on the target output of the model (i.e., fuel consumption). especially, a previous study states that characteristic acceleration and mechanics speed square area unit extremely indicative of the fuel consumption for a given duty cycle. This study argues that characteristic acceleration is directly associated with the inertia work required to accelerate the vehicle and mechanics speed square captures the impact of aeromechanics on fuel consumption .

It is important to capture the change in kinetic and potential energy during the duty cycle because these changes in the energy state of the vehicle can be significant for short distances when compared to the amount of total energy consumed by fuel. Over an extended distance, the percentage of fuel energy converted to kinetic and/or potential energy is reduced.

B. Model Output

The output of the model is average fuel consumptionin l/100km for every window. so as to get the common consumption, fuel rates area unit collected from the will bus. As within the case of road grade, and since artificial duty cycles area unit derived froma random choice of real duty cycle segments, discontinuities within the fuel rate area unit discovered from one phase to successive (Figure 2). The impact of those discontinuities isn't important asa result of the fuel rates area unit averaged over the complete window so as to calculate the output of themodel (i.e., average fuel consumption).

An analysis of the segments in the real data collected from the field shows a variance in average fuel consumption over all the trips. For example, a 20% difference in fuel consumption was observed betweengood and bad driver behavior over entire trips. Moreover, variances in average fuel consumption arealso observed for different window sizes.

Table II shows the mean and standard deviation of the average fuel consumption for the 1, 2, and 5 km windows acrossall trips. While the mean fuel consumption across all windows is relatively constant, the standard deviation decreases as the window size increases.

In summary, all the input features of the proposed modelare derived using the above methodology from the vehicle speed and the road grade sampled at a rate of 1 Hz. These variables can be obtained from a telematics device. In this study, these

variables were derived from sensor values broadcasted on the CAN bus. The accuracy of the model will vary depending on the source of the data and the sampling frequency. The accuracy of the model is also subject to the accuracy of the output feature. Fuel consumption obtained from the CAN bus can have an error as high as5% compared to the actual fuel consumption. Better accuracy can be obtained by using flowmeters. However, flowmeters are more expensive. Fuel consumption levelsfrom the CAN bus are used in [7] as well as in this paper and high precision fuel sensors are used in [3]. Aspects related to the accuracy of the data sources will be explored in future work.

C. MODEL VALIDATION

The seven predictors listed in Section IV are used as input to the neural network model. This constitutes the first layer of the network. The first layer then feeds into a hidden layer with 5 neurons. In turn, the hidden layer feeds into an output player with a single neuron. Figure 3 shows the RMSE during training for three modelswith window sizes 1, 2 and 5 km. In the top plot, each data point corresponds to the RMSE values after trainingthe model with a group of 500 windows.

This plotindicates that all models converge to a RMSE value less than 0.2 l/100km. However, the convergence rates for themodels are different. In fact, the 5 km starts with a RMSEvalue of 0.16 l/100km after 500 training windows and this RMSE value reaches 0.08 l/100km when the model converges. The corresponding values for the 1 km modelare 0.34 l/100km and 0.14 l/100km, respectively.

Whencoupled 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 aggregatingthe 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.

This finding aligns with previous studies.

For example,in [14], it was found that the trip distance is an importantindicator and that predicting fuel consumption over longroute segments for small vehicles in urban areas has better accuracy. In this previous study, 64% of the trips covered a distance ≤ 5 km. Similarly, it was found that collecting data over 10 minutes intervals resulted in a better accuracy than 1 minute intervals. In either case, we believe that extending the data collection interval promotes a linear relationship between fuel consumption and distance traveled. While this approach yields a good average fuel consumption prediction over long distances, point- wise predicted fuel consumption may not adequatelytrack actual values.

TABLE III

PREDICTIVE ACCURACY OF THE FUEL CONSUMPTION MODELS FOR 1, 2 AND 5 km AGGREGATION WINDOWS.

Window	1 *km*	2 *km*	5 *km*
CD	0.91 (0.0066)	0.87 (0.0085)	0.79 (0.0136)
RMSE (l/100km)	0.0132 (0.0005)	0.0142 (0.0005)	0.0234 (0.0008)
MAE (l/100km)	1.88 (0.0626)	1.69 (0.0515)	1.43 (0.0466)
$MAPE_{pk}$	3.74% (0.12%)	4.20% (0.13%)	5.83% (0.19%)
Points	32,089	23,106	6,061

Table III shows that the 1 km model has better performancethan the other two window sizes across all metrics. As previously mentioned, these performance metrics evaluate the performance of the model point-wise. In particular, the coefficient of determination (CD) for the 1 km model is equal to 0.91 which indicates that the model is able to track the actual fuel consumption for each 1 km of distance traveled. As the window size increases, the CD decreases. In terms of MAE and CD, the proposed model shows an improvement over despite the fact that high precision fuel sensors are used in [3] [7]. The RMSE of the models is also less than 0.025 l/100km which is lower than the results obtained. That said, the test distance in this paper is higher than the one used in [7]. Longer distances favor lower RMSE. The MAP Epk values for themodels are also within ranges of fuel consumption accuracyfor models reported in [4]. However, in this paper the errorbetween actual and predicted is compared at the level of each window whereas in [4], the error is reported for the entire trip.

The performance metrics shown in Table III seem to indicate that the proposed models are using highly predictive input features and that these features are adequately mapped to the output space of the model. In order to understand the contribution of each predictor, the AIW values of the predictors are calculated and summarized in Table IV.

TABLE IV

ADJUSTED INFLUENCE OF WEIGHTS (AIW) FOR THE PREDICTORS IN THE PROPOSED MODEL

Window	1 *km*	2 *km*	5 *km*
No. of Stops	1.49	2.29	4.63
Stop Time	0.62	1.24	3.44
Avg. Moving Speed	13.73	10.78	8.98
$\tilde{a}$ v^2_{aero}	12.47	14.32	12.98
CKE CPE	11.73	11.64	10.30
Bias	17.04	16.13	12.26
	13.73	11.45	9.38
	29.21	32.15	38.03

The importance of the number of stops and the stop time increases as the window size increases. This is expectedsince fewer stops are observed in the 1 km window compared to the 2 or 5 km windows. All the remaining predictors have high AIW across all window sizes. In fact, eliminating any of these predictors resulted in models with lower predictive accuracy. The increase in the AIWs for the number of stops and the stop time withincreasing window sizes coupled with the decrease in AIWs for the remaining predictors indicates that as the window size increases, the model relies less on the vehicle’s dynamics and more on events related to the distance traveled in order to estimate fuel consumption. Moreover, Table IV indicates that the two new predictorsintroduced in this paper have comparable contribution towards fuel consumption prediction to that of average moving speed, characteristic acceleration and aerodynamic speed .

IV. CONCLUSION

- This paper presented a machine learning model that canbe conveniently developed for each heavy vehicle in a fleet. The model relies on seven predictors: number of stops, stop time, average moving speed, characteristic acceleration, aerodynamic speed squared, change in kinetic energy and change in potential energy. The last two predictors are introduced in this paper to help capture the average dynamic behavior of the vehicle. Allof the predictors of the model are derived from vehicle speed and road grade. These variables are readily available from telematics devices that are becoming an integral part of connected vehicles. Moreover, the predictors can be easily computed on-board from these two variables. The model predictors are aggregated overa fixed distance traveled (i.e., window) instead of a fixedtime interval. This mapping of the input space to the distance domain aligns with the domain of the target output, and produced a machine learning model for fuelconsumption with an RMSE < 0.015 l/100km.
- 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. Selecting an adequate window size should take into

consideration the cost of the model in terms of data collection and on-board computation. Moreover, the window size is likely to be application-dependent. For fleets with short trips (e.g., construction vehicleswithin a site) or urban traffic routes, a 1 km window size is recommended. For long-haul fleets, a 5 km window size may be sufficient. In this study, the dutycycles consisted of both highway and city traffic andtherefore, the 1 km window was more adequate than the 5 km window. Future work includes understanding these differentiating factors and the selection of the appropriate window size. Expandingthe model to other vehicles with differentcharacteristics such as varying masses and aging vehicles is being studied. Predictors for these characteristics will be added in order to allow for thesame model to capture the impact on fuel consumption due to changes in vehicle mass and wear. Future work also includes investigating the minimum distance required for training each model and analyzing how often does a model need to be synchronized with the physical system in operation by using online training in order to maintain theprediction accuracy of the model.

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