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A MACHINE LEARNING MODEL FOR AVERAGE FUEL CONSUMPTION IN HEAVY VEHICLES

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ABSTRACT:

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 approach is used in conjunction with seven predictors derived from vehicle speed and road grade to produce a highly predictive neural network model for average fuel consumption in heavy vehicles. 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 predictors of the model are aggregated over fixed window sizes of distance traveled. Different window sizes are evaluated and the results show that a 1 km window is able to predict fuel consumption with a 0.91 coefficient of determination and mean absolute peak-to-peak percent error less than 4% for routes that include both city and highway duty cycle segments.

Keywords: ML,DL, High Accuracy, fuel.

1. 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 indepth 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 represent AN abstract mapping from AN input house consisting ofa specific set of predictorsto an output house thatrepresentsthe target output, during this case average fuel consumption [3], [4]. Statistical models, that also are data-driven and establish 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 vehiclesin 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.

2. LITERATURE SURVEY

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 strategiesfor 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 conditionsfor 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

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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

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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.

PROPOSED SYSTEM

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 for routes that embrace each town and main road duty cycle segments.

3. METHODOLOGY

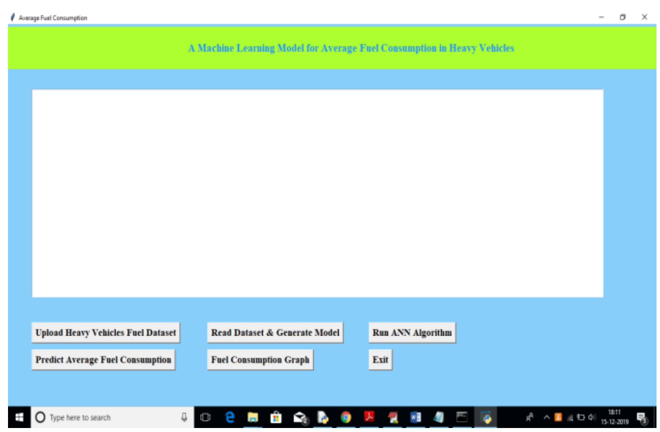
Run ANN Algorithm: Using this model we can create ANN object and then feed train and test data to build ANN model.

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.

Screen shots

To run this project double click on ‘run.bat’ file to get below screen



In above screen click on ‘Upload Heavy Vehicles Fuel Dataset’ button to upload train dataset

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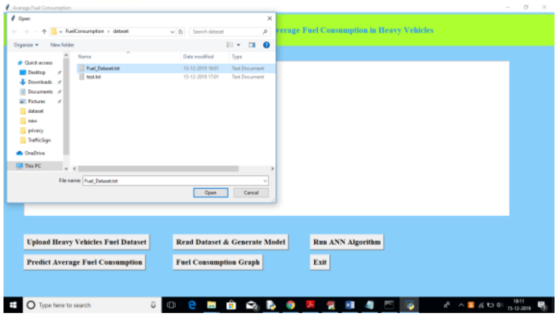
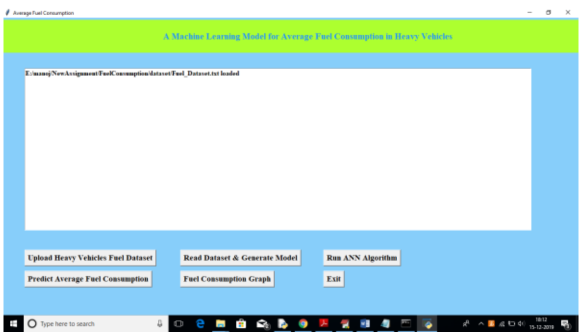
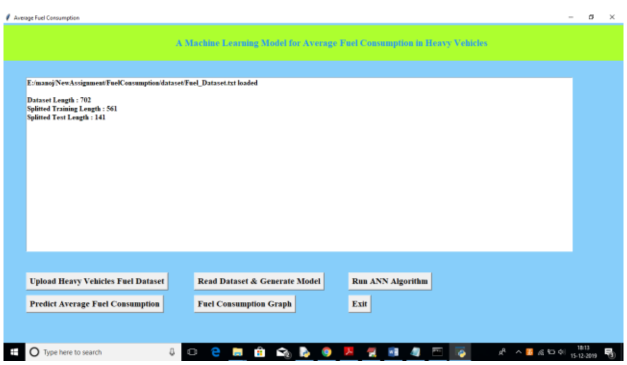


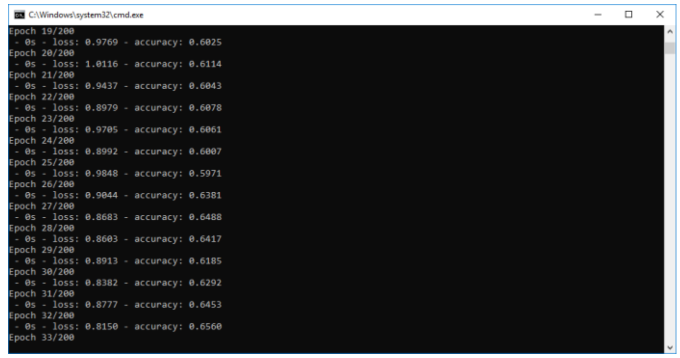
In above screen uploading ‘Fuel_Dataset.txt’ which can be used to train model. After uploading dataset will get below screen



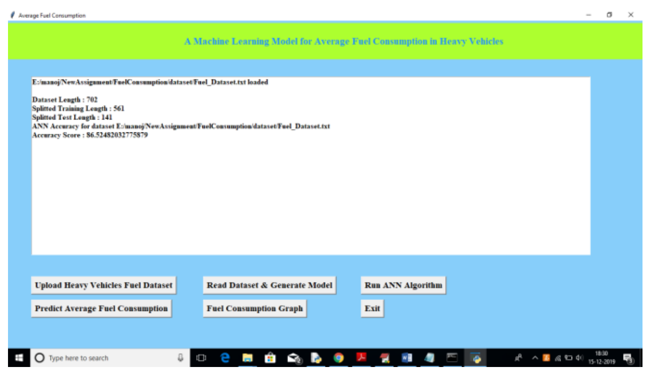
Now in above screen click on ‘Read Dataset & Generate Model’ button to read uploaded dataset and to generate train and test data



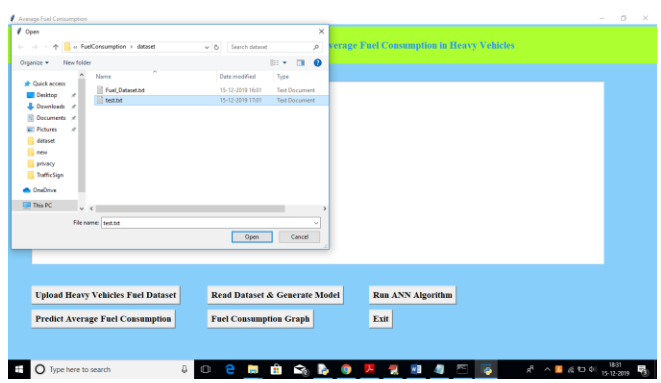
In above screen we can see total number of records in dataset, number of records used for training and number for records used for testing. Now click on ‘Run ANN Algorithm’ button to input train and test data to ANN to build ANN model.



In above black console we can see all ANN processing details, After building model will get below screen



In above screen we got ANN prediction accuracy upto 86%. Now click on ‘Predict Average Fuel Consumption’ button to upload test data and to predict consumption for test data



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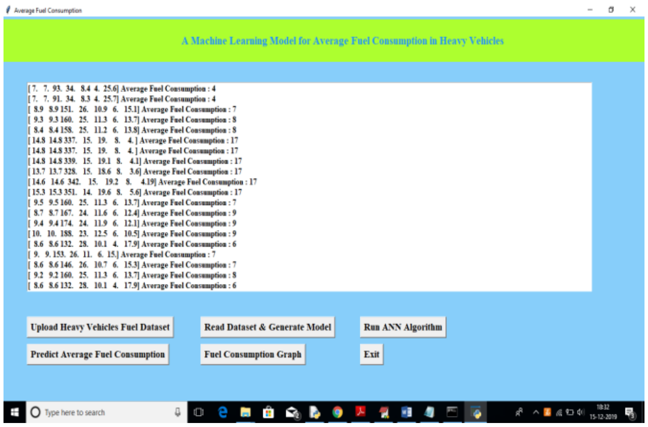
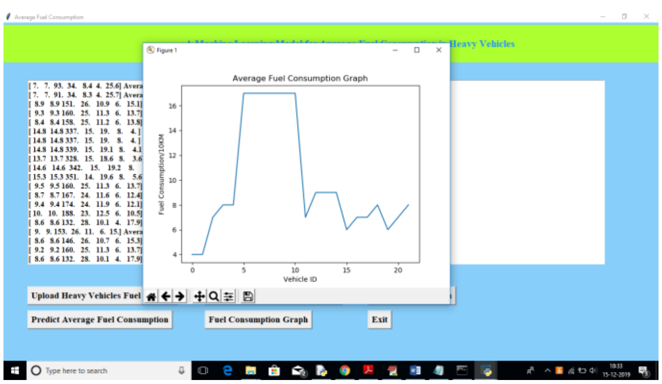
After uploading test data will get fuel consumption prediction result in below screen



In above screen we got average fuel consumption for each test record per 100 kilo meter. Now click on 'Fuel Consumption Graph' to view below graph



In above graph x-axis represents test record number as vehicle id and y-axis represents fuel consumption for that record.

Conclusion: Using this paper and ANN algorithm we are predicting fuel consumption for test data

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 fixed time 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.

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