PREDICTION OF FUEL CONSUMPTION AND UTILIZATION IN HEAVY VEHICLES USING MACHINE LEARNING ALGORITHMS

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ABSTRACT
This is essentially an information rundown strategy focusing on distance rather than time span for developing customised AI models for fuel utilisation. An exceptionally foresighted neural organisation model for typical fuel utilisation in big trucks is developed using this methodology along with seven indicators obtained from vehicle speed and street level. We forecast typical fuel usage in large cars using machine learning algorithms like ANN (Artificial Neural Networks). Seven notable datasets have been selected. To create the ANN model, each characteristic obtained from heavy vehicles—such as the frequency of stops, the duration of stops in absolute terms, and so forth—is employed as an informative index.
Keywords: Artificial neural networks (ANN), customised AI algorithm, run down approach, flow meter.

1. INTRODUCTION

1.1 Motivation

Depending on the requirements of the intended application in question, there are trade-offs between the aforementioned methodologies principally in terms of cost and accuracy. This study proposes a model that is easily created for individual heavy vehicles and can be used to a large fleet of heavy vehicles. A fleet manager may optimise route planning for all of the vehicles in the fleet using accurate models of each individual vehicle's expected fuel consumption. By doing this, they can ensure that the route assignments are in line with lowering the fleet's overall fuel consumption and emissions.

These types of fleets can be found in a variety of industries, including product transportation by road, public transportation, construction trucks, and refuse trucks, among others. Without having a detailed understanding of the vehicle's specific physical characteristics and measurements, the methodology must be applied to and adapted to a variety of vehicle technologies (including future ones) and configurations across a fleet of vehicles to be effective. Machine learning is the technique of choice when considering the specified accuracy versus the value of the event, as well as the adaptation of an individualized model for each vehicle within the fleet, as a result of these requirements.

II. LITERATURE SURVEY

2.1 Related Work

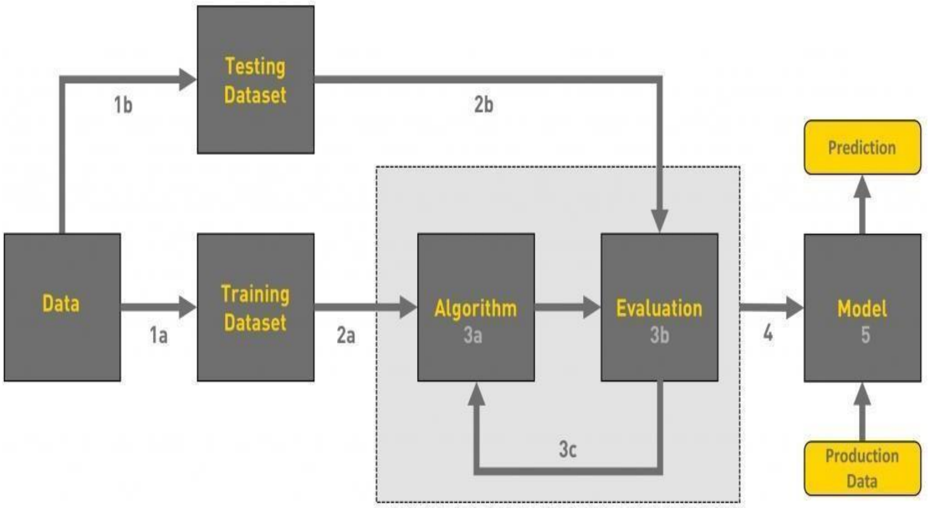
To demonstrate normal fuel utilization, physical science-based, artificial intelligence-based, and measurable models have been used. The Environmental Protection Agency and the European Commission developed full vehicle reproduction models based on physical science for rock solid vehicles. When compared to real-world estimates obtained from a flow meter, these models are capable of predicting normal fuel consumption with an accuracy of 3 percent. This level of precision comes at the expense of a significant amount of effort in terms of advancement. As mentioned above, physics-based, machine learning, and statistical models have all been used to model average fuel consumption. The EPA and the European Commission developed physics-based, full vehicle simulation models for heavy duty vehicles. These models are capable of predicting average fuel consumption with an accuracy of ±3% compared to real measurements obtained from a flow meter. This level of accuracy comes at the cost of a substantial development effort. At the other end of the modelling spectrum are statistical procedures which are applied under strict testing conditions to ensure that the reported results are standardized and repeatable. For example, the model proposed by the Code of Federal Regulation (CFR) estimates fuel consumption for new vehicles by using well defined statistical methods for specific duty cycles created from segments of real-world trips. Similarly, the SAE J1321 standard is used to estimate fuel consumption after-market modifications or under varying operating conditions for trucks and buses. This standard compares similar vehicles following the same route under similar operating conditions using real data collected from the field. For example, the standard was used in to compare the fuel consumption of a control vehicle to that of two test vehicles after changing lubrication fluids in the engine, transmission and axle. The standard was also used in to measure the performance of three fuel technologies in two vehicles operating in coal mines. The generalizable characteristics of machine learning models to different vehicles and different operating conditions made this modelling methodology attractive for fuel consumption prediction in many studies. In the remainder of this section, we discuss these models with respect to the underlying machine learning technique, the representation of the input space

III. PROPOSED METHODOLOGY

A common application of Artificial Neural Networks (ANN) is in the development of digital models for complex systems. The models proposed in this paper highlight some of the difficulties that machine learning models face when the input and output domains are incompatible with one another. Fuel consumption over the distance travelled during the study period is calculated from the input data, which is aggregated over time in 10-minute intervals. o denotes the response or output of the complex system, and F(p) denotes the transfer function between it and the system. F(p) denotes the transfer function between the system and the predictors, and o denotes the response or output of the system. The Feed Forward Neural Networks (FFNNs) that are used in this paper are described in detail below (FNN).

Architecture of Proposed System

An architectural diagram is a representation of a system that is used to abstract the overall outline of a piece of software from its details. It is an important tool because it provides a comprehensive view of the physical deployment of the software system as well as a roadmap for its evolution.



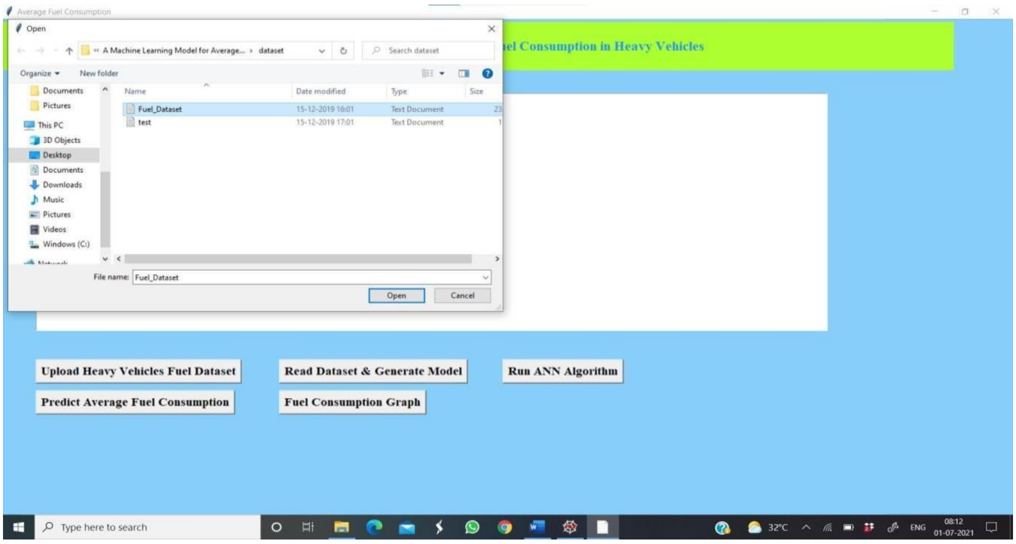
Modules

The approaches used to build fuel consumption models can be split into three categories in this regard:
Models based on physics: These models are based on a detailed grasp of the physical system.
Model-based models: This model is based on a deep knowledge of the physical system.
Model-based models: This model is based on a deep knowledge of the natural system. This model was used to assess the vehicle's many components' dynamics.
Machine learning data-driven models were abstract mappings from an input data containing a set of predictors to an output sequence containing the intended outcome.

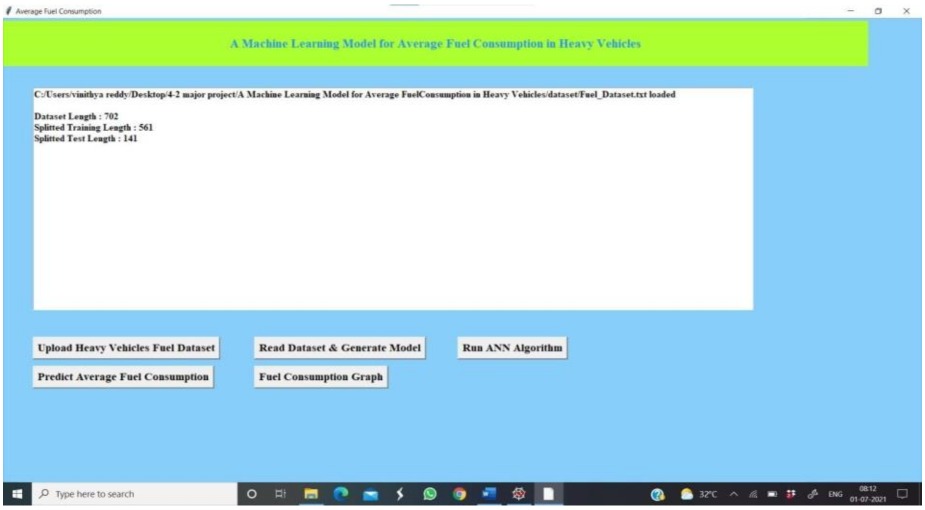
Statistical models: This model is likewise data-driven, and they build a link between a set of predictors' probability distribution and the intended outcome.

V. RESULTS

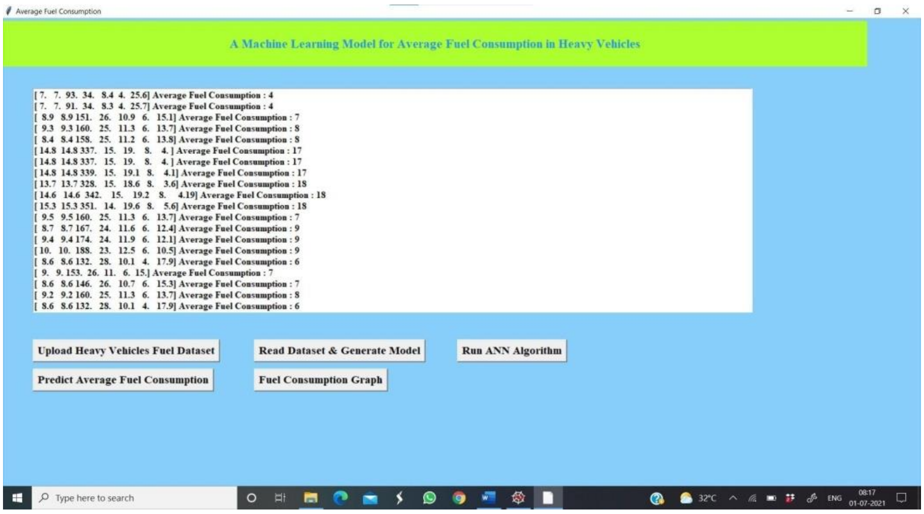
This is the screen where we click on 'upload heavy vehicles fuel dataset' button to upload train dataset



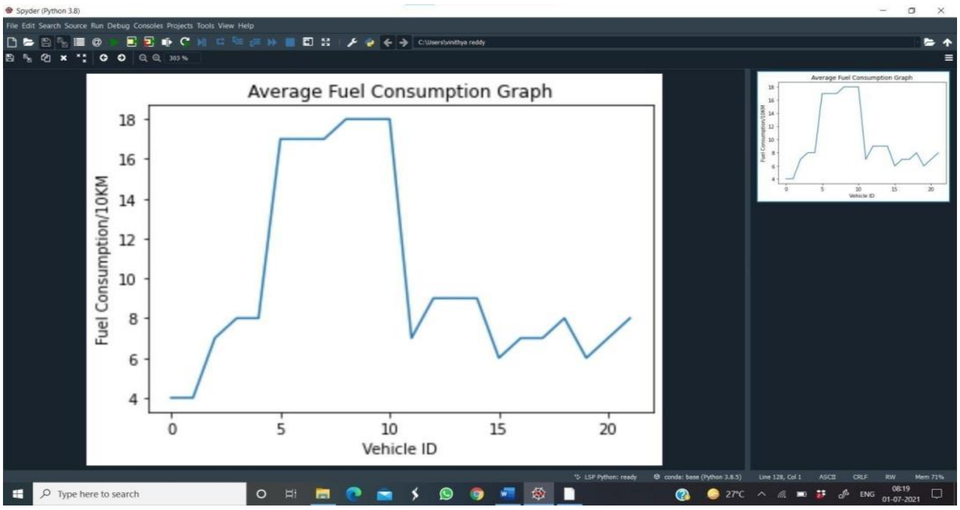
This is the screen where we click on ‘read data set and generate model’ button to read uploaded data set and to generate train and test data



This is the screen where we click on ‘predict average fuel consumption’ button to upload test data and to predict consumption for test data.



In above screen we got average fuel consumption for each test record



This the graph where, x-axis represents test record number as vehicle id and y-axis represents fuel consumption for that record.

FUTURE SCOPE

Future work will also include determining the shortest distance required for training each model, as well as determining how frequently a model must be synchronized with the physical system in operation using online training in order to maintain the prediction accuracy of the model.

CONCLUSION

In order to save time and money, this project developed a machine learning model that can be simply adjusted for each heavy vehicle in a fleet. The model uses seven predictors to forecast the number of stops, the interval between stops, the average moving speed, the characteristic acceleration (also known as aerodynamic speed squared), and the change in kinetic and potential energy. In order to better represent the vehicle's typical dynamic behaviour over the course of a day, the last two predictors are introduced in this study. All predictors are computed using vehicle speed and road grade as model inputs. Fortunately, telemetric devices, which are becoming an increasingly important part of connected vehicles, are readily available. Furthermore, the predictors can be quickly and easily calculated on-board using only these two variables.

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