



MACHINE LEARNING MODEL FOR AVERAGE FUEL CONSUMPTION IN HEAVY VEHICLE

Meka Subrahmanya Vara Prasad (MCA Scholar), B V Raju College, Vishnupur,
Bhimavaram, West Godavari District, Andhra Pradesh, India, 534202.

G. Ramesh Kumar, B V Raju College, Vishnupur, Bhimavaram, West Godavari District,
Andhra Pradesh, India, 534202.

Abstract

we used vehicle travel 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 travelled. 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.

1. INTRODUCTION

Fuel consumption models for vehicles are of interest to manufacturers, regulators, and consumers. They are needed across all the phases of the vehicle life-cycle. we focus on modeling average fuel consumption for heavy vehicles during the operation and maintenance phase. In general, techniques used to develop models for fuel consumption fall under three main categories:

Physics-based models:-which are derived from an in-depth understanding of the physical system. These models describe the dynamics of the components of the vehicle

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.

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.

a model that can be easily developed for individual heavy vehicles in a large fleet is proposed.

Relying on accurate models of all of the vehicles in a fleet, a fleet manager can optimize the route planning for all of the vehicles based on each unique vehicle predicted fuel consumption thereby ensuring the route assignments are aligned to minimize overall fleet fuel consumption. These types of fleets exist in various sectors including, road transportation of goods , public transportation , construction trucks and refuse trucks .

For each fleet, the methodology must apply and adapt to many different vehicle technologies (including future ones) and configurations without detailed knowledge of the vehicles specific physical characteristics and measurements.

2. EXISTING SYSTEM

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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.

Disadvantages of existing system:

Physics-based models, which are derived from an in-depth understanding of the physical system. These models describe the dynamics of the components of the vehicle each time step using detailed mathematical equations.

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.

3. PROPOSED SYSTEM

As mentioned above Artificial Neural Networks (ANN) are often used to develop digital models for complex systems. The models proposed in [15] highlight some of the difficulties faced by machine learning models when the input and output have different domains. In this study, the input is aggregated in the time domain over 10 minutes intervals and the output is fuel consumption over the distance traveled during the same time

period. The complex system is represented by a transfer function $F(p) = o$, where $F(\cdot)$ represents the system, p refers to the input predictors and o is the response of the system or the output. The ANNs used in this paper are Feed Forward Neural Networks (FNN).

Training is an iterative process and can be performed using multiple approaches including particle swarm optimization [20] and back propagation. Other approaches will be considered in future work in order to evaluate their ability to improve the model's predictive accuracy. Each iteration in the training selects a pair of (input, output) features from F_{tr} at random and updates the weights in the network. This is done by calculating the error between the actual output value and the value predicted by the model

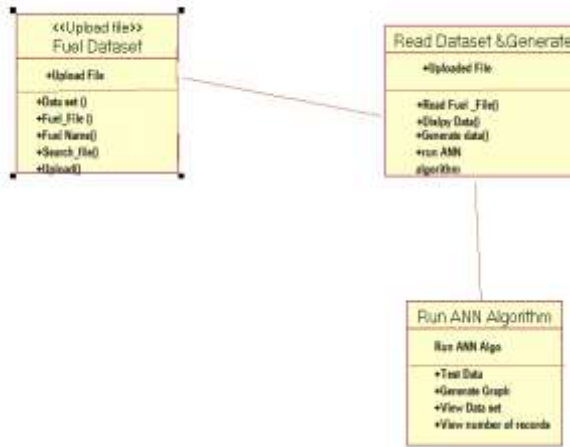
ADVANTAGES OF PROPOSED SYSTEM:

Data is collected at a rate that is proportional to its impact on the outcome. When the input space is sampled with respect to time, the amount of data collected from a vehicle at a stop is the same as the amount of data collected when the vehicle is moving.

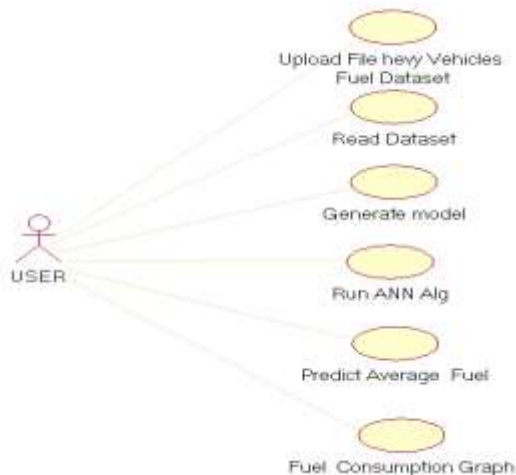
The predictors in the model are able to capture the impact of both the duty cycle and the environment on the average fuel consumption of the vehicle (e.g., the number of stops in an urban traffic over a given distance).

Data from raw sensors can be aggregated on-board into few predictors with lower storage and transmission bandwidth requirements. Given the increase in computational capabilities of new vehicles, data summarization is best performed on-board near the source of the data.

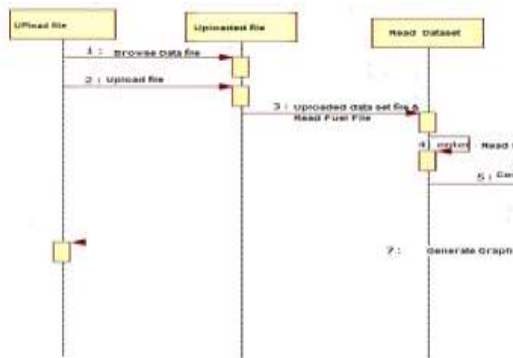
CLASS DIAGRAMS



USE CASE DIAGRAMS



SEQUENCE DIAGRAMS



4. CONCLUSIONS

This paper presented a machine learning model that can be 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 behaviour of the vehicle. All of 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 over a 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 fuel consumption with an RMSE < 0.015 l/100 km.

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 onboard computation. Moreover, the window size is likely to be application-dependent. For fleets with short trips (e.g., construction vehicles within 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 duty cycles consisted of both highway and city traffic and therefore, 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. Expanding the model to other vehicles with different characteristics such as varying masses and aging vehicles is being studied. Predictors for these characteristics will be added in order to allow for the same model to capture the impact on fuel consumption due to changes in vehicle mass and wear.

5. REFERENCES

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