Average Fuel Consumption in Heavy Vehicles Using Supervised Learning

S.Guru Prasad, P. Karthik[2], V.Sai Karthik[3], V.Sai Kumar[4], Mr.J.Prema Sagar[5]

[1,2,3,4]*B.Tech. Student, Department of Computer Science and Engineering,*

18b61a05c9@nmrec.edu.in, 19b61a05c4@nmrec.edu.in, 19b61a05f8@nmrec.edu.in, 19b61a05g0@nmrec.edu.in

[5]*Assistant Professor, Department of Computer Science and Engineering,*

Nalla Malla Reddy Engineering College, Hyderabad, India

Abstract*— 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

In this project we implement many different vehicle technologies (including future ones) and configurations without detailed knowledge of the vehicles specific physical characteristics and measurements. These requirements make machine learning the technique of choice when taking into consideration the desired accuracy versus the cost of the development and adaptation of an individualized model for each vehicle in the fleet. 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. 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).

2. PROPOSED SYSTEM

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 perliters kilometer.

3. LITERATURE REVIEW

Modeling heavy/mediumduty fuel consumption based on drive cycle properties.

This paper presents multiple methods for predicting heavy/medium-duty vehicle fuel consumption based on driving cycle information. A polynomial model, a black box artificial neural net model, a polynomial neural network model, and a multivariate adaptive regression splines (MARS) model were developed and verified using data collected from chassis testing performed on a parcel delivery diesel truck operating over the Heavy Heavy-Duty Diesel Truck (HHDDT), City Suburban Heavy Vehicle Cycle (CSHVC), New York Composite Cycle (NYCC), and hydraulic hybrid vehicle (HHV) drive cycles. Each model was trained using one of four drive cycles as a training cycle and the other three as testing cycles. By comparing the training and testing results, a representative training cycle was chosen and used to further tune each method. HHDDT as the training cycle gave the best predictive results, because HHDDT contains a variety of drive characteristics, such as high speed, acceleration, idling, and deceleration. Among the four model approaches, MARS gave the best predictive performance, with an average percent error of −1.84% over the four chassis dynamometer drive cycles. To further evaluate the accuracy of the predictive models, the approaches were applied to real-world data. MARS outperformed the other three approaches, providing an average percent error of −2.2% over four real-world road segments. The MARS model performance was then compared to powertrain modeling results over HHDDT, CSHVC, NYCC, and HHV drive cycles using NREL's Future Automotive Systems Technology Simulator (FASTSim). The results indicated that the MARS method achieved comparable predictive performance with FAST Sim.

Application of machine learning for fuel consumption modelling of trucks

This paper presents the application of three Machine Learning techniques to fuel consumption modelling of articulated trucks for a large dataset. In particular, Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) models have been developed for the purpose and their performance compared. Fleet managers use telematic data to monitor the performance of their fleets and take decisions regarding maintenance of the vehicles and training of their drivers. The data, which include fuel consumption, are collected by standard sensors (SAE J1939) for modern vehicles. Data regarding the characteristics of the road come from the Highways Agency Pavement Management System (HAPMS) of Highways England, the manager of the strategic road network in the UK. Together, these data can be used to develop a new fuel consumption model, which may help fleet managers in reviewing the existing vehicle routing decisions, based on road geometry. The model would also be useful for road managers to better understand the fuel consumption of road vehicles and the influence of road geometry. Ten-fold cross-validation has been performed to train the SVM, RF, and ANN models. Results of the study shows the feasibility of using telematic data together with the information in HAPMS for the purpose of modelling fuel consumption.

4. METHODOLOGY

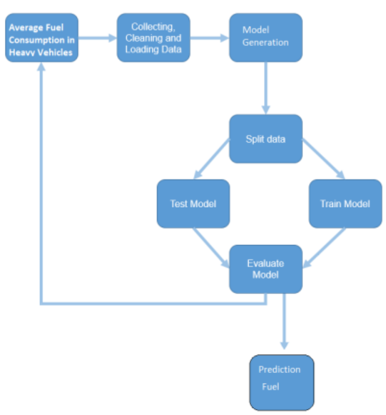
Data Collection: Gather relevant data on heavy vehicles and their fuel consumption. This data may include variables such as vehicle weight, engine specifications, driving conditions, speed, distance traveled, fuel usage, and any other factors that might affect fuel consumption. The data can be obtained from sources such as vehicle sensors, telematics systems, fuel logs, and historical records.

Data Preprocessing: Clean and preprocess the collected data to ensure its quality and usability. This step involves handling missing values, removing outliers, and transforming variables as needed. Data preprocessing is crucial to ensure accurate and reliable analysis.

Exploratory Data Analysis (EDA): Perform exploratory data analysis to gain insights into the dataset. This includes visualizing the data, calculating descriptive statistics, and identifying patterns or correlations between variables. EDA helps in understanding the relationships between fuel consumption and other factors.

Feature Engineering: Identify and engineer relevant features that can improve the accuracy of fuel consumption prediction. This may involve creating new features or transforming existing ones. For example, converting categorical variables into numerical representations or calculating fuel efficiency metrics.

Model Selection: Choose an appropriate modeling technique based on the characteristics of the data and the specific objectives of the analysis. Commonly used regression algorithms for fuel consumption prediction include linear regression, decision trees, random forests, support vector regression (SVR), and neural networks. The selection depends on factors such as interpretability, model complexity, and performance metrics.



Model Training: Split the dataset into training and testing sets. Use the training set to train the selected model using the chosen algorithm. During training, the model learns the relationships between the input features and the target variable (fuel consumption) based on the training data.

Model Evaluation: Evaluate the trained model's performance using the testing set. Use appropriate evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), and R-squared to assess the model's accuracy and predictive capability. Model evaluation helps in understanding how well the model generalizes to unseen data.

Model Optimization: Fine-tune the model by adjusting hyperparameters or trying different algorithms to improve its performance. This can involve techniques such as cross-validation, grid search, or Bayesian optimization. Optimization aims to achieve the best possible model performance.

Prediction and Analysis: Once the model is trained and optimized, use it to make predictions on new, unseen data. Apply the model to estimate the average fuel consumption for heavy vehicles based on their specific characteristics and input features. Analyze the results, assess the model's accuracy, and interpret the findings to gain insights into fuel consumption patterns and factors driving efficiency.

Iterative Refinement: Fuel consumption in heavy vehicles is influenced by various factors, and the modeling process can be iterative. Refine the analysis and model as new data becomes available or as new insights are gained. Continuously update and improve the methodology to adapt to changing conditions and enhance accuracy.

RESULTS

The results for the proposed system are shown below:

TABLE 3.1.1: Table of results.

Table 1 shows the result of the proposed model used to obtain the video summarization using the speech of the video. The algorithm gives less than 5 seconds of error video as output for the input given.

TABLE 4.1.2: Table of processing time and Memory usage.

Table 2 shows the results with memory usage and processing time. Here the memory usage and processing time results depend on the total time of the input video and the summary time requested by the user.

5. DISCUSSION

Cost Considerations: Fuel consumption directly affects the operational costs of heavy vehicles. Higher fuel consumption leads to increased expenses for fleet operators, which can have a significant impact on their bottom line. Therefore, optimizing fuel consumption is crucial for minimizing costs and maximizing profitability.

Environmental Impact: Heavy vehicles, especially those powered by diesel engines, contribute significantly to greenhouse gas emissions and air pollution. Fuel consumption reduction can help mitigate these environmental effects by reducing carbon dioxide (CO_2) emissions and improving air quality, which is essential for achieving sustainability goals.

Average Fuel Consumption in Heavy Vehicles

```
__________________________________________
___________________
   |                              |
   |     Factors Affecting Fuel Consumption
|
   |                              |
   |                              |
   |  Vehicle Design      Driving Behavior
Road Conditions  |
   |   |           |           |    |
   |   V           V           V      |
   |                              |
   |          Fuel Consumption          |

|__________________________________________
___________________|
```

Factors Affecting Fuel Consumption: Several factors influence the average fuel consumption of heavy vehicles. These include vehicle weight, engine efficiency, aerodynamics, driving behavior, road conditions, load carried, and vehicle maintenance. Understanding and managing these factors can lead to more efficient fuel usage.

Technological Advancements: Technological advancements have played a crucial role in improving fuel efficiency in heavy vehicles. Engine technologies such as direct injection, turbocharging, and hybrid systems have been developed to optimize fuel consumption. Additionally, the use of lightweight materials, aerodynamic designs, and advanced control systems has contributed to better efficiency.

Driver Training and Behavior: Driver behavior and training have a significant impact on fuel consumption. Proper training programs can educate drivers on efficient driving techniques, including maintaining optimal speeds, avoiding excessive idling, and utilizing engine braking. By promoting fuel-efficient driving habits, fleet operators can achieve substantial fuel savings.

Data Analytics and Telematics: The advent of telematics systems and data analytics has enabled the collection and analysis of real-time vehicle data. By leveraging this technology, fleet managers can monitor fuel consumption patterns, identify inefficiencies, and make data-driven decisions to optimize fuel usage across their fleets.

Regulatory Measures and Incentives: Governments and regulatory bodies have implemented measures to incentivize fuel efficiency and emission reductions in heavy vehicles. Fuel economy standards, emissions regulations, and financial incentives for adopting cleaner technologies are some of the initiatives aimed at encouraging fuel consumption reduction.

Future Trends: The future of heavy vehicle fuel consumption revolves around further advancements in engine technologies, electrification, and alternative fuels such as natural gas, hydrogen, and biofuels. Additionally, the integration of autonomous driving systems and intelligent route planning can contribute to optimized fuel usage.

Overall, the discussion on average fuel consumption in heavy vehicles encompasses economic, environmental, and technological aspects. By addressing this topic, stakeholders can work towards more sustainable and cost-effective transportation solutions while reducing the carbon footprint associated with heavy vehicle operations.

6. CONCLUSION

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 behavior 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/100km. Different model configurations with 1, 2, and 5 km window sizes were evaluated.

REFERENCES

[1] S. Wickramanayake and H. D. Bandara, "Fuel consumption prediction of fleet vehicles using machine learning: A comparative study," in Moratuwa Engineering Research Conference (MERCon), 2016. IEEE, 2016, pp. 90–95.

[2] L. Wang, A. Duran, J. Gonder, and K. Kelly, "Modeling heavy/mediumduty fuel consumption based on drive cycle properties," SAE Technical Paper, Tech. Rep., 2015.

[3] Fuel Economy and Greenhouse gas exhaust emissions of motor vehicles Subpart B - Fuel Economy and Carbon-Related Exhaust Emission Test Procedures, Code of Federal Regulations Std. 600.111-08, Apr 2014.

[4] SAE International Surface Vehicle Recommended Practice, Fuel Consumption Test Procedure - Type II, Society of Automotive Engineers Std., 2012.

[5] F. Perrotta, T. Parry, and L. C. Neves, "Application of machine learning for fuel consumption modelling of trucks," in Big Data (Big Data), 2017 IEEE International Conference on. IEEE, 2017, pp. 3810–3815.

[6] S. F. Haggis, T. A. Hansen, K. D. Hicks, R. G. Richards, and R. Marx, "In-use evaluation of fuel economy and emissions from coal haul trucks using modified

[7] A. Ivanco, R. Johri, and Z. Filipi, "Assessing the regeneration potential for a refuse truck over a real-world duty cycle," SAE International Journal of Commercial Vehicles, vol. 5, no. 2012-01-1030, pp. 364–370, 2012.

[8] A. A. Zaidi, B. Kulcsr, and H. Wymeersch, "Back-pressure traffic signal control with fixed and adaptive routing for urban vehicular networks," IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 8, pp. 2134–2143, Aug 2016.

[9] J. Zhao, W. Li, J. Wang, and X. Ban, "Dynamic traffic signal timing optimization strategy incorporating various vehicle fuel consumption characteristics," IEEE Transactions on Vehicular Technology, vol. 65, no. 6, pp. 3874–3887, June 2016.

[10] G. Ma, M. Ghasemi, and X. Song, "Integrated powertrain energy management and vehicle coordination for multiple connected hybrid electric vehicles," IEEE Transactions on Vehicular Technology, vol. 67, no. 4, pp. 2893–2899, April 2018.