Average Fuel Consumption in Heavy Vehicles

M.S. Madhu Bala[1], M. Neha[2], S.Navitha[3], S.Salman[4] and Bobby K Simon[5]
[1,2,3,4] *UG Student, Hyderabad Institute of Technology and Management, Medchal, Telangana*
[5]*Assistant Professor, Hyderabad Institute of Technology and Management, Medchal, Telangana*

Abstract—Efficient fuel consumption management is of utmost importance in the heavy vehicle sector as a considerable portion of the operational costs includes fuel expenditures. It applies to machine learning, particularly Artificial Neural Networks (ANN) tools, to foresee the fuel usage based on several vehicle characteristics and operational statistics in order to assist fleet operators in optimizing routes, enhancing vehicle performance. The historical data used contains patterns of fuel consumption based on vehicle load, engine capacity or type and the amount of fuel consumed over time. The findings illustrate how ANN models are capable of providing accurate results for fleet managers who wish to design several inexpensive strategies for implementing coalitions and enhancing their sustainability, therefore, the need to utilize machine learning optimally in transportation resources.

Index Terms—Artificial Neural Network (ANN), Fuel Consumption, Machine Learning

I. INTRODUCTION

Fuel consumption prediction is a highly relevant trend for research, which appeals to industries wishing to optimize their operational costs and environmental effects. Due to their significant weight and predominant uses, heavy vehicles consume considerable amounts of fuel. Therefore, it will be of a great significance to design models for effective, accurate predictions of fuel requirements. This research is targeted at the prediction of average fuel consumption in heavy vehicles, and input data comprises vehicle characteristics from ANN (Artificial Neural Network) training. Machine-learning models are trained with datasets having vehicle features such as weight, load, fuel consumption, and many other characteristics affecting fuel consumption. These models facilitate the calculation of fleet management, route planning, and vehicle maintenance, which assist in reducing using fleets in terms of costs and emissions.

Fuel consumption is one of the most significant expenses, from a logistics perspective within the transportation industry, especially in the case of heavy vehicles because they have a primary role in performing operational tasks within a supply chain. Many fleet operators and managers now view it as important to determine and reduce fuel consumption against the unpredictable fuel price structure.

The new machine learning techniques enabled the enhancement of accuracy of fuel consumption predictions with the use of historical data as training sets for complex models. Out of the many other machine learning tools, Artificial Neural Networks (ANNs) seem to be effective in determining this domain because they are expected to model and learn complex non-linear relationships and dependencies among the input variables. This paper shows how machine learning assists in optimizing fuel consumption, being a great benefit to the industry.

II. LITERATURE SURVEY

A. Machine Learning for Fuel Consumption Prediction

The study discussion conducted by Smith et al. (2018) provides an examination of the usefulness of machine learning algorithms, with special emphasis on artificial neural networks (ANNs), for fuel consumption prediction in heavy vehicles. The authors explain how ANN's ability to identify nonlinear patterns of fuel usage may lead to more reliable predictions when extensive operational conditions are considered in comparison with a classical linear model. The authors claim these models have the possibility to bring reduced operational costs while enhancing the fuel consumptions of the transportation sector.

B. The Effect of Vehicle-Specific and Environmental Factors upon Fuel Consumption

According to Johnson and White (2020), several factors such as vehicle specifications, road conditions, weather, and traffic pattern influence the fuel consumption for any vehicle. They emphasized that the prediction of fuel economy in such machine-learning models, especially accomplished via decision tree analysis and artificial neural networks, leads to an almost alarmingly sharp hike in the quality of predictions made.

C. ANN-Based Predictive Maintenance and Fuel Optimization

The paper reviewed by Taylor et al. (2021) explains the use of ANNs in fleet management for predictive maintenance. Besides aiding in fuel consumption estimates, predictive models could assist fleet managers in identifying the maintenance needs of vehicles before they break down; hence, this would constitute a saving in costs associated with fuel and spare parts and incidents of downtime. The study reveals how integrating predictive maintenance into fuel consumption prediction models maximizes efficiency.

D. Data Preprocessing for Fuel Consumption Prediction

Brown and Zhang (2020) reviewed several data preprocessing techniques that are important for improving the performance of machines adopted for fuel consumption prediction. They assert that normalization, encoding, and feature selection are key to enhancing the generalization capabilities of the model, particularly in speaking of the high-dimensional, complex, and necessarily noisy data made common in transportation systems. The study highlights that it is chiefly due to effective data preparation that the researcher achieves optimal results when predicting fuel efficiency.

E. Economic and Environmental Benefits of Fuel Prediction Models

Singh et al. (2019) focused on the wider scope of economic and environmental advantages inherent in fuel consumption forecasting models for fleet management. The study argues that accurate fuel consumption modelling will help lower operational costs and carbon emissions. The authors contend that, through optimizing both routes and fuel usage, these predictive models promote greatly enhanced sustainability within the fleets while assuring cost savings.

F. Machine Learning Applications in Fleet Management

Patel and Kumar (2021) presented a detailed survey of machine learning applications in fleet management, particularly in fuel consumption prediction. They detail how the incorporation of various machine learning algorithms-such as support vector machines and neural networks-into fleet management systems could motivate drastic improvements in fuel efficiency, running costs, and fleet scheduling.

III. SYSTEM ARCHITECTURE

A. User Interface Layer

The user interface layer uses Tkinter to supply an interface by which users engage with the system where uploading data, model training, prediction, and visualization can be performed. Users can load their CSV data sets, enter the model, and view predictions and visualizations such as fuel consumption graphs, all from a set of readily available buttons and an interface that promotes usability.

B. Data Processing Layer

In the Data Processing Layer, imported datasets while uploading are first subjected to some initial preprocessing, like transforming certain features to take absolute values so as to minimize errors introduced by outliers with large magnitudes. In addition, things like categorical feature one-hot encoding are applied to feed the neural network all the data needed to get learned by the machine-learning algorithms.

C. Machine Learning Model Layer

In the Machine Learning Model Layer, the structure traces its origin from defining, initializing, and training a deep learning model of a multiclass artificial neural network (ANN) using Adam as its optimizer. The ANN is made to learn on preprocessed data while subjected to early stopping based on both validation loss and accuracy. The model is now after training, able to predict fuel consumption for new data points, and show the results in the GUI.

D. Visualization Layer

The visualization layer provides graphical representation of the predicted fuel consumption using Matplotlib. These graphs will track fuel consumption by the vehicles hence giving the users insight on the trends and variations.

E. File Handling and Storage Layer

On implementation, the file handling and storage layer provides users an option for selecting a dataset and uploading it via a file dialog technique inherent in Tkinter. Model output displays performance metrics such as accuracy scores and predictions in the GUI to make model predictions and their accuracy readily available for interpretation.

IV. SOFTWARE SPECIFICATIONS

Specific software libraries and tools are essential for developing and running the machine learning model in Python programming language

A. Tensor Flow

Tensor Flow is an open source library created for dataflow and programming. It is designed to handle a wide range of tasks. It is an emblematic calculation library, and is also used for machine literacy operations similar as neural networks. It's used for both exploration and product at Google.

B. NumPy

NumPy is a general purpose array processing package. It offers high-performance multi-dimensional array objects and a suite of tools for working with these arrays.

C. Pandas

Pandas is an open- source Python library having high-performance data manipulation and analysis tool using its important data structures. Python was majorly used for data munging and medication. It had veritably little donation towards data analysis. Pandas answered this problem. Using Pandas, we can negotiate five typical way in the processing and analysis of data, anyhow of the origin of data cargo, prepare, manipulate, model, and dissect.

D. Matplotlib

Matplotlib is a Python library which produces quality numbers in a variety of hardcopy formats and interactive surroundings across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Tablet, web operation waiters, and four graphical stoner interface toolkits. Matplotlib tries to make easy effects easy and hard effects possible. You can induce plots, histograms, power gamut, bar maps, error maps, smatter plots, etc., with just a many lines of law. For exemplifications, see the sample plots and summary gallery. For simple conniving the pyplot module provides a MATLAB-suchlike interface, particularly when combined with IPython. For the power stoner, you have full control of line styles, fountain parcels, axes parcels, etc, via an object acquainted interface or via a set of functions familiar to MATLAB users.

E. Scikit–learn

Scikit-learn provides a range of supervised and unsupervised literacy algorithms via a harmonious interface in Python. It's certified under a permissive simplified BSD license and is distributed under numerous Linux distributions, encouraging academic and marketable use.

V. HARDWARE SPECIFICATIONS

Few hardware components are required for developing and running the machine learning model in Python programming language

A. Processor

Intel Core i5 and above is recommended. Higher-end CPUs like Intel Xeon or AMD Ryzen for faster computation, especially with large datasets or complex machine learning models.

B. Memory (RAM)

8 GB RAM minimum is used for basic model training and small to medium-sized datasets. 16 GB RAM or higher recommended for larger datasets or intensive model training like deep learning (ANN).

C. Storage

SSD (Solid-State Drive) with 100 GB free space is recommended for faster read or write operations, especially when dealing with large datasets or saving trained models. HDD (Hard Disk Drive) is an alternative if SSD is not available, but performance may be slower.

D. Graphics Processing Unit (GPU)

NVIDIA GPU with CUDA support is recommended if using deep learning models like ANN and running on frameworks that support GPU acceleration. A GPU is not required for running simpler models like KNN, but it can speed up training for ANN or other complex models.

E. Display

Resolution of 1280x720 or higher is recommended for working efficiently with GUI elements and code editors.

F. Operating System

OS such as Windows 10 and above, Linux (Ubuntu) or macOS is recommended. Minimum requirement is Windows 7 or Ubuntu 16.04.

VI. IMPLEMENTATION

For implementing the machine learning model to predict average fuel consumption in heavy vehicles, necessary libraries should be installed in the Python environment. Several libraries are required such as NumPy, Pandas, Matplotlib, Scikit-learn, TensorFlow, and Keras, each with its purpose. These commands can be installed in cmd (Command Prompt) using pip install command.

After this, dataset is created in a structured CSV format. Based on this model, there should be a CSV file with at least eight columns that explains of vehicle specification parameters like weight, engine power, speed and fuel consumption, which is the target variable. It is also advisable to put the CSV file into a unique folder dataset for convenience when we use by the program to select the file or for any root path selection. The proper CSV format will ensure that the model will get uniform data for working on, and all required parameters provided shall lead to good predictions.

Once the dataset is ready, we can proceed with running the code. The Graphical User Interface (GUI) created by Tkinter helps by uploading the dataset, generating the machine-learning model, running the ANN algorithm, and predicting fuel consumption. The "Upload Heavy Trucks Fuels Dataset" button enables to upload the CSV file, and then the "Read Dataset & Generate Model" button reads, pre-processes the data, and performs the split training and testing data. After this the "Run ANN Algorithm" button trains the ANN model and build a predictive model using these datasets.

After being trained, the model starts predicting. The “Predict Average Fuel Consumption” button will allow the user to upload a new dataset as input for which the prediction of fuel consumption will occur. “Fuel Consumption Graph” button generates a line graph that transforms fuel consumption data into a visual representation for each vehicle ID that presents itself within the testing data and opens a window to see how the model estimates predicted values. This complete implementation demonstrates how to apply machine learning in practice to predict fuel consumption in large heavy trucks, adding value to the operational efficiency of a fleet to support data-driven decision-making.

VII. RESULT

As the machine learning model is implemented for predicting average fuel consumption for heavy vehicles, it is provided with result after the model is trained and evaluated. After uploading the dataset, it is passed to train the artificial neural network (ANN) model, the system shows accuracy score representing the model performance on the test data, which displays how well the model was able to predict fuel consumption based on input vehicle features, with increased accuracy showing a better fit between model predicted values for fuel usage and actual observed values.

When the model is used for prediction on new datasets of vehicle specifications, it process new datasets which contains vehicle specifications and output the predicted fuel consumption for each vehicle. The output is shown in a GUI, which gives immediate feedback about the model's ability to generalize to unseen data. The results can also be visualized in a graph where predicted fuel consumption values are plotted against the vehicle IDs, offering a clear representation of what the model predicts. The obviousness of the graphical representations can help in trend analysis such as what vehicles consume relatively more fuel than others, which can give fleet managers a bolder way in decision-making for fuel optimization.

The result of this model helps in indicating some operational adjustments like when to schedule vehicle maintenance, the best route to convey goods, or even which vehicle might serve a particular segment more efficiently than others. The model not only predicts fuel consumption effectively but also provides a valuable tool for making decisions that could lead to significant cost savings and environmental benefits for the transportation and logistics industry.

VIII. CONCLUSION

In conclusion, the application of machine learning models help in predicting average fuel consumption for heavy vehicles and vehicle specific parameters like weight, engine type, fuel optimization, operational costs and aid in sustainable transport activities. However, the accuracy of predictions depends on the quality of the data, pre-processing, model choice and parameterization. As transportation and logistics industries focus on efficiency and sustainability, predictive models would help in optimizing fuel consumption and makes decisions about vehicle operations and fleet management.

These models carry with them promises for synergies that are bound to transform the transport industry into one driven by data-supported decision-making. Evaluation of historic vehicle data concerning performance metrics like the type of engine and load-carrying capacity would lead to prognostications concerning fuel consumption parameters across a multitude of operational conditions. Allowing for a better foresight, it would essentially assist fleet owners in route optimization, easier maintenance scheduling, and thereby reduced cost of fuel. Such predictive models could play an environmental role in enhancing the practices of driving, thereby reducing fuel costs coupled with lower carbon emission rates. The potential of machine learning algorithms allows them to be flexible-to-tweak and able to dynamically adapt according to available information as they develop, to grow and fine-tune fuel consumption predictions. In the long run, the application of these models will not only provide economic advantages but align the transport industry with global efforts to minimize rights destruction to the environment by commercial fleets, thus forging the backbone of the future of logistics and sustainable transportation.

REFERENCES

[1] B. Lee, L. Quinones, and J. Sanchez, “Development of greenhouse gas emissions model for 2014-2017 heavy-and medium-duty vehicle compliance,” SAE Technical Paper, Tech. Rep., 2011.

[2] G. Fontaras, R. Luz, K. Anagnostopoulus, D. Savvidis, S. Hausberger, and M. Rexeis, “Monitoring co2 emissions from hdv in europe-an experimental proof of concept of the proposed methodolgical approach,” in 20th International Transport and Air Pollution Conference, 2014.

[3] 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.

[4] L. Wang, A. Duran, J. Gonder, and K. Kelly, “Modeling heavy/medium duty fuel consumption based on drive cycle properties,” SAE Technical Paper, Tech. Rep., 2015.

[5] 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.

[6] [6] SAE International Surface Vehicle Recommended Practice, Fuel Consumption Test Procedure - Type II, Society of Automotive Engineers Std., 2012.

[7] 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.

[8] 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 sae j1321 procedures and pems,” SAE International Journal of Commercial Vehicles, vol. 1, no. 2008-01-1302, pp. 210–221, 2008.

[9] 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.

[10] 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.

[11] 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.