Fuel Net: Artificial Intelligence Tool for Fuel Consumption Prediction in Heavy Vehicles

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Abstract

This project aims to develop one such solution by utilizing the FuelNet model, which focuses on predicting and enhancing fuel efficiency in heavy vehicles. By analyzing real-time data and historical patterns, FuelNet can accurately predict fuel consumption, empowering fleet operators and logistics companies to optimize their operations and reduce operating costs. Compared to traditional manual methods, this AI-powered tool represents a significant improvement, offering adaptability, precision, and a commitment to environmental sustainability in heavy vehicle operations. As the world increasingly emphasizes eco-friendly and cost-effective transportation solutions, FuelNet emerges as a key technology driving the transport industry towards a greener and more efficient future. By leveraging the power of AI, we can make substantial strides in improving fuel efficiency, reducing emissions, and promoting a more sustainable transportation system.

1. Introduction

The need for energy has been globally boosted as the community and industrial demands have steadily grown. Although renewable energy has become the interest of many industries, non-renewable energy still provides more than 80%. The primary non-renewable energy sources are natural gas, oil, and coal, responsible for most greenhouse gas (GHG) emissions [1]. The mining industry has been in practice for many centuries to extract the minerals from the earth. Therefore, it has been a significant contributor to the current improvement of modern life. Thus, such a main industry consumes a large amount of energy, and supplying the required energy has been a major challenge for mining stockholders. The main operational categories in mining processed include extraction, transportation, and ore processing [2, 3]. Haul trucks are utilized for material transportation from the pits to the desired destinations (plants, stockpiles, or waste dumps) based on the material types (ore or overburden/waste). About half of the total operating costs in open-pit mines are associated with the haulage systems [4, 5]. The continuous global increase in energy prices, energy demand, and environmental problems related to GHG emissions highlight an important challenge for the mining industry. Diesel fuel as the traditional energy source is the primary power source in surface mining due to its cost and transportation flexibility, especially in the mines located remotely. The electrical power is the second-ranked energy source if the mine location uses the electricity network grid. In addition, underground mining prefers to use electrical power in order to reduce exhaust gas and decrease safety hazards and ventilation costs. Moreover, stationary machinery such as comminution circuits, dewatering pumps, and ventilation pumps mostly uses electrical power [3].

According to a survey by the Department of Energy of the US [6], the mining industry's energy is 2% gasoline, 10% coal, 22% natural gas, 32% electricity, and 34% diesel. The energy used most for material handling is diesel fuel at 87% [6]. Also, material transportation accounts, on average, more than a third of energy consumption in the mines [7], which is the highest consumption of energy, followed by processing and extraction. A study has shown that loading and hauling activities have the largest share in GHG emissions [8]. Haul trucks are operated with other machinery including loaders, excavators, and shovels, regarding the production capacity and site layout [2]. In the haulage operations of mining, the haul trucks consume a significant amount of fuel, and generate a remarkable number of emissions [9]. The haul truck fuel consumption in mining is unique and requires customized research. Mining roads (ramp) have more difficult conditions than highways, and the amount of dust produced is usually higher. In addition, the haul truck payload may exceed 300 tons. Moreover, the cycles of this operation are shorter than transportation in the other industries. Improving the haul truck fuel consumption has a significant effect on reducing the pollutants and GHGs. Therefore, this has led to some research works in order to improve the haul trucks' energy efficiency.

2. Literature Survey

The most important studies on the haul truck fuel consumption and the related issues are as follows. Kecojevic and Komljenovic [10] have examined the effects of engine load factors and power on a truck's fuel consumption and have determined the amount of a truck's CO2 emission. The authors have considered the original equipment manufacturers haul trucks for this objective. The study conducted by Antoung and Hachibli [11] have addressed the technological concerns of power-saving and motor efficiency improvement in mining machinery. They mainly focused on the technical functioning of the mining equipment and motor components, and how to reduce friction can be achieved. In another study, an integrated data environment system has been developed by Bogunovic et al. [12] to analyze the energy consumed in an open-cast coal mine. Chingooshi et al. [13] have studied mining smart energy management strategies and have highlighted the critical parameters of creating opportunities to increase energy efficiency. Sahoo et al. [14] have provided a generic benchmarking model for dump truck energy consumption in surface mines based on vehicle dynamics, engine characteristics, and mine's topography. Kecojevic et al. [15] have established the relationships among energy production, energy consumption, and energy cost, as these factors relate to the extraction of a surface bituminous coal mine. Carmichael et al. [16] have investigated the haul truck fuel consumption costs and gas emissions in surface mining operations. In this research work, the simulations performed do not consider the variables related to the hauling truck fuel consumption.

Liu et al. [17] have compared carbon emissions and energy consumption for transportation belt conveyors and truck based on the theory in surface coal mines. A process analysis-life cycle analysis has been constructed to determine the carbon emission factors and a calculated energy consumption model. Siami-Irdemoosa and Dindarloo [18] have predicted fuel consumption of haul trucks by utilizing an artificial neural networks model based on the cyclic activities. They determined the haul truck fuel consumption in one cycle as the dependent variable and loaded travel time, loaded idle time, empty travel time, loading time, etc., as the independent variables. Soofastaei et al. [19] have investigated the payload variance on haul truck fuel consumption in Australia's surface coal mine. They also looked at GHGs and costs of haul truck fuel consumption. Rodovalho et al. [20] have created a method to identify and analyze the variables related to the hauling truck fuel consumption in open-pit mines. In this research work, the mathematical modeling tools and statistical analysis techniques accompanied with multiple linear regressions have been used to investigate road maintenance and construction variables on fuel consumption of haul trucks. The cyclic activities' effects on fuel consumption of haul trucks have been studied by Dindarloo and Siami-Irdemoosa [21] using the partial least squares regression and the autoregressive integrated moving average methods.

An artificial neural network (ANN) has been developed by Soofastaei et al. [9] to predict haul truck fuel consumption in the surface mines. They determined the haul truck fuel consumption based on the truck weight, total resistance, and truck speed according to the best engine performance of the haul trucks. Peralta et al. [22] have considered a truck's maintenance effect on the truck energy consumption in the mining operations. Truck-specific fuel consumption was estimated using the regression analysis based on the equipment reliability, gross mass weight, and distance as the independent variables. Jassim et al. [23] have developed an ANN model for predicting off-highway trucks' energy consumption and CO2 emissions. They used discrete event simulations in order to generate synthetic data for training and testing the prediction model according to a database and various project conditions.

3. Proposed System Design

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

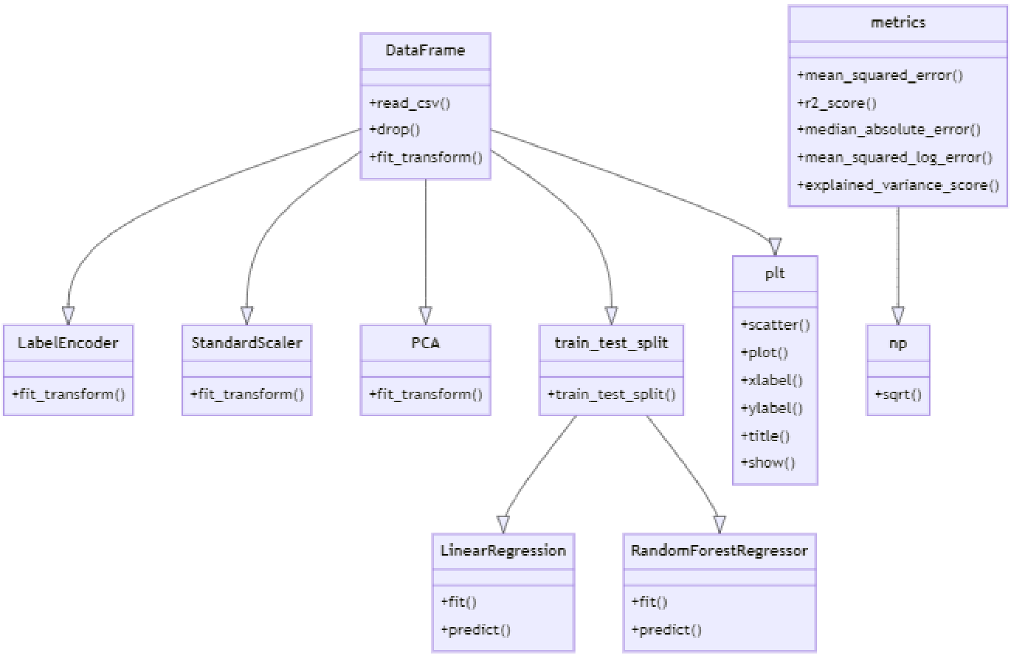

Figure 1. UML diagram of proposed model.

3.1 Random Forest Algorithm

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

Operation

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

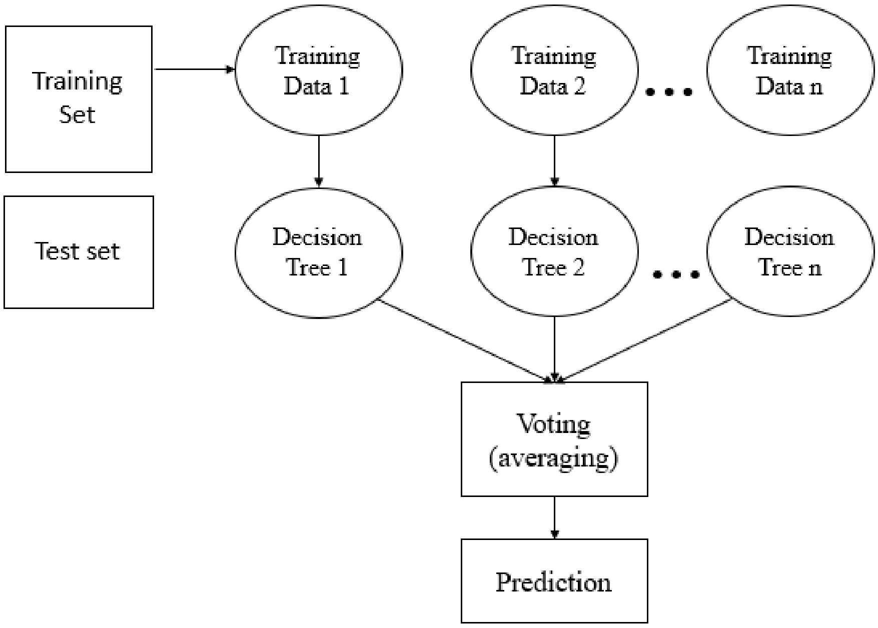

Figure. 2: Random Forest algorithm.

4. Results and description

In the below figure provides a visual representation of the sample dataset that serves as the foundation for predicting fuel consumption. The dataset includes various attributes related to heavy vehicles, such as the vehicle's make, model, engine size, number of cylinders, transmission type, and more. These attributes collectively provide insights into the characteristics of the vehicles that can influence their fuel consumption patterns. Each row in the dataset corresponds to a specific heavy vehicle, and the columns represent the different attributes associated with each vehicle. This figure offers an initial view of the raw data that will be used for training and evaluating the ML model's predictions.

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY
0	2014	ACURA	ILX	COMPACT	2.0	4	AS5	Z	9.9
1	2014	ACURA	ILX	COMPACT	2.4	4	M6	Z	11.2
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	6.0
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	12.7
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	12.1
...	...	...	...	...	...	...	...	...	...
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0	6	AS6	X	13.4
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2	6	AS6	X	13.2
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0	6	AS6	X	13.4
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2	6	AS6	X	12.9
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2	6	AS6	X	14.9

1067 rows × 13 columns

Figure 3: Sample dataset used for predicting the fuel consumption using ML model.

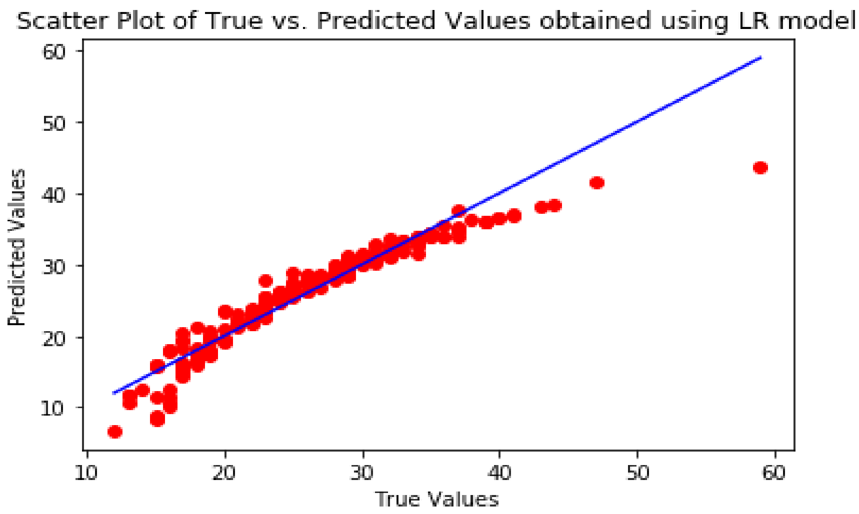

Figure 4: Displays the scatter plot for LR model.

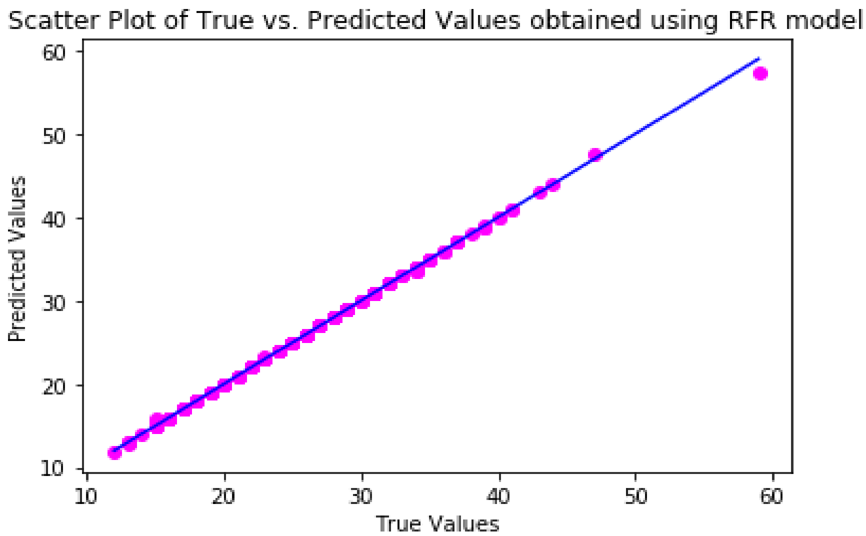

Figure 5: Displays the scatter plot for RFR model.

5. Conclusion

This project focused on predicting fuel consumption in heavy vehicles with a comparative analysis of two regression models such as LR and RFR. The results of this analysis led to several key conclusions. First and foremost, the RFR model demonstrated superior predictive performance compared to the LR model. It consistently achieved lower values for important metrics such as MSE, RMSE, and MSLE. These metrics are indicative of the model's ability to provide more accurate predictions of fuel consumption, measured in miles per gallon (MPG), for heavy vehicles. However, it's important to note that this enhanced predictive performance with RFR comes at the cost of increased model complexity and greater computational requirements. RFR excels at capturing complex relationships and nonlinear patterns in the data, making it an attractive choice when the interpretability of the model is not a primary concern.

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