



A Machine Learning Model of Average Fuel Consumption in Heavy Vehicles

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Abstract: In this paper 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 segment

Keywords: vehicle modeling, neural networks, average fuel consumption, data summarization, fleet management

1.0 INTRODUCTION

Fuel utilization models for vehicles are important to producers, controllers, and customers. They are required across every one of the periods of the vehicle life-cycle. In this paper, we center around displaying normal fuel utilization for weighty vehicles during the activity and upkeep stage. Compromises among the above procedures are basically regarding cost and precision according to the prerequisites of the planned application. This exploration was upheld to a limited extent by Allison Transmission, Inc.

2.0 REVIEW OF LITERATURE

Ability to display and foresee the fuel utilization is essential in upgrading mileage of vehicles and forestalling deceitful exercises in armada the board. numerous techniques for anticipating weighty/medium-obligation vehicle fuel utilization in light of driving cycle data. presents the utilization of three Machine Learning procedures to fuel utilization displaying of verbalized trucks for an enormous dataset. Specifically, Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) models have been produced for the reason and their presentation thought about.

2.1.1 EXISTING 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 liters per kilometer. 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)

2.1.2 DISADVANTAGES OF EXISTING SYSTEM

Collected over a time period to predict the corresponding fuel consumption in terms of either gallons per mile or liters per kilometer.

2.1.3 PROPOSED SYSTEM



In this concept to predict average fuel consumption in heavy vehicles using Machine Learning Algorithm such as ANN (Artificial Neural Networks). 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.

2.1.4 ADVANTAGES OF PROPOSED SYSTEM

It is 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.

3.0 UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

The Primary goals in the design of the UML are as follows:

1. Offer consumers an expressive, ready-to-use visual modelling language so they can create and trade meaningful models.
2. Offer methods for specialization and extendibility to expand the fundamental ideas.
3. Not depend on a certain development methodology or programming language.
4. Offer a formal foundation on which to comprehend the modelling language.
5. Promote the commercial expansion of OO tools.

4.0 USE CASE DIAGRAMS

4.1 USE CASE DIAGRAM

In the Unified Modeling Language (UML), a use case diagram can summarize the details of your system's users (also known as actors) and their interactions with the system. To build one, you'll use a set of specialized symbols and connectors. An effective use case diagram can help your team discuss and represent:

1. Scenarios in which your system or application interacts with people, organizations, or external systems
 2. Goals that your system or application helps those entities (known as actors) achieve
- The scope of your system

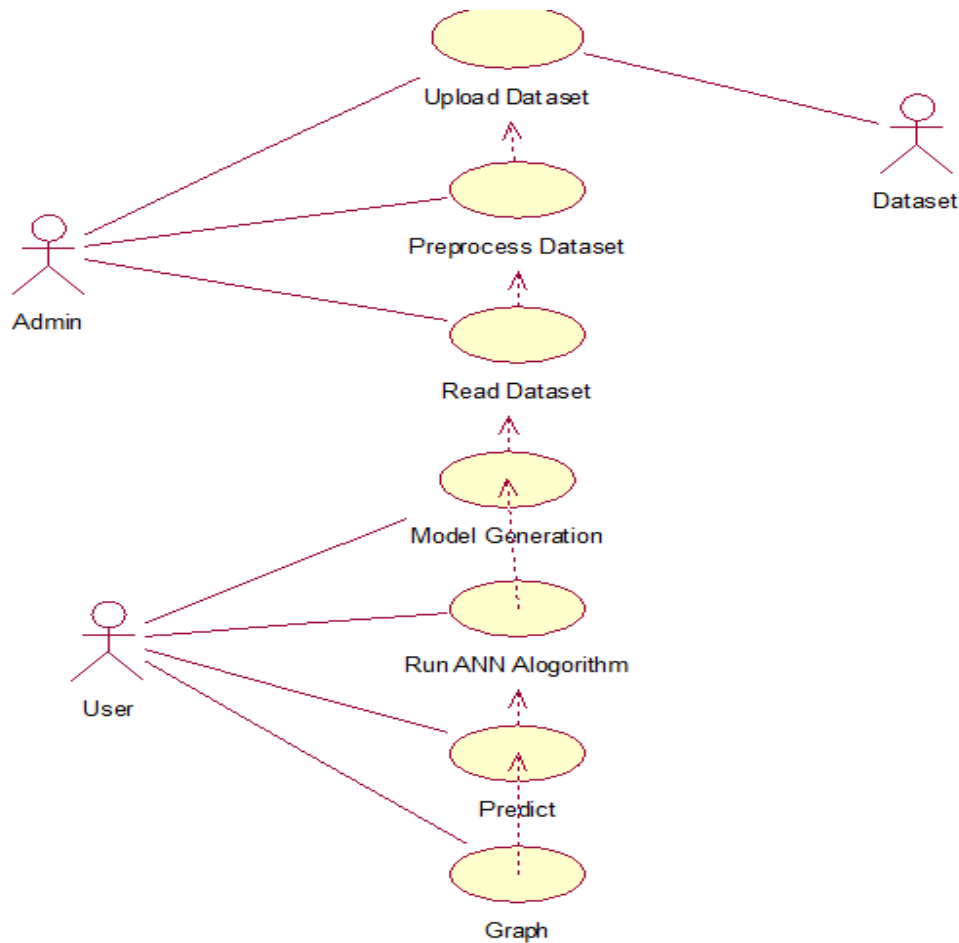


Figure: use case diagram

4.2 CLASS DIAGRAMS

The main purpose of class diagrams is to build a static view of an application. It is the only diagram that is widely used for construction, and it can be mapped with object-oriented languages. It is one of the most popular UML diagrams.

Following are the purpose of class diagrams given below:

- It analyses and designs a static view of an application.
- It describes the major responsibilities of a system.

It is a base for component and deployment diagram

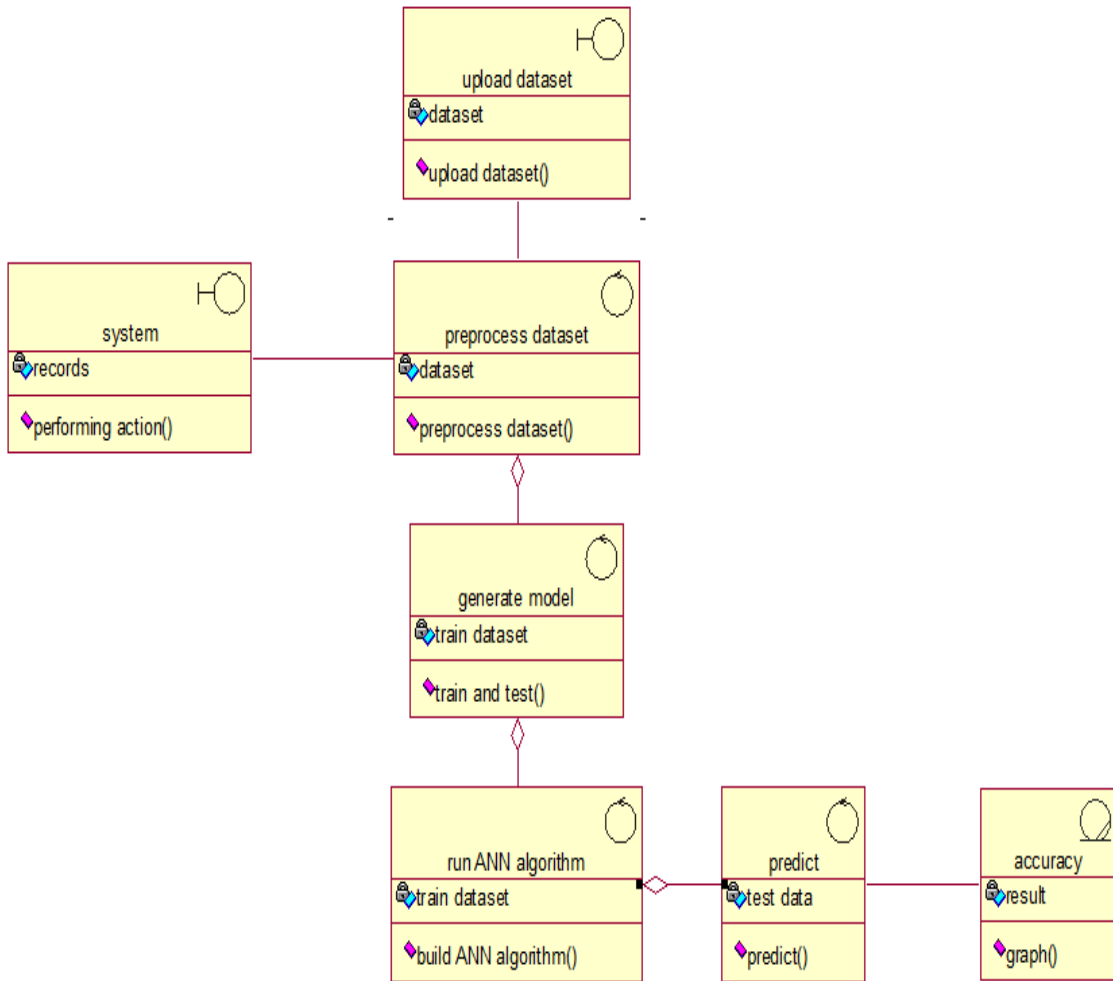


Figure: class diagram

4.3 ACTIVITY DIAGRAM

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions.

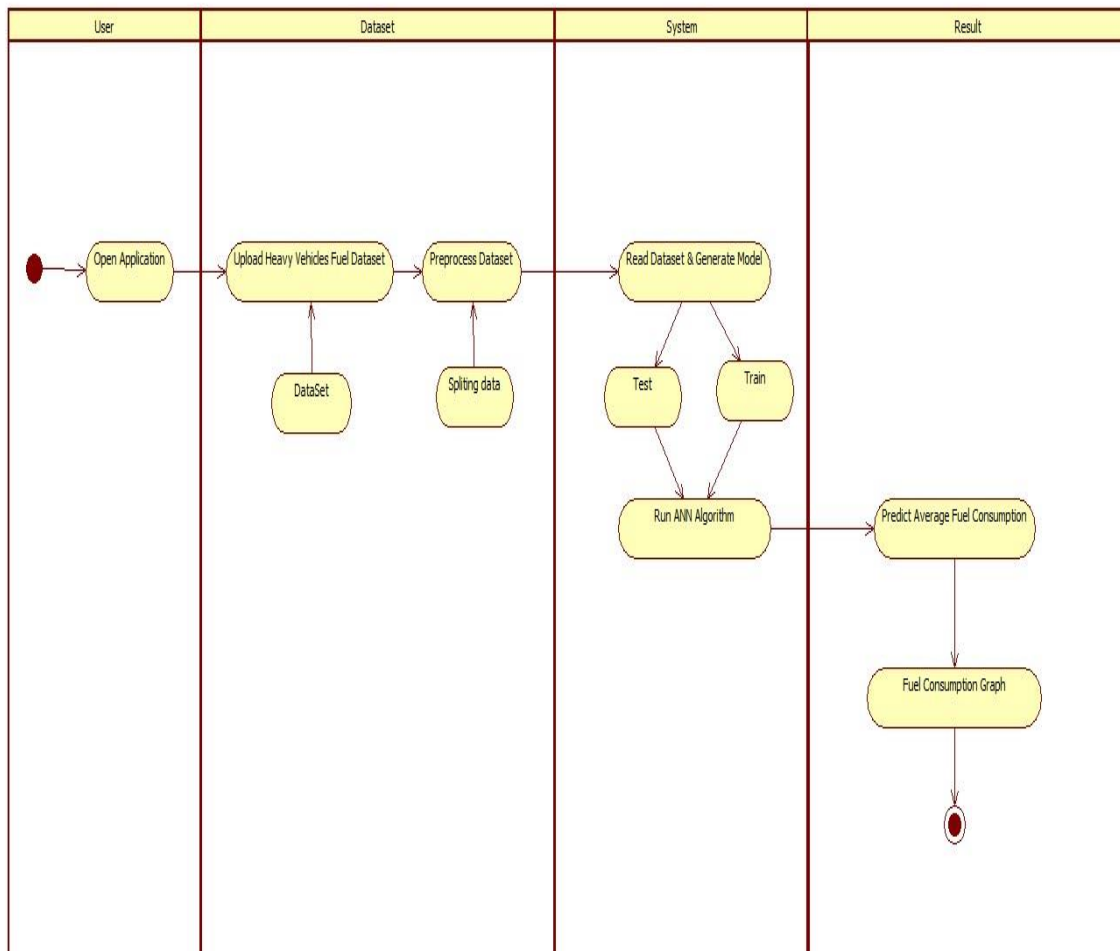


Figure: activity diagram

4.4 SEQUENCE DIAGRAM

The sequence diagram represents the flow of messages in the system and is also termed as an event diagram

- To model high-level interaction among active objects within a system.
- To model interaction among objects inside a collaboration realizing a use case.
- It either models generic interactions or some certain instances of interaction.

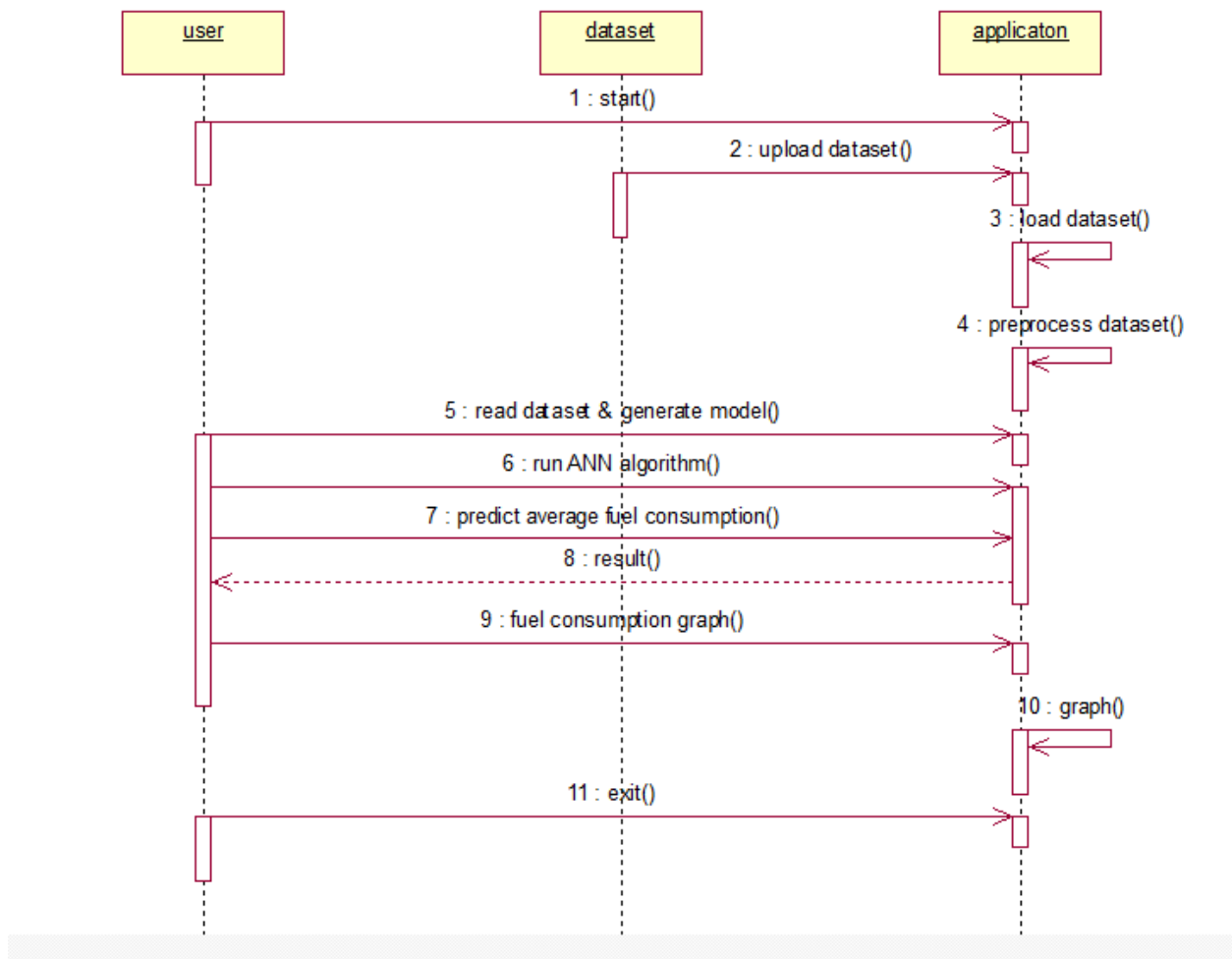


Figure: Sequence diagram

5. CONCLUSION

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 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.

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.



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