Machine Learning Model For Average Fuel Consumption In Heavy Vehicles.

Mrs..T. Sruthi*, Devasari Yashwanth kumar**, Kummari Sharath Chandra***, Kistamgari Vikas****, Nerella Sai Vikas *****

*(Information Technology, Malla Reddy Institute of Technology and Science, maisammaguda, Dhullapally, Via Hakimpet Post, Secunderabad-500100 Telangana India.
Email: Sruthi.thirunagari29@gmail.com)

** (Information Technology, Malla Reddy Institute of Technology and Science, maisammaguda, Dhullapally, Via Hakimpet Post, Secunderabad-500100 Telangana India.
Email: Yashudevasari@gmail.com)

***(Information Technology, Malla Reddy Institute of Technology and Science, maisammaguda, Dhullapally, Via Hakimpet Post, Secunderabad-500100 Telangana India.
Email: Sharathchandra5013@gmail.com)

****(Information Technology, Malla Reddy Institute of Technology and Science, maisammaguda, Dhullapally, Via Hakimpet Post, Secunderabad-500100 Telangana India.
Email : Vikas.mahendar15@gmail.com)

*****(Information Technology, Malla Reddy Institute of Technology and Science, maisammaguda, Dhullapally, Via Hakimpet Post, Secunderabad-500100 Telangana India.
Email: Saivikasnerella@gmail.com)

ABSTRACT

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.

Note: ***This paper advocates a data summarization approach based on distance rather than the traditional time period when developing individualized machine learning models for fuel consumption.***

I. INTRODUCTION

Fuel consumption models for vehicles are of interest to manufacturers, regulators, and consumers. They are needed across all the phases of the vehicle lifecycle. In this paper, we focus on modeling average fuel consumption for heavy vehicles during the operation and maintenance phase.

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 at each time step using detailed mathematical equations.

II. LITERATURE SURVEY

S. Wickramanayake and H. D. Bandara, arranged Fuel utilization forecast of armada vehicles exploitation AI. They trained an ability to display and anticipate the fuel utilization is significant in improving efficiency of vehicles and forestalling offensive exercises in armada the board. Fuel utilization of a vehicle relies upon a few interior components like distance, vehicle qualities, and driver conduct, conjointly as outside factors like street conditions, traffic, and climate. L. Wang, A. Duran, J. Gonder, and K. Kelly created Displaying substantial/medium duty fuel utilization upheld drive cycle properties. They trained various ways for foreseeing weighty/ medium duty vehicle fuel utilization upheld driving cycle data.

A polynomial model, a recorder fake neural net model, a polynomial neural organization model, and a variable accommodative relapse sp lines (MARS) model were created and checked exploitation data gathered from skeleton testing performed on a package conveyance diesel truck operational over the extraordinary modern Diesel Truck (HHDDT), city territory genuine Vehicle Cycle (CSHVC), new work Composite Cycle (NYCC), and water powered half breed vehicle (HHV) drive cycles. H. Almer, et. al., compares the accuracy of the proposed fuel consumption models with respect to input data collected at 1 minute and 10 minute intervals and concludes that the 10 minute interval yields more accurate models.

Vehicle weight is not typically available as a standard sensor and the weight was estimated using the suspension. In this paper, we also use vehicle speed and road grade to derive the predictors of the proposed model. G. Fontaras, R. Luz, K. Anagnostopoulus, D. Savvidis, S. Hausberger, and M. Rexeis, et. al. utilized perception gas outflows from hdv in europe-a test confirmation of develop of the arranged methodological approach.

As shown by them, the European Commission in joint coordinated effort with genuine Obligation Vehicle makes, the city College of Innovation and completely totally extraordinary counseling and investigation bodies has been setting up a beginner authoritative system for perception and news gas emanations from genuine Obligation Vehicles (HDVs) in Europe. H. A. Rakha, K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck, et al. proposed a method to calibrate the VT-CPFM model parameters for passenger cars by using US EPA city and highway cycles and fuel economy ratings. The model parameters calibrated under one scenario might require recalibration for new scenarios, which is time-consuming.

SYSTEM ARCHITECTURE:

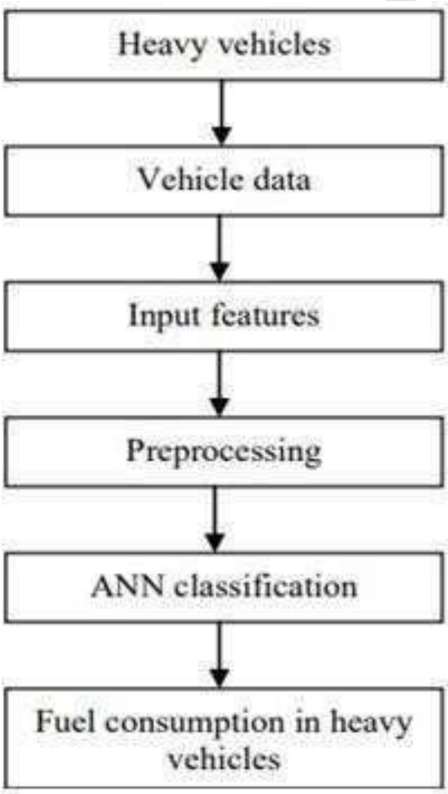
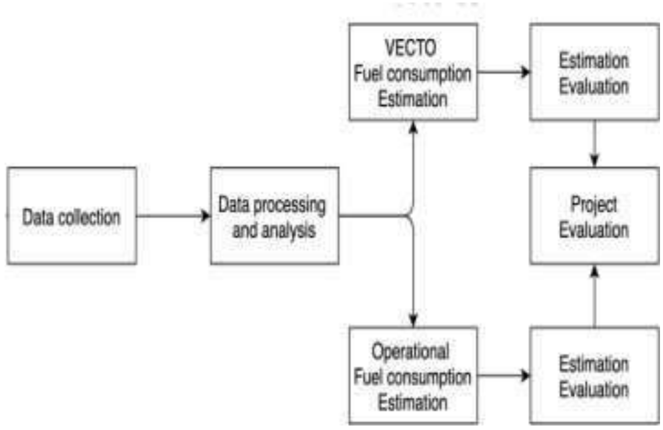


Fig.no-1

BLOCK DIAGRAM:



III. SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/ or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

TYPES OF TESTS

A. Unit testing

Unit testing involves the design of test cases that validate that the internal decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration.

This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

B. System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

C. Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

D. Functional Testing

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

- Valid Input : identified classes of valid input must be accepted.
- Invalid Input : identified classes of invalid input must be rejected.
- Functions : identified functions must be exercised.
- Output : identified classes of application outputs must be exercised.
- Systems/Procedures : interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

E. White Box Testing

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

F. Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .you cannot "see" into it. The test provides inputs and responds to outputs without considering how the software works.

G. Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

IV. CONCLUSION & FUTURE ENHANCEMENT

A. 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.

B. Future Enhancement:

Future work also includes investigating the minimum distance required for training each model and analyzing how often does a model need to be synchronized with the physical system in operation by using online training in order to maintain the prediction accuracy of the model.

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