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A MACHINE LEARNING MODEL FOR AVERAGE FUEL CONSUMPTION IN HEAVY VEHICLES

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ABSTRACT: 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. 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 traveled. 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.

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

1. INTRODUCTION

Fuel consumption models for vehicles are of interest to manufacturers, regulators, and consumers. They are needed across all the phases of the vehicle life-cycle. In this paper, we focus on modeling average fuel consumption for heavy vehicles during the operation and maintenance phase. In general, techniques used to develop models for fuel consumption fall under three main categories: • Physics-based models, which are derived from an indepth understanding of the physical system. These models describe the dynamics of the components of the vehicle at each time step using detailed mathematical equations [1], [2]. • Machine learning models, which are data-driven and represent an abstract mapping from an input space consisting of a selected set of predictors to an output space that represents the target output, in this case average fuel consumption [3], [4]. • Statistical models, which are also data-driven and establish a mapping between the probability distribution of a selected set of predictors and the target outcome [5], [6]. Trade-offs among the above techniques are primarily with respect to cost and accuracy as per the requirements of the intended application.

Several previous models for both instantaneous and average fuel consumption have been proposed. Physics-based models are best suited for predicting instantaneous fuel consumption [1], [2] 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 [3] 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 [4]. 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 timebased scale of the input domain to the distance-based scale of the output domain (i.e., average fuel consumption).

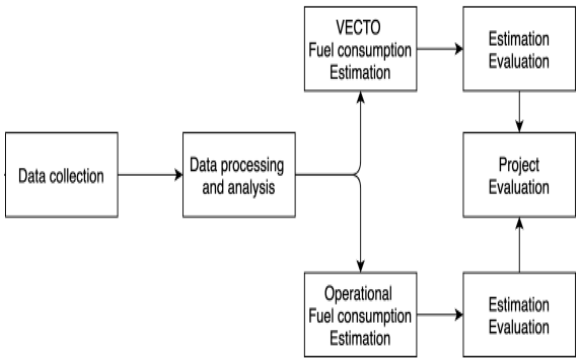

Fig.1: Example figure

Using the same scale for both the input and output spaces of the model offers several benefits: • Data is collected at a rate that is proportional to its impact on the outcome. When the input space is sampled with respect to time, the amount of data collected from a vehicle at a stop is the same as the amount of data2 collected when the vehicle is moving. • The predictors in the model are able to capture the impact of both the duty cycle and the environment on the average fuel consumption of the vehicle (e.g., the number of stops in an urban traffic over a given distance). • Data from raw sensors can be aggregated on-board into few predictors with lower storage and transmission bandwidth requirements. Given the increase in computational capabilities of new vehicles, data summarization is best performed on-board near the source of the data. • New technologies such as V2I and dynamic traffic management [10]–[12] can be leveraged for additional fuel efficiency optimization at the level of each specific vehicle, route and time of day.

2. EXISTING SYSTEM

Trade-offs among the above techniques are primarily with respect to cost and accuracy as per the requirements of the intended application. In this

paper, a model that can be easily developed for individual heavy vehicles in a large fleet is proposed. Relying on accurate models of all of the vehicles in a fleet, a fleet manager can optimize the route planning for all of the vehicles based on each unique vehicle predicted fuel consumption thereby ensuring the route assignments are aligned to minimize overall fleet fuel consumption. These types of fleets exist in various sectors including, road transportation of goods [7], public transportation [3], construction trucks [8] and refuse trucks [9]. For each fleet, the methodology must apply and adapt to 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 cost2 of the development and adaptation of an individualized model for each vehicle in the fleet.

Existing model that can be easily developed for individual heavy vehicles in a large fleet is proposed. Relying on accurate models of all of the vehicles in a fleet, a fleet manager can optimize the route planning for all of the vehicles based on each unique vehicle predicted fuel consumption thereby ensuring the route assignments are aligned to minimize overall fleet 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. 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-topeak percent error less than 4% for routes that include both city and highway duty cycle segments.

3. PROPOSED SYSTEM

As mentioned above Artificial Neural Networks (ANN) are often used to develop digital models for complex systems. The models proposed in [15] highlight some of the difficulties faced by machine learning models when the input and output have different domains. In this study, the input is aggregated in the time domain over 10 minutes intervals and the output is fuel consumption over the distance traveled during the same time period. The complex system is represented by a transfer function $F(p) = o$, where $F(\cdot)$ represents the system, p refers to the input predictors and o is the response of the system or the output. The ANNs used in this paper are Feed Forward Neural Networks (FNN). Training is an iterative process and can be performed using multiple approaches including particle swarm optimization and back propagation. Other approaches will be considered in future work in order to evaluation their ability to improve the model‘s predictive accuracy. Each iteration in the training selects a pair of (input, output) features from Ftr at random and updates the weights in the network. This is done by calculating the error between the actual output value and the value predicted by the model.

Advantages of proposed system :

• Data is collected at a rate that is proportional to its impact on the outcome. When the input space is sampled with respect to time, the amount of data collected from a vehicle at a stop is the same as the amount of data collected when the vehicle is moving.

• The predictors in the model are able to capture the impact of both the duty cycle and the environment on the average fuel consumption of the vehicle (e.g., the

number of stops in an urban traffic over a given distance).

• Data from raw sensors can be aggregated on-board into few predictors with lower storage and transmission bandwidth requirements. Given the increase in computational capabilities of new vehicles, data summarization is best performed on-board near the source of the data.

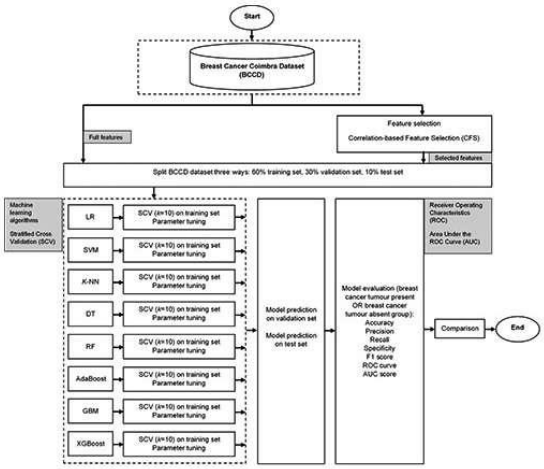

Fig.2: System architecture

4. RELATED WORK

4.1 Development of greenhouse gas emissions model for 2014-2017 heavy-and medium-duty vehicle compliance.

Vehicles of light-duty families are subject to mandatory testing for certification and compliance. Unlike the light-duty sector where a vast majority of vehicles are mass produced for generally similar purposes, medium- and heavy-duty vehicles are commonly custom-made. Permutations of engines, transmissions, axles, chassis frames, auxiliary equipment, and numerous other specific consumer requirements have resulted in tens or hundreds of thousands of truck configurations for some truck classes or applications in the fleet for any given year. To help manage the regulatory testing burden on truck manufacturers and the government agencies, the Environmental Protection Agency has created the Greenhouse gas Emissions Model which is to be jointly used by both agencies as the primary tool to certify vocational and combination tractor heavy-duty vehicles (Class 2b through Class 8 heavy-duty, excluding heavy-duty pickups or vans). This paper describes the simulation tool, including essential features and assumptions used in tool development. The model has been validated using Class 7 and Class 8 combination tractor data obtained from chassis dynamometer testing and benchmarked against a widely available commercial vehicle simulation tool.

4.2 Monitoring co2 emissions from hdv in europe-an experimental proof of concept of the proposed methodolgical approach:

The European Commission in joint collaboration with Heavy Duty Vehicle manufactures, the Graz University of Technology and other consulting and research bodies has been preparing a new legislative framework for monitoring and reporting CO2 emissions from Heavy Duty Vehicles (HDVs) in Europe. In contrast to passenger cars and light commercial vehicles, for which monitoring is performed through chassis dyno measurements, and considering the diversity and particular characteristics of the HDV market, it was decided that the core of the proposed methodology should be based on a combination of component testing and vehicle simulation. Emphasis is put on accurately simulating the performance of different vehicle components and achieving realistic fuel consumption

results. A proof of concept was launched aiming to test and prove that these targets are achievable. A series of experiments were conducted on 2 different trucks, a Daimler 40ton Euro VI, long haul delivery truck with semi-trailer and a DAF 18 ton Euro V rigid truck. Measurements were performed at the Joint Research Centre's HDV chassis dyno labs and on the road. A vehicle simulator (Vehicle Energy Consumption Calculation Tool - VECTO) has been developed to be used for official monitoring purposes and the results of the measurements were used for its validation.

4.3 Fuel consumption prediction of fleet vehicles using machine learning: A comparative study:

Ability to model and predict the fuel consumption is vital in enhancing fuel economy of vehicles and preventing fraudulent activities in fleet management. Fuel consumption of a vehicle depends on several internal factors such as distance, load, vehicle characteristics, and driver behavior, as well as external factors such as road conditions, traffic, and weather. However, not all these factors may be measured or available for the fuel consumption analysis. We consider a case where only a subset of the aforementioned factors is available as a multi-variate time series from a long distance, public bus. Hence, the challenge is to model and/or predict the fuel consumption only with the available data, while still indirectly capturing as much as influences from other internal and external factors. Machine Learning (ML) is suitable in such analysis, as the model can be developed by learning the patterns in data. In this paper, we compare the predictive ability of three ML techniques in predicting the fuel consumption of the bus, given all available parameters as a time series. Based on the analysis, it can be concluded that the random forest technique produces a more accurate prediction compared to both the gradient boosting and neural networks.

4.4 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 FASTSim.

4.5 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. The study also shows that although all the three methods make it possible to develop models with good precision, the RF slightly outperforms SVM and ANN giving higher R-squared, and lower error.

5. ALGORITHMS

Artificail Neural Network (ANN):

Artificial Neural Network Tutorial provides basic and advanced concepts of ANNs. Our Artificial Neural Network tutorial is developed for beginners as well as professions. The term "Artificial neural network" refers to a biologically inspired sub-field of artificial intelligence modeled after the brain. An Artificial neural network is usually a computational network based on biological neural networks that construct the structure of the human brain. Similar to a human brain has neurons interconnected to each other, artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes. Artificial neural network tutorial covers all the aspects related to the artificial neural network. In this tutorial, we will discuss ANNs, Adaptive resonance theory, Kohonen self-organizing map, Building blocks, unsupervised learning, Genetic algorithm, etc.

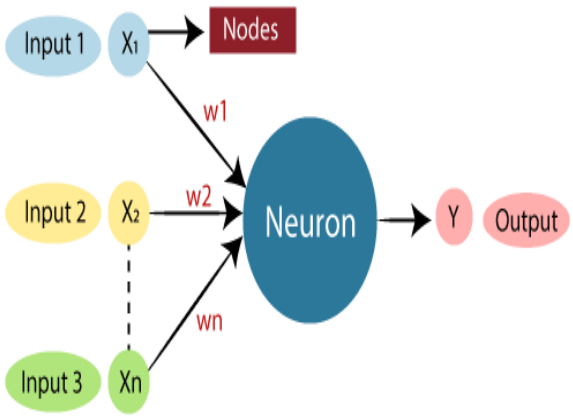

Fig.3: ANN model

An Artificial Neural Network in the field of Artificial intelligence where it attempts to mimic the network of neurons makes up a human brain so that computers will have an option to understand things and make decisions in a human-like manner. The artificial neural network is designed by programming computers to behave simply like interconnected brain cells. There are around 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 and 100,000. In the human brain, data is stored in such a manner as to be distributed, and we can extract more than one piece of this data when necessary from our memory parallelly. We can say that the human brain is made up of incredibly amazing parallel processors. We can understand the artificial neural network with an example, consider an example of a digital logic gate that takes an input and gives an output. "OR" gate, which takes two inputs. If one or both the inputs are "On," then we get "On" in output. If both the inputs are "Off," then we get "Off" in output. Here the output depends upon input. Our brain does not perform the same task. The outputs to inputs relationship keep changing because of the neurons in our brain, which are "learning".

An artificial neural network is an attempt to simulate the network of neurons that make up a human brain so that the computer will be able to learn things and make decisions in a humanlike manner. ANNs are created by programming regular computers to behave as though they are interconnected brain cells. Every linkage calculation in an Artificial Neural Network (ANN) is similar. In general, we assume a sigmoid relationship between the input variables and the activation rate of hidden nodes or between the hidden nodes and the activation rate of output nodes.

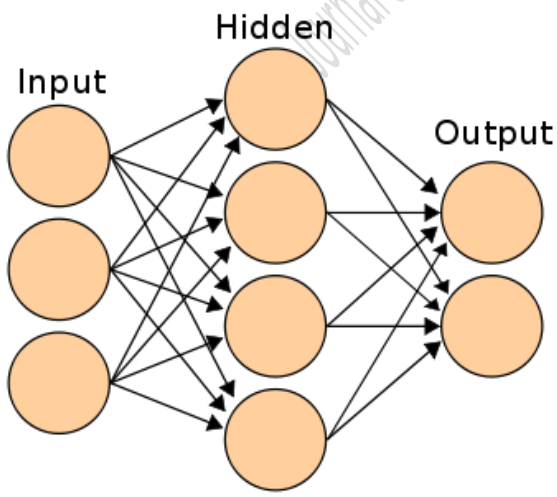

Fig.4: ANN model

6. EXPERIMENTAL RESULTS

Fig.5: Home screen

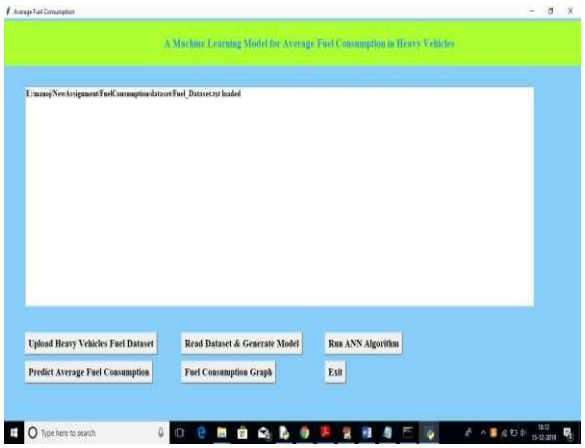

Fig.6: Upload heavy vehicle fuel dataset

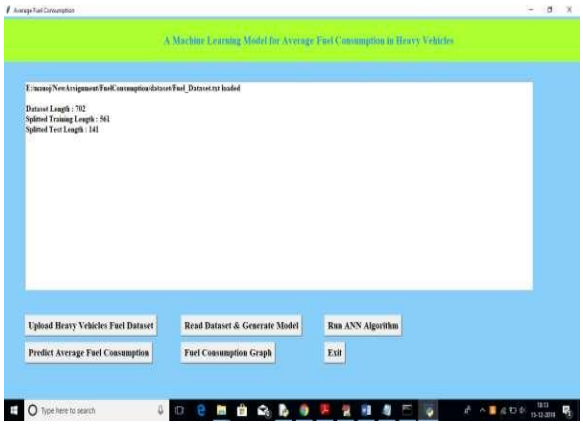

Fig.7: Read dataset & generate model

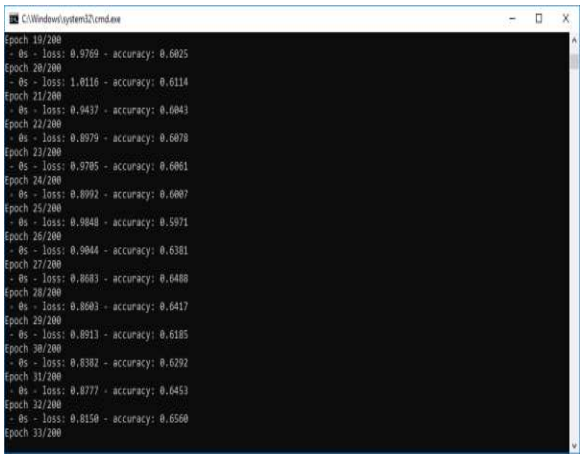

Fig.8: Run ANN algorithm

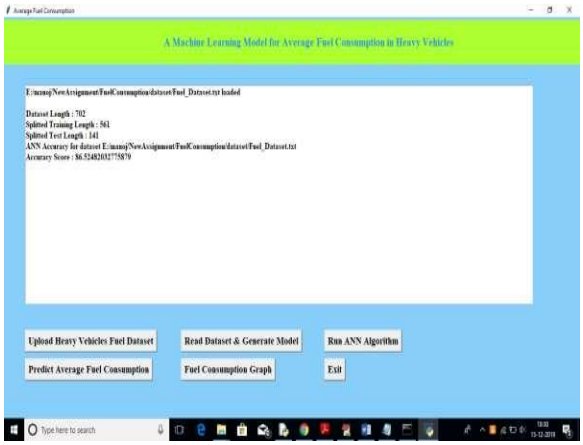

Fig.9: ANN accuracy screen

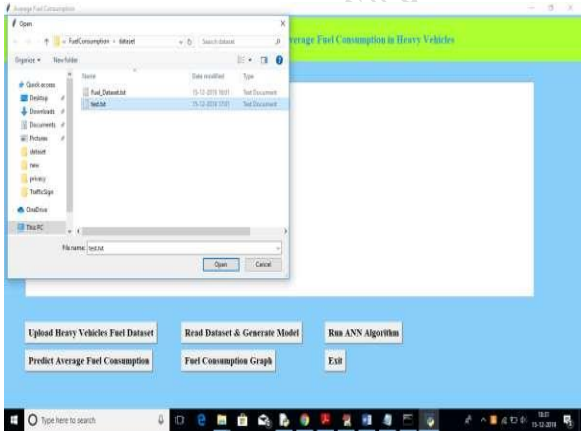

Fig.10: Upload test data

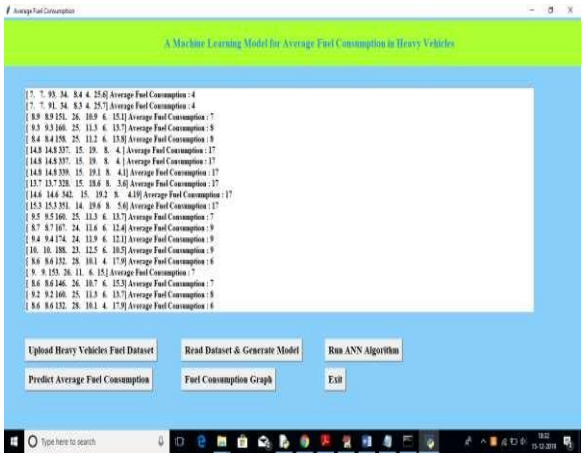

Fig.11: Predict average fuel consumption

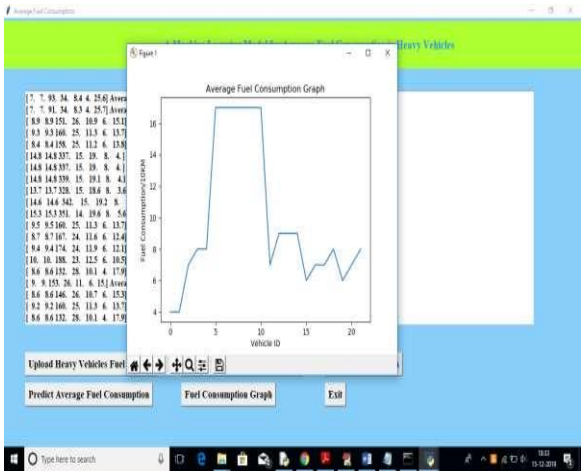

Fig.12: Fuel consumption graph

7. 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.

8. FUTURE SCOPE

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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