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Heavy duty vehicle fuel consumption modelling based on exploitation data by using artificial neural networks

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Abstract

One of the ways to improve the fuel economy of heavy duty trucks is to operate the combustion engine in its most efficient operating points. To do that, a mathematical model of the engine is required, which shows the relations between engine speed, torque and fuel consumption in transient states. In this paper, easy accessible exploitation data collected via CAN bus of the heavy duty truck were used to obtain a model of a diesel engine. Various polynomial regression, K-Nearest Neighbor and Artificial Neural Network models were evaluated, and based on RMSE the most relevant sets of parameters for the given algorithm were selected. Finally, the models were compared by using RMSE and Absolute Relative Error scores for 5 test samples. These represent the whole engine's operating area. Apart from goodness of fit, the models were analyzed in terms of sensitivity to the size of the training samples. ANN and KNN proved to be accurate algorithms for modeling fuel consumption by using exploitation data. The ANN model was ranked best, as it required less observations to be trained in order to achieve an absolute relative error which was lower than 5%. A conventional method, i.e. polynomial regression, performed significantly worse than either the ANN or the KNN models. The approach presented in this study shows the potential for using easy accessible exploitation data to modeling fuel consumption of heavy duty trucks. This leads to the reduction of fuel consumption having a clear positive impact on the environment.

Keywords: neural networks, combustion engine, heavy duty truck, fuel economy, fuel consumption, refuse collection vehicle

1 Introduction

Trucks, whether used for freight transportation or as utility vehicles, play an important role in a countries economy and improving their fuel efficiency can undoubtable prove highly beneficial. One of the ways to improve the fuel economy is to operate the combustion engine at its most efficient operating points. It is particularly significant when it comes to performing duty cycles by the vehicle. For instance, when

the engine runs the hydraulic or electric power receiver in the body. However, the information about the engine provided by the manufacturers does not cover the full engine characteristics and it is impossible to determine an optimal duty cycle in terms of the engine's speed and load. Conventional methods for obtaining general engine characteristics use engine or chassis dynamometers. This is associated with high costs. What is more, they provide steady state characteristics, which can lead to relatively high errors when used to model fuel consumption in transient states. This study presents methods for using exploitation data collected from a utility truck in order to obtain a mathematical model of the engine. Such model should provide an accurate fuel consumption prediction for any simulated duty cycle of the vehicle. Then, it can be used to compare the duty cycles and lead to an optimal design of the drivetrain, which will set the engine into its more efficient operating points during its work. In this study three models are presented: polynomial regression, K-Nearest Neighbor and Artificial Neural Network. The performance levels of the models are compared based on the RMSE and Absolute Relative Error over 5 test samples. Each of the samples has various observation distributions representing various operating areas of the engine. The models are also analyzed in terms of the influence of the trainset size on the model accuracy. As the result of this study, the KNN and the ANN models show high accuracy in fuel consumption prediction for even relatively small trainsets. Thus, by using easily accessible exploitation data it is possible to obtain an accurate model of the engine and use it to improve fuel consumption.

This paper is organized as follows. Section 2 describes the collected data and the principles of the truck's operation. Section 3 explains the selection of test samples. Polynomial regression, KNN and ANN models are described in sections 4, 5 and 6 respectively. Section 7 explains the validation of the models by using test samples, followed by discussion in Section 8. The conclusions derived from the results are presented in the last section.

2 Exploitation data description

The analysis presented in the paper is based on data collected using the vehicle's CAN bus. This was done using the FMS-interface [1]. This is an open standard, which gives third parties access to vehicle data, containing among others: engine speed **n**, torque **T** and fuel consumption $\mathbf{G_e}$. The examined truck was a Scania P320, working as a Refuse Collection Vehicle (RCV). The chassis was equipped with a diesel engine (9.3 dm^3 of displacement, max power = 235 kW, max torque = 1600 Nm)[2]. The engine parameters were recorded for 8 hours, with the frequency of 10 Hz. This resulted in 290000 observations. This corresponds to a representative day of RCV operation, which is described further in the text. Although the FMS-interface is an optional interface in a truck, a large number of RCV (and other heavy duty vehicles) are equipped with it when purchased. Therefore, data collection does not require any modification of the vehicle's systems nor does it require additional measuring devices, except for the data logger. Similarly, the tests conducted on the trucks using FMS interface are described in [3,4].

A regular day of the RCV operation consists of short distance travels and frequent stops. The truck stops close to a bin or set of bins, collects the waste and moves to another bin. The distances between stops and time spend collecting waste is dependent on the number of bins to be emptied, their size and distribution in the operating area. Approximately twice a day, the RCV needs to be discharged at the garbage dump. However, this has a minor effect on the presented analysis.

Most of rear loaders RCVs are equipped with a hydraulic system powered by a twin-flow, fixed displacement pump. The pump supplies the power to two separate circuits: the compactor circuit and the lifter circuit. The former drives a compaction mechanism, the ejector plate and the cylinders which lift the tailgate. The latter is used to operate the lifting mechanism. The principles of RCV operations are discussed in detail in [5,6,7]. In terms of truck's engine operation, it is important that when the RCV stops, the engine is idling i.e. its speed is close to 600 rpm. Then the hydraulic pump is turned on by the driver, and it is possible to operate the lifting mechanism. The engine speed remains the same, due to low power demand and sufficient oil flow provided by the pomp. When the compactor is activated, the engine speed is raised to 900 rpm. This value can be arbitrarily set by the RCV manufacturer, and usually ranges from 850 to 1050 rpm. The lifting mechanism can be operated regardless of the engine speed, and is not related to the compactor.

The above description explains measuring points distribution in an n-T domain of the data collected during a regular operation day. This is presented as a 2D histogram in Fig. 1. Approximately 50% of the time the engine speed was around 600 rpm, which corresponds to vehicle's stops and idling. This time periods are related to the stops due to traffic, the stops pending pump activation, and the lifter operation (without compacting). In general, the low values of torque for n=600 rpm on the histogram are related to the former, and higher values to the latter. The second concentration of the measuring points is related to waste compaction, when the engine speed is set to 900 rpm. It represents about 15% of the daily operation time.

3 Selection of test samples

All models presented in further sections, are evaluated using a cost function. In most cases, the cost function is related to the difference between the real response value and the one calculated by the model. The final model is obtained by minimizing this error using e.g. Least Squares Method, Gradient Descend [8] etc. A widely used approach is to split the dataset into a training and a testing set, typically in a percentage proportion of 70:30, 80:20 or 85:15. Then the model is trained using the train set, to obtain the lowest product of the cost function. Then, a response value is predicted using the test set, and real values are compared with predicted ones. Based on this, a model accuracy score can be calculated, such as Root Mean Squared Error (RMSE). The non-uniform distribution of the observations leads to a good fit of the model in the areas of high observation density, but a relatively poorer fit elsewhere. Splitting the dataset randomly does not solve this problem, because distribution in the test set is analogous to the one in the train set. In order to assess accuracy of the reconstructed

performance map of the engine, test samples from different areas in n-T domain are needed. Thus, 5 test samples were selected, each representing 20 succeeding seconds of the engine's operation. The paths in n-T domain of each sample are presented in Fig. 2. Test sample 1 covers the range of 1200-1450 rpm and 200-750 Nm. Test sample 2 may be assigned to the RCV body operation when the engine speed is raised from idling at 600 rpm to 900 rpm while the compacting mechanism is activated. Test sample 3 covers 1100-1250 rpm and a larger spectrum of torque: 0-1000 Nm. Test samples 4 and 5 represent the engine operation during driving, from idle engine speed to higher values of up to 1600 rpm. They also cover a wide range of torque, up to 900 and 1400 Nm per sample 4 and 5 respectively. In the following sections, the models are validated and compared by using RMSE and Absolute Relative Error for these 5 test samples.

4 Polynomial regression model

The data collected can be used to reconstruct the engine's performance map, as they contain information about the engine speed, the torque and the fuel consumption. Conventional methods, used during tests on chassis dynamometers or in laboratories, assume that the engine operates in a quasi–steady state i.e. the changes on its parameters do not exceed previously specified values at a given time [9]. The engine's performance map is also termed as a general engine characteristic. It is a vector function given by equation: $Y = f(n,T);\ (n,T) \in L$. Where L is a range of engine operating points. A polynomial surface of G_e values is obtained by an approximation of the measured values of G_e in the n-T domain using the least squares method [10,11].

However, as described in [12], during regular daily operation the engine works mostly in transient states. Thus, applying the conventional method to the data presented in this paper, may lead to inaccuracy in the fuel prediction when using polynomial regression model. This is due to the time delay Δt between the change of input variables: engine rotational speed and torque, and the engine's response (Ge). This is presented in Fig. 3, where the Δt can reach up to 1.5 s. Because of that, a large number of similar observations with similar n and T can correspond to significantly different Ge.

A common practice is to use the engine's performance map obtained in quasi-steady states in order to model fuel consumption in transient states [10,11,13]. In this paper, transient state observations are used to evaluate the performance map, and then the model is used for fuel consumption modelling. This is the only possible approach for applying the conventional method using exploitation data, due to the very limited number of observations present in quasi-steady states [12].

A polynomial regression model was used, as one of the three algorithms in this study, to reconstruct the engine performance map. Later on is referred to as the Polynomial Regression Model (PRM). The polynomial function may be of arbitrary degree, however higher degrees are associated with higher risk of overfitting. In this paper polynomial surfaces of 2nd, 3rd, 4th and 5th degree are exanimated.

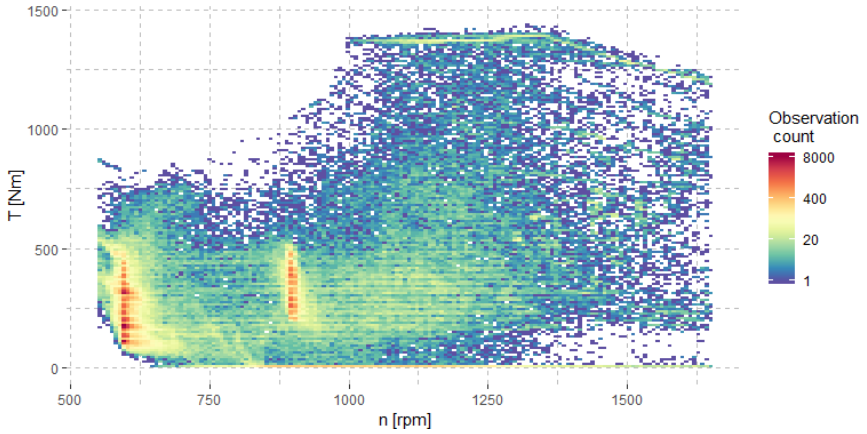

Fig. 1. Histogram of the observations. Engine data collected during a regular working day of the RCV.

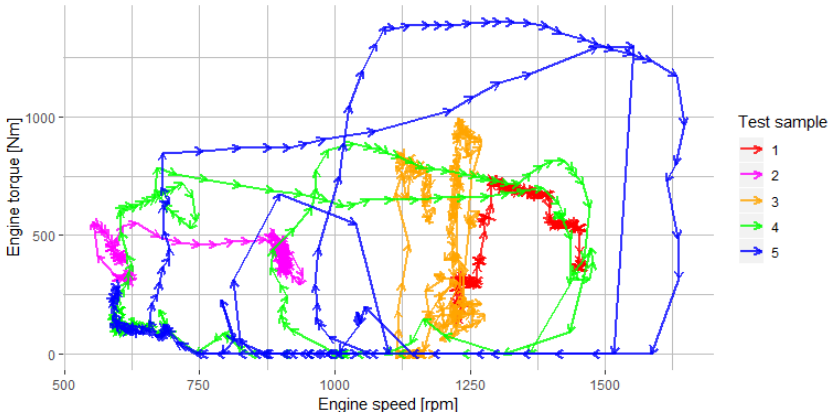

Fig. 2. Test samples measuring points presented as paths in n-T domain.

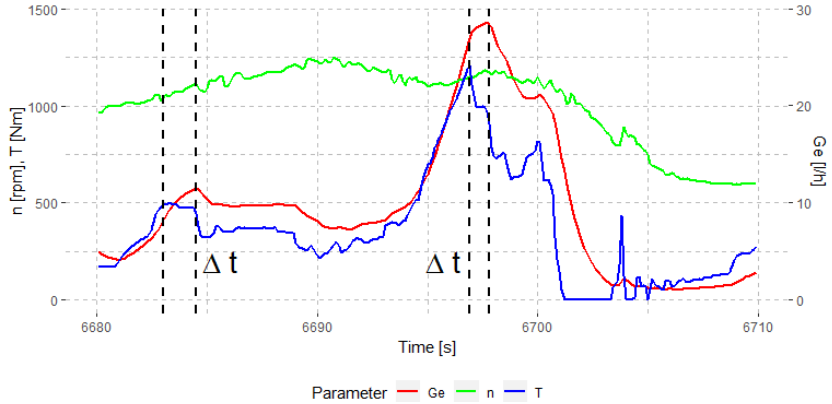

Fig. 3. Engine operation in a transient state. Time delay Δt between the input values (n and T) and the response (Ge)

Each of the models was trained 30 times on the given train set. The train set consisted each time of a randomly selected sample from the dataset. The influence of the sample size was also considered. The models were trained on 22 sample sizes, which logarithmically increase in the range between 100-250000 observations. As a result, for each model 660 RMSE scores were calculated, 30 for each sample size. These scores were calculated both for the training set and for the 5 test samples and are presented in Fig. 4. For sample sizes larger than 1000 observations, the RMSE become similar for both the training and the testing data sets. However, for small number of observations (<1000) the overfitting in 4th and 5th degree models is apparent. Thus, for the comparison with alternative algorithms in following sections, the 3rd degree polynomial regression model was selected.

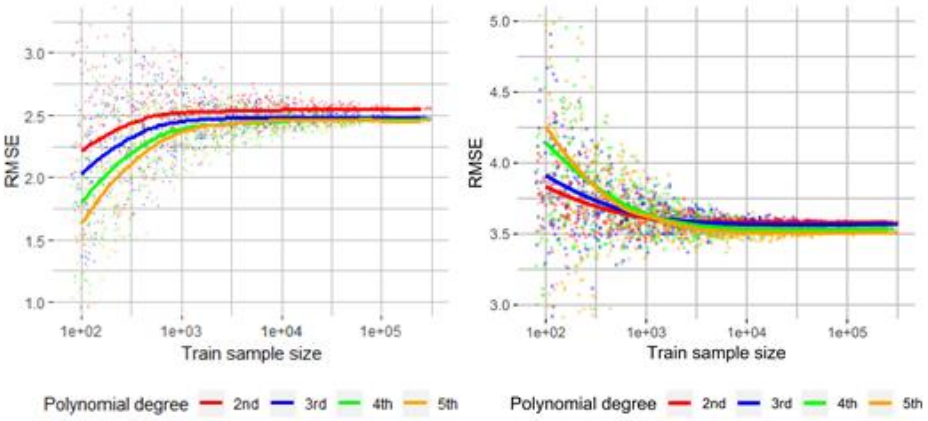

Fig. 4. Polynomial regression models scores: left) RMSE train; right) mean RMSE for all 5 test samples. Scores smoothed by using LOESS.

5 K-Nearest Neighbor model

PRM uses a surface to approximate the engine's performance map. However, given enough observations, it is possible to find similar observations to the one used to predict engine fuel consumption. Moreover, this method is also useful with relatively large datasets with a uniform distribution of observations. The accuracy of the model is expected to correlated with the size of the dataset size and/or its uniform distribution. To find similar observations, a K-Nearest Neighbors (KNN) algorithm can be applied [8]. The principle of KNN is that the algorithm calculates the Euclidean distances of all of the observations in the dataset for a given input value. Then the algorithm chooses k-number of the closest observations. In classification problems, the predicted class is the class of the majority of k-nearest samples. In regression, such as in this paper, the predicted value is an average of the value of the k-nearest samples.

In the analysis of transient states of combustion engines, the inclusion of information related to speed and torque changes in the model, generally results in a higher accuracy of the model. In [14] as additional input variables: derivatives of n and T

were used. In [15] a number of values from a time window before observation were considered. However, the examined engines differ from the one presented in these papers in terms of size, ignition type and even emission regulations which they need to comply to. There is no direct suggestion as to which additional values preceding observations should be included in order to obtain an accurate model. Moreover, it seems that this issue depends on the inertia of the engine, which is directly related to the engine displacement. In this research it was assumed, that changes should be consider up to 1.5 s before the measuring point.

In this paper four KNN models were calculated. The first model (KNN 1) considers n and T as input variables, and assign G_e to the one nearest value (k=1). The second model (KNN 2) consists of 8 input variables: n, T, n_{500}, T_{500}, n_{1000}, T_{1000}, n_{1500}, T_{1500}. The subscript indicates the number of milliseconds before the observation. For example, n_{500} indicates the engine speed value 500 ms before the actual measuring point. Consequently T_{1000} indicates the value of the engine's torque 1000 ms before. KNN 2 also considers only one nearest point (k=1). Models KNN 3 and KNN 4 corresponds to KNN 1 and KNN 2, however the k value was not set in advance, but was chosen from values based on the lowest RMSE values obtained through cross validation.

Before training the models, the data was centered and scaled, so the mean and standard deviation of each variable were 0 and 1 respectively. Then, a 10-folds cross validation was performed for each model, and the mean RMSE value was calculated. This score is referred to as the training score later in the text. Models KNN 3 and KNN 4 were cross-validated multiple times, each for different k value ranging from (3, 5, …, 17, 19). The models with the lowest RMSE were then selected.

Next, the accuracy of the models was validated by using 5 test samples. In order to investigate the influence of the sample size on the model score, the procedure described above was conducted multiple times for random samples of different sizes in the range of 100 to 250000 observations, similarly to PRM, 30 times per sample size. Results for train RMSE scores and mean RMSE for 5 test samples are presented in Fig. 5. KNN models with input 8 variables clearly outperform the ones with 2 variables. Moreover, lower RMSE values for KNN 4 than KNN 2 suggest, that for k-values greater than 1 the accuracy of the model improves. The best K-Nearest Neighbors model was selected for further comparison. This corresponds to the KNN 4.

6 Artificial Neural Network model

The artificial neural network model used in this study is the ANN. This model is based on a multi-layer feedforward artificial neural network, that is trained with stochastic gradient descent using back-propagation. A rectifier was used as activation function [15]. In order to produce an optimal ANN, a combination of 3 sets of predictors and 7 sets of hidden layers were analyzed, resulting in 21 models. The models are summarized in Table 1. A subscript in the predictors notation indicates the time in milliseconds before the observation, similarly as for KNN models. Additionally, Δ indicates that the variable corresponds to the difference between the actual value and

the value of x milliseconds before; e.g. Δn_{1500} corresponds to difference between actual n and n_{1500}. One hidden layer or two hidden layers with equal number of neurons were used.

Table 1. ANN model possible configuration: 3 sets of predictors and 7 sets of hidden layer resulted in combination of 21 models

	Set of predictors	Neurons in hidden layers
Set 1	n, T	5, 10, 20, 50 5-5, 10-10, 20-20
Set 2	n, T, Δn_{500}, Δn_{1000}, Δn_{1500}, ΔT_{500}, ΔT_{1000}, ΔT_{1500}	
Set 3	n, T, n_{500}, T_{500}, n_{1000}, T_{1000}, n_{1500}, T_{1500}	

Before training the models, the data was centered and scaled, so that the mean and standard deviation of each variable were 0 and 1 respectively. Each neural network model was computed 30 times with a 10-fold cross-validation for each size of training sample in the range of 100-250000; the epochs were set to a 100. To measure the performance of the model RMSE was used. To select most accurate ANN model from 21 possible, the mean cross-validation RMSE values from the training process were compared. Results are shown in Fig. 6. On the left graph, the scores are grouped by the set of predictors. Set 1 is clearly underperforming regardless of sample size, with a constant RMSE around 2.5. Sets 2 and 3 are convergent for large sample sizes to RMSE=0.6, but the latter is much better for sample sizes smaller than 5000 observations. On the right graph, only the scores from Set 3 were shown and grouped by the set of hidden layers. The RMSE decreases along with the increase of sample size, and the largest differences between the models can be observed for small training sample size. Based on that, the best ANN model was selected for comparison with PRM and KNN. The best model has 8 input variables (Set 3) and 50 neurons in 1 hidden layer.

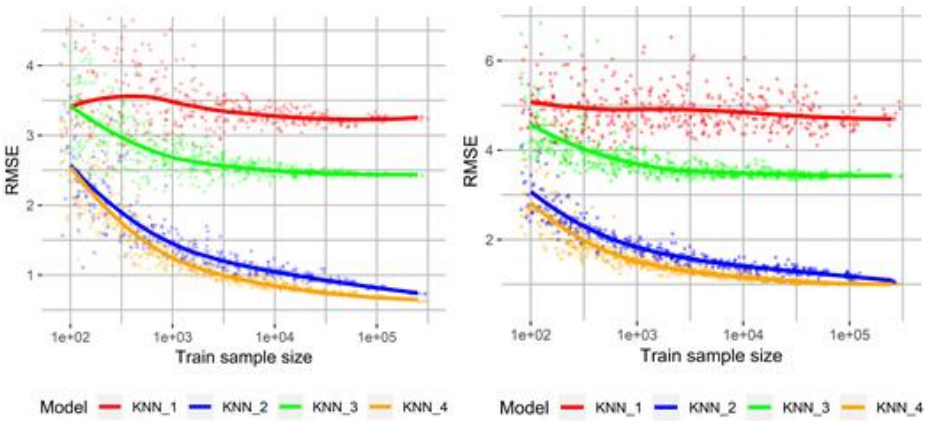

Fig. 5. KNN models comparison for increasing training sample size: left) mean cross-validation RMSE; right) mean RMSE for all 5 test samples. Scores smoothed by using LOESS.

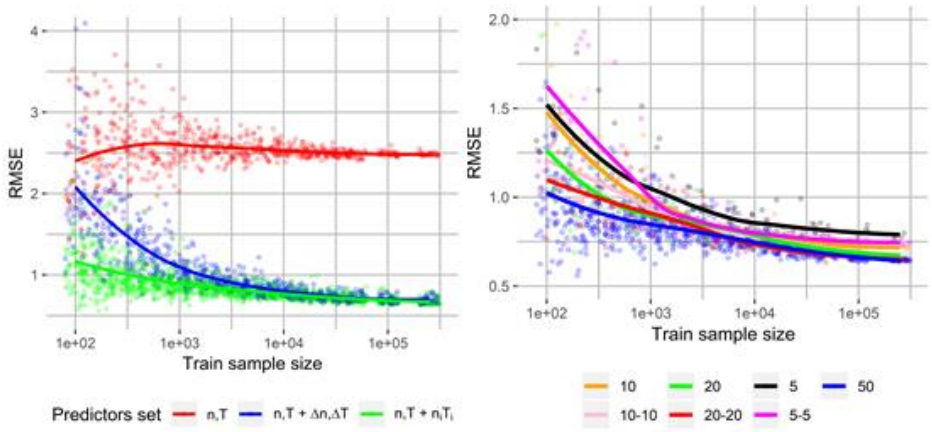

Fig. 6. ANN models comparison: left) mean cross-validation RMSE for 3 sets of predictors; right) mean cross-validation RMSE for best set of predictors (Set 3) for different configuration of hidden layers. Scores smoothed by using LOESS.

7 Models' validation by using 5 test samples

In previous sections three algorithms for diesel engine fuel consumption model were described. They were polynomial regression, K-Nearest Neighbors and Artificial Neural Networks. For each of the algorithms a model with optimal parameters was selected, according to the lowest RMSE values. In this section a validation of these three models is presented by using 5 test samples described in section 2. Each model was trained 30 times on a random sample of the given size and for each test sample the fuel consumption was predicted. Two measures of model accuracy were used: RMSE and the Absolute Relative Error (ARE). The ARE is a percentage difference between real total fuel used and predicted total fuel used in a given test sample. While RMSE assesses the goodness of the model fit, the ARE focuses on the engineering application of the model. The results are presented in Fig. 7, where mean values are represented by the lines and the shaded areas shows the ± standard deviation.

8 Discussion

The test samples have significantly different distribution of observations compering to the training samples. Moreover, each of the test samples cover distinctive operating areas of the engine. Thus, in order to assess the accuracy of the model, each test sample should be considered separately. It is possible that a particular model fits the data well, due to the similar distribution of observations both in the train and the test sample X. At the same time, the fit is rather poor in the test sample Y, which has a different distribution. The best algorithm (ANN, KNN or PRM) should deliver a good fuel consumption prediction, despite the test sample distribution. It should also represent the whole operating area of the engine (n-T domain) with satisfactory accuracy. Con-

sidering RMSE values, ANN and KNN clearly outperform the more traditional method PRM in every test sample. Although the scores are similar for both methods ANN and KNN for large sample sizes, the KNN performs significantly worse than the ANN for smaller sample sizes. The ANN model appears to be relatively insensitive to trainset size, e.g. in test sample 1 the RMSE slightly decreased from 1.1 to 0.8, while for the KNN model it started of with a RMSE value of 3.2 for sample size equal 100 and decreased to 0.9. There is no improvement for the PRM model when the trainset size exceeds 1000 observations and the RMSE is several times higher than in other models, however the standard deviation decreases. Although the RMSE values vary in every test sample, the ANN model appears to be the best model in each of them.

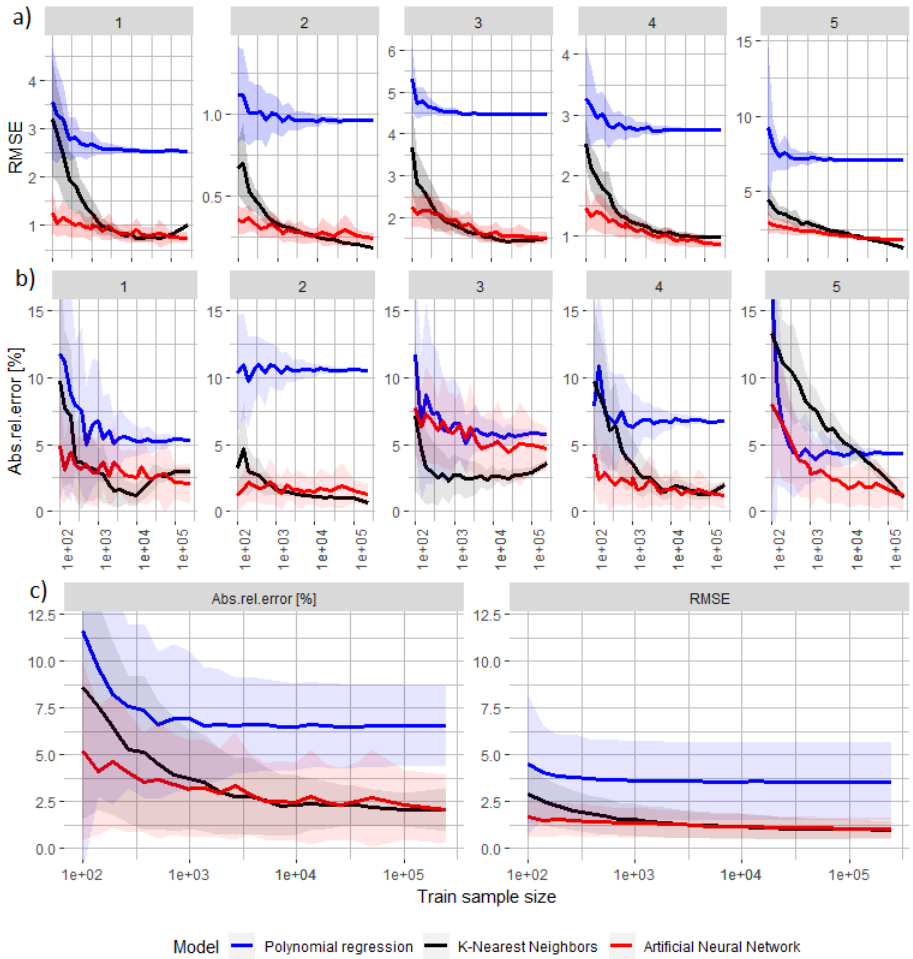

Fig. 7. Comparison between the models: ANN (red), KNN (black) and polynomial regression (blue): a) Mean RMSE for each test sample; b) Absolute Relative Error for each test sample; c) mean values of RMSE and Absolute Relative Error for all test samples. Shaded areas represent ± standard deviation

The Absolute Relative Error allows comparing models in terms of the final result of fuel consumption prediction. Even if a particular model does not fit well to each of the observation (high RMSE), the total amount of fuel predicted in the test sample may be close to the real value. In other words, for some points the model predicts higher G_e, and for other points lower values of G_e. Then, the differences are neutralized when the total fuel consumption is calculated. Values of ARE below 5% are considered as satisfactory from the perspective of engineering application.

In test sample 1,2 and 4 the ANN model fulfills the above criterion regardless of trainset size. In samples 3 and 5 more than 5000 and 500 data samples are needed, respectively. The KNN model performs worse and is highly sensitive to the trainset size. This is more evident in sample 5, where more than 10000 observations are needed to obtain a ARE score ARE below 5%. However, the KNN seems to be a reasonable model to apply when the training data set size is larger than 10000 observations. On the contrary, the PRM model performs poorly regardless of trainset size. It scores below 5% only in test sample 5. Thus, the application of polynomial regression, by using exploitation data, appears to be problematic in this case. This conventional method is computationally cheap and intuitive, because it can be displayed as a surface in 3D. However, its accuracy in fuel consumption modelling is unacceptable and an Artificial Neural Network model should be used instead.

Conclusions

Real exploitation data from a heavy duty vehicle was used in this paper to evaluate a model of fuel consumption in a diesel engine. Polynomial regression, which is a conventional method used for fuel consumption modeling for the engine operating in quasi-steady states, under performed in comparison with K-Nearest Neighbor and Artificial Neural Network models. Both the KNN and the ANN models were evaluated by using 8 variables instead of 2. This resulted in a high accuracy of the models and low values of Absolute Relative Error (<5%). The KNN model, as expected, appeared to be more sensitive to the size of the training sample than the ANN one. This study shows, that the Artificial Neural Network is a more robust algorithm for the modeling of fuel consumption in transient states of combustion engine operation. The K-Nearest Neighbor model present also satisfactory accuracy. On the contrary, the use of polynomial regression is not recommended due to the high Absolute Relative Error obtained in fuel consumption prediction (>6%).

The presented approach of using data logged via CAN bus of the vehicle in order to reconstruct the characteristics of the engine proved to be accurate and can be applied for fuel consumption modeling of heavy duty trucks. Such models may be used to optimize the design or configuration of the drivetrains and to allow a comparison between the trucks selected to performed similar tasks. Knowing beforehand the amount of fuel required to perform a given task for similar vehicles, can help to select the more efficient one. This is important and useful information for truck users, as it will allow them to make fuel savings while at the same time reducing the impact to the environment.

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