Neural Models for Benchmarking of Truck Driver Fuel Economy Performance

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Abstract: The transport industry is a primary contributor towards emissions that impact climate change. Fuel economy is also of critical importance to the profitability of road freight transport operators. Empirical evidence identified a variety of factors impacting fuel consumption, including route inclination, payload and truck driver behaviour. This creates the need for accurate fuel usage models and objective methods to distinguish the impact of drivers from other factors, in order to enable reliable driver performance assessment. We compiled a data set for 331 drivers completing 7332 trips over 21 routes to obtain evidence of the impact of route, payload and driver behaviour on fuel economy. We then extracted various regression and neural models for fuel economy and used these models to remove the impact of route inclination and payload, allowing the impact of driver performance to be measured more accurately. All models demonstrated significant out-of-sample predictive ability. Neural models in general outperformed regression models, while amongst neural models radial basis models slightly outperformed multi-layer perceptron models. The significance of compensating for factors not controlled by the driver was verified by demonstrating large differences in driver performance ranking before and after compensating for route inclination and payload.

1 INTRODUCTION

The contribution of the transport sector towards greenhouse gas emissions has been widely researched and is estimated at around 29% of all emissions caused by human activities (United States Environmental Protection Agency, 2019). While the contribution of passenger vehicles towards GHG emissions is expected to be gradually eliminated over the next few decades through a transition to electric vehicles and clean production of electricity, this transition will be more challenging for long haul freight trucks, due to the large distances covered by these vehicles. Heavy-duty vehicle GHG EPA regulations are projected to reduce CO_2 emissions by about 270 million metric tons over the life of vehicles built under the EPA program, saving about 530 million barrels of oil. The proposed program includes standards that would further reduce GHG emissions and improve the fuel efficiency of medium and heavy-duty trucks (United States Environmental Protection Agency, 2019).

While these efforts towards reducing the environmental impact of long haul trucks should be encouraged, road freight transport still remains an essential element of the global economy. This is specifically relevant in regions with limited availability of rail infrastructure (Hoffman, 2010); for example road transport is responsible for 76% of cargo movement in South Africa; this figure is even higher in other African countries (Havenga, 2013). Compared to the rest of the world the cost of transport in Africa is much higher as a fraction of the total cost of delivered goods - 18% compared to a global average of less than 10% (Anon., 2014). Fuel cost is the single biggest contributor to the cost of road transport operations, representing approximately 40% of operating costs (Naidoo, 2013). Fuel economy is therefore a critical element to be managed by road freight transport operators to ensure continued profitability in a very competitive industry.

Historical research in the field of fuel consumption modeling identified the primary factors that impact on consumption; this includes driver proficiency, payload and route inclinations (Weille, 1966) (Biggs, 1988) (Bennett and Greenwood, 1995). Much of the work in this field focused on the modeling of fuel consumption in terms of engine characteristics and driving style (Rakha and Wang, 2017) (Delgado, et al., 2011). Other studies applied a Big Data approach to large vehicle fleets, mostly driving on flat roads and at constant speeds (Perrottaa, et al., 2019) as well as the use of

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telematics solutions to improve fuel consumption (Hoffman and Van der Westhuizen, 2014).

The use of neural networks to model the fuel economy of trucks has been the topic of several research studies (Zhigang Xu, 2018) (Jian-Da Wu, 2012) (Elnaz Siami-Irdemoosa, 2015) (Hassanean S.H. Jassim, 2018). In all of these studies one of the objectives was to identify techniques that will provide the most accurate modeling of fuel economy in terms of the input factors mentioned above. While satisfactory results were achieved through the research efforts listed above, none of those studies tried to remove the contributions of factors not controlled by the driver, like route inclinations and payload, before assessing the performance of the driver. This is of critical importance, as the only factors that can be readily influenced to reduce emissions and fuel costs without negatively impacting the economic function fulfilled by transport is the behavior of the driver. Many road transporters offer schemes of incentives and penalties for fuel efficient driving behavior. This creates the need for an accurate and objective method to distinguish the impact of drivers from other factors, in order to enable fair and consistent driver performance evaluations.

In previous work we developed linear and nonlinear regression fuel economy models for long haul freight trucks using route inclination and payload as explanatory variables (Hoffman and Van der Westhuizen, 2019). We also used these models to evaluate driver fuel economy performance after compensating for factors not controlled by the driver (Hoffman and Van der Westhuizen, 2019). In the absence of such performance corrections, drivers are assessed by simply calculating their average fuel economy over all trips, completed over a variety of routes and carrying varying payloads. This may lead to inaccurate outcomes as not all drivers are employed on identical sets of routes driving trucks carrying identical payloads. The primary purpose of this paper is to improve on the modelling abilities of regression models by employing various neural network architectures. In this study we included radial basis networks and multilayer perceptron networks.

Based on available evidence we state the hypothesis that the presence of factors not under the control of the truck driver, like route inclinations and payload differences, will significantly impact the performance outcomes for truck drivers if not properly compensated for. In order to prove our hypothesis, we will extract regression and neural models to quantify the impact on fuel economy of factors not controlled by drivers. These models will then be used to remove the impact of such factors in order to arrive at a residual fuel economy from which the impact of route and payload has been removed and that is mainly determined by driver performance. This is expected to produce a performance measure that is more reliable than a simple average of the original fuel economy over all driver trips and that can be used to assess driver performance more objectively.

We then compare the performance of drivers prior to model correction with driver performance after applying such correction. For this purpose, we defined two measures of driver performance: the first is whether the driver performed above or below the average performance measured over all drivers; the second is the ranking achieved by each driver when sorting the performance of all drivers from best to worst. In addition, we also investigate the extent to which driver identity and driver behaviour can be used to model the above residual fuel economy. In each case the abilities of the different modelling techniques will be compared in terms of their out-of-sample abilities to correctly predict fuel economy and residual fuel economy.

The rest of the paper is structured as follows: section 2 describes the process to collect a representative set of fuel consumption data, and describes the different routes that were covered by the available data set. In section 3 we extract statistical measures of fuel economy for the population as well as per route and driver to provide evidence of the need for a driver performance model. Section 4 focuses on the extraction of empirical models that will allow us to isolate the impact of the driver on fuel consumption. In section 5 we estimate the impact of model compensation on driver performance measurement. In section 6 we conclude and make recommendations for future research work.

2 COLLECTION OF FUEL CONSUMPTION AND INPUT FACTOR DATA

The purpose of our fuel usage data collection exercise was to ensure that we cover all the aspects to be investigated in this study. We collected data from a fleet of 468 vehicles that cover most of the major routes in Southern Africa, as displayed in Figure 1 below. This allowed us to generate a significant amount of statistics on routes that include widely ranging inclinations (e.g. relatively flat from Johannesburg to Cape Town versus uphill and downhill from Durban to Johannesburg and back where the Drakensberg mountain range has to be crossed). Data was collected over a period of two calendar years, which is important as the road transport industry tends to be cyclic.

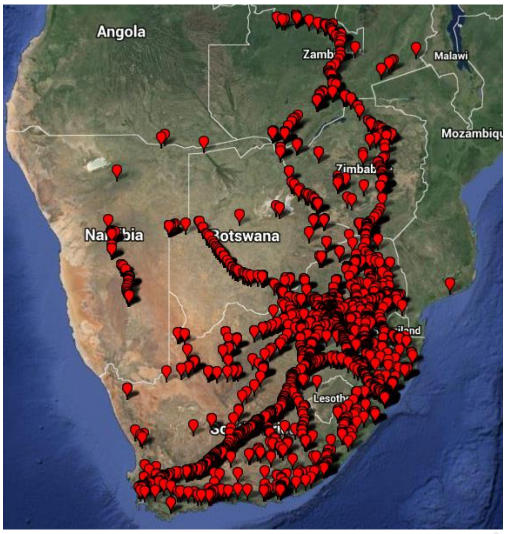

Figure 1: Trip start positions for all trips in the study.

To create a reliable set of fuel consumption performance benchmarks, we subdivided the data into subsets per major route that is covered. Different fuel performance levels can be expected to be achieved on different routes based on the number of expected stops, the likelihood of encountering congested traffic and the average incline. As the fleet of vehicles did not only cover a defined set of standard routes the major routes had to be derived from the GPS tracking data itself. This is discussed in more detail in the sections below.

The GPS tracking systems used by these vehicles collect fuel usage data via the CAN bus system. While fuel usage is measured continuously by way of a flow meter, most of the installed units of this system were configured to only store and communicate the aggregate consumption as from when the engine was switched on until it was switched off again; this is done mostly to save on communication costs. Due to the way that trucks are operated many trips last only a very short duration, e.g. where a vehicle is moved within a depot. As the fuel efficiency figures expressed as km/l would not be useful over such short distances and as the focus of this work is the fuel efficiency when trucks are driven over much longer distances, we filtered out all trips with a trip distance of shorter than 100 km.

To obtain confirmation of the impact of route specific factors, we subdivided the data into subsets per major route that is covered. In order to quantify the relationship between inclines and consumption, incline data was extracted from Google Maps by using the route descriptions as defined by the set of GPS coordinates representing each route (Gong, et al., 2014). The final determinant of fuel usage that was investigated is payload, as the load carried by a vessel is expected to have a major impact on its fuel usage over a specific route, specifically for routes that include steep inclines. Payload data was collected from trip records and weighbridge measurements before departure from origin.

3 EXTRACTING STATISTICS FOR ROUTE AND DRIVER FUEL ECONOMY

The statistics for the variables related to fuel economy measured across 7,332 observations are summarised in Figure 2 below, while the histograms for trip time, fuel economy and payload are displayed in Figure 2 below. It is clear that fuel economy displays large variations between trips, which motivates our efforts to quantify the contribution of each significant factor towards such variations.

Table 1: Trip statistics over all observations.

Statistic	Ave	Median	Std	Min	Max
TripTime (h)	2,87	2,91	1,08	0,83	6,59
Fuel Econ (km/l)	2,06	2,03	0,43	1,18	7,34
Payload (tons)	29,01	34,00	8,69	1,00	39,98
MaxSpeed (km/h)	85,29	85,00	1,74	75,00	98,00
Speeding Time	22,62	0,00	172,39	0,00	5 621
MaxBrake	5,28	5,00	1,59	2,00	27,00
Excessive BrakeTime	0,00	0,00	0,10	0,00	6,00
MaxAccel	2,74	3,00	0,74	2,00	24,00
Excessive AccelTime	0,01	0,00	0,36	0,00	25,00
MaxRPM	1930	1900	203	1500	7600
Excessive RPMTime	0,01	0,00	0,47	0,00	28,00
Excessive IdleTime	42,71	0,00	124,73	0,00	2 187
Standing Time (s)	447	311	444	15	1073
ElevGain (m)	1159	967	892	148	2746
ElevLost (m)	-969	-968	586	-1873	-163
MaxSlope asc	0,09	0,07	0,07	0,01	0,28
MaxSlope desc	-0,06	-0,07	0,05	-0,18	-0,01
AveSlope asc	0,01	0,01	0,01	0,00	0,04
AveSlope desc	-0,01	-0,01	0,01	-0,04	0,00
ElevGain (m/km)	6,63	4,45	4,84	0,79	21,74
ElevLost (m/km)	-5,68	-5,88	3,47	-22,33	-0,94

The available data included observations for 21 different routes, most of which were frequently driven over the relevant period by a set of 331 drivers. In order to investigate the impact of route characteristics and driver behaviour, the available data set was categorized per route. Figure 3 displays the number of trips available per route as well as the average fuel economy per route, sorted from highest to lowest. It can be seen that the average fuel economy per route varies by almost a factor of two from the least to the most fuel efficient. Figure 4 displays the histogram of average fuel economy per driver across all routes. For drivers the spread of averages is even wider than for routes; this may however partly be as a result of route inclination and payload variations.

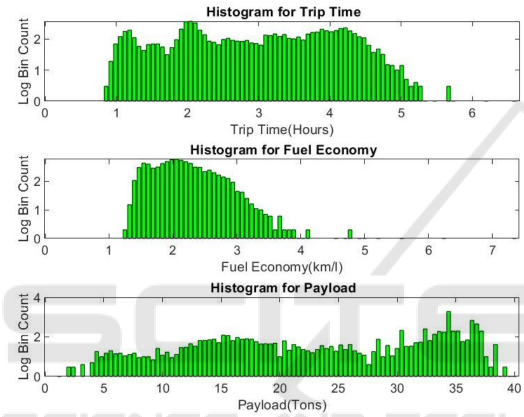

Figure 2: Histograms for trip times, fuel economy and payload.

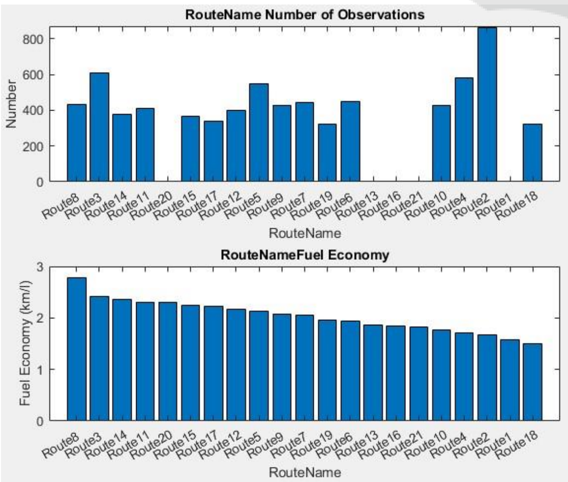

Figure 3: Number of trips and average fuel economy per route.

In Figure 5 we display the driver average fuel economy histograms for a few individual routes; it can be seen that within a specific route the variation in performance between drivers is not quite as big as across all routes. The driver variations within the same route are however sufficiently large to justify a more accurate comparison between drivers, aimed at quantifying the potential for fuel economy improvement, should all drivers perform at the same level.

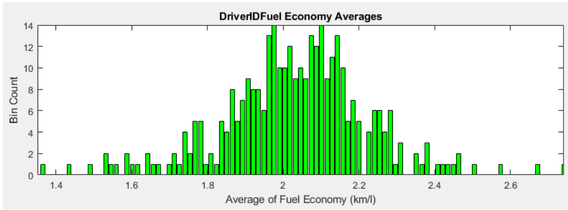

Figure 4: Histogram of average fuel economy per driver for all routes.

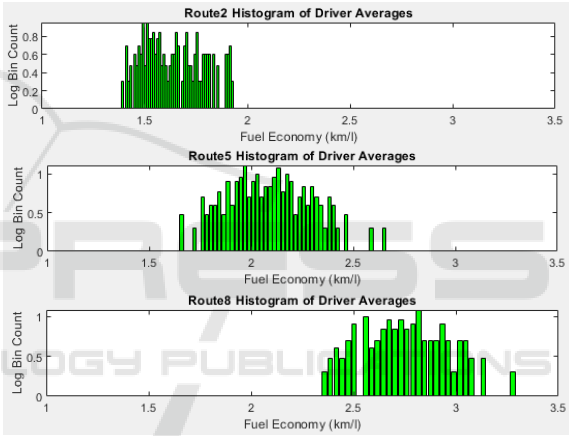

Figure 5: Histograms of average fuel economy per driver for individual routes.

4 EXTRACTING EMPIRICAL FUEL ECONOMY MODELS

In a previous article (Hoffman and Van der Westhuizen, 2019) we described the extraction of linear fuel economy regression models, as well as nonlinear regression models based on the following formula:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i}^{\beta_2} + \hat{\beta}_3 X_{2i}^{\beta_4} + \dots + \hat{\beta}_{2n-1} X_{ni}^{\beta_{2n}} \tag{1}$$

where

$\hat{Y}_i$ is the estimated fuel economy value for observation i

X_{ni} are the values of input variables for observation i

$\hat{\beta}_{0}$ - $\hat{\beta}_{2n}$ are the estimates of the population regression slopes and exponents as indicated above.

In this paper we expand this work by also extracting neural network models using identical input and target variables, and comparing the results produced by the different models. The first type of neural model is a generalized regression neural network (GRNN) that is a variation on radial basis function networks. The network architecture is illustrated in Figure 6 below.

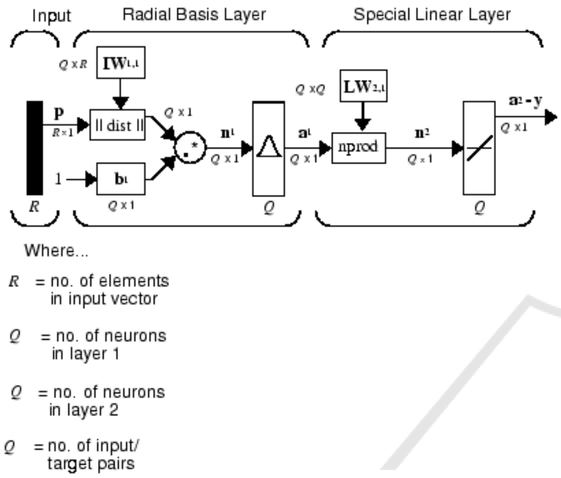

Figure 6: Architecture of the GRNN network.

This network uses a *spread* parameter to regularize the input-output relationship; the value of *spread* is the distance between the centre of a radial basis function and the points where its magnitude has decreased by a factor of 2. Larger values of *spread* therefore result in smoother input-ouput mappings. We experimented with GRNN models where the value of *spread* was allowed to vary between 1 and 2024 in steps by a factor of 2. The number of radial basis functions equalled the number of training observations.

The second type of neural network that was used is the multilayer perceptron, using a single hidden layer with sigmoid transfer functions and a linear output layer. In this case the number of hidden nodes is used to regularize the input-output mapping: larger numbers of hidden nodes provide more accurate fitting within the training set, but may lead to overfitting, resulting in lack of generalization ability in the test set, while a smaller number of hidden nodes will result in less good fits for the training set but more closely matching goodness of fit for the test set. In our case we allowed the number of hidden nodes to vary between 2 and 32.

We extracted models using all four modeling techniques (linear regression, nonlinear regression, GRNN and MLP NN) from the earliest 70% of all observations, and predicted fuel economy for the remaining 30% of observations. In order to compare our results with results from previous research, we first extracted models using driver, route and payload factors as inputs. Input factors were selected by ranking potential inputs based on absolute value of linear correlations between inputs and fuel economy. Table 2 provides the Pearson correlation coefficients between a list of available input factors and fuel economy. We only included input factors with a correlation coefficient of at least 0.1 with the model target. Once a ranked input factor has been selected, we only considered additional factors that had a correlation with already selected factors of less than 0.4, as the use of several higly correlated inputs results in unstable model parameters.

Table 2: Correlation coefficients between fuel economy and potential explanatory variables.

Inputs	Corr	Inputs	Corr
Max Speed	-0,133	Payload	-0,174
Speeding Time	-0,044	Elev Gain (m)	-0,627
Max Brake	0,018	Elev Lost (m)	0,465
Excessive Brake Time	-0,010	Max Slope Asc	-0,581
Excessive Accel Time	-0,016	Max Slope Desc	0,333
Max RPM	-0,378	Ave Slope Asc	-0,594
Excessive RPM Time	-0,014	Ave Slope Desc	0,443
Excessive Idle Time	0,026	Elev Gain (m/km)	-0,611
Standing Time	0,061	Elev Lost (m/km)	0,385

The list of model parameters selected on this basis included Elevtion Gain, Max RPM, Payload and Max Speed. Elevation Lost and some other factors were not selected based on their high correlations with Elevation Gain, that was selected first as it had the highest absolute correlation with fuel economy.

The regression coefficients for the linear and nonlinear regression models are displayed in Table 2 to Table 4 below. For the nonlinear regression models both the input factor coefficients and exponents are given; for the linear models the exponents are always 1 as indicated. It can be seen that the relationships between some inputs factors and fuel economy is significantly nonlinear, as some exponents deviate substantially from a value of 1.

Figure 7 and Figure 8 displays scatterplots of Target vs Output for the regression and neural models respectively. Based on the scatterplots the model fits for the test sets appear to be very similar to that for the training sets, which indicates that the models have good generalization capability. It can also be seen that the neural models provide a superior fit of output to target compared with the regression models, while the GR neural network seem to be slightly superior to the MLP network. These observations will be confirmed using correlation analysis.

Table 3: Regression coefficients for general fuel economy models.

Input Factor		Linear	Nonlinear
Constant		3,279	4,292
Max Speed	Coeff	0,006	0,007
	Exp	1,000	0,945
Max RPM	Coeff	-0,001	-0,001
	Exp	1,000	0,933
Payload	Coeff	-0,008	-0,101
	Exp	1,000	0,514
Elevation Gain	Coeff	0,000	-0,136
	Exp	1,000	0,348

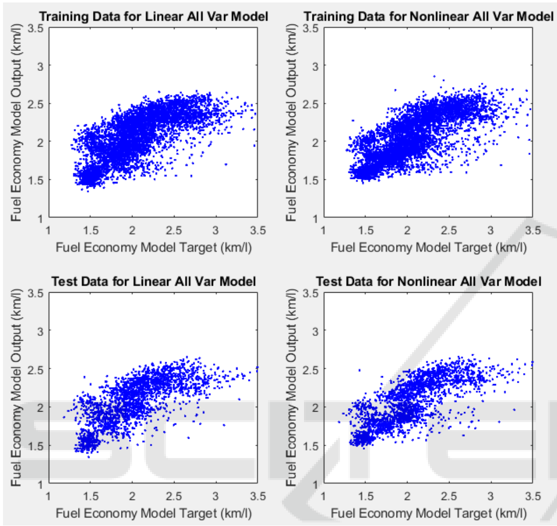

Figure 7: Scatterplots for linear and nonlinear regression Targets and Outputs.

More insight into nature of the various modelling techniques is obtained by constructing input-output graphs where one input is varied across its entire range of values, while the remaining variables are kept constant at their average values. As we created the outputs using artificial inputs values, it is not possible to display corresponding target values. We constructed such graphs for the four model types, and repeated this for different levels of regularization applied to the neural models to observe the impact of changing the *spread* parameter and the number of hidden nodes. In the Figure 9 and Figure 10 below we display the relationship between Elevation Gain as input and the modelled Fuel Economy as output for different levels of regularization applied to the neural models.

It can be seen that all models display a similar trend in the modelled relationship. When low levels of regularization are applied to the neural models, they tend to display extreme variations in the output, which is indicative of overfitting. When the level of regularization is increased, most of this behaviour disappears, and the relationships are much closer to those for the regression models. Similar results are obtained when using Payload as input variable, as displayed in Figure 11 and Figure 12.

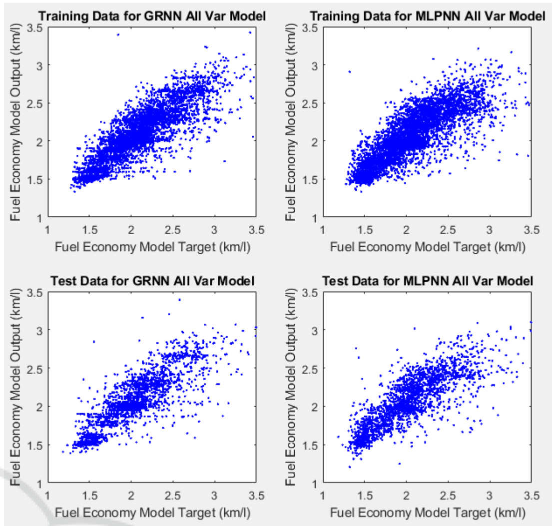

Figure 8: Scatterplots for GRNN and MLP neural network Targets and Outputs.

We subsequently extracted models that only used inputs not impacted by driver behaviour; regression coefficients for these models are displayed in Table 4 below. To assess driver impact on performance, we extracted both a driver behavioural model, that utilizes behavioural variables like Maximum RPM, Speeding Time and Maximum Speed as inputs (regression coefficients displayed in Table 5), as well as a driverID model, that uses driver identity as input.

To model the impact of driver identity we defined driver dummy variable inputs (one variable per driver that assumes the value of one when the respective driver is present and zero otherwise). A positive driver ID regression model coefficient indicates above average performance while a negative model coefficient indicates below average performance. We then proceeded to extract both driver models using the residuals of the route inclication and payload models as targets. For the driverID model we thus obtain regression model coefficients that provide a direct indication of driver performance, compensated for the impact of route and payload. Comparison between the two sets of driver ID model coefficients before and after correcting for non-driver factors will provide a clear indication of the impact of model correction.

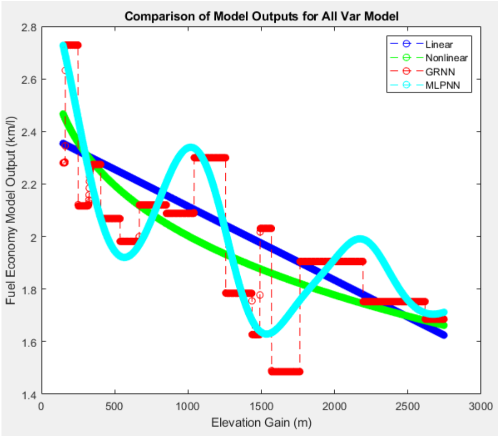

Figure 9: Elevation Gain vs Fuel Economy for all four model types, using low levels of regularization for neural models.

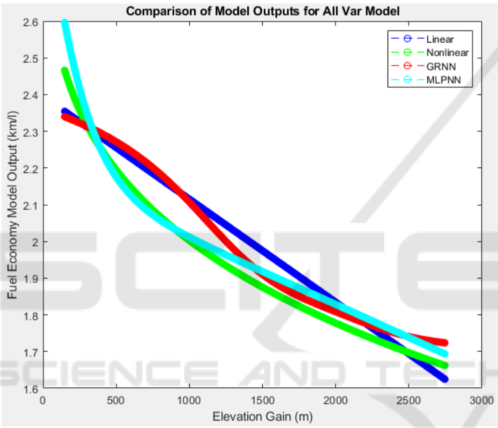

Figure 10: Elevation Gain vs Fuel Economy for all four model types, using high levels of regularization for neural models.

In order to evaluate model accuracy, we calculated the correlations between model outputs and target variables both for the training and test sets, as displayed in Table 6 to Table 9 below. It can be seen that the models that include driver, route and payload inputs have the biggest correlations between output and target, as would be expected. Most of the correlation obtained in the training set is retained in the test set, indicating that the observed relationships between fuel economy and the respective explanatory variables are strong and consistent. It can also be seen that the nonlinear regression models perform slightly superior to the linear regression models, while the neural models outperform the regression models, both for the general, the route & payload and the driver models. The driver behavioural model, that uses Max RPM, Max Brake and Max Speed as inputs, perform slightly better than the driver ID model, that uses driver identity as input.

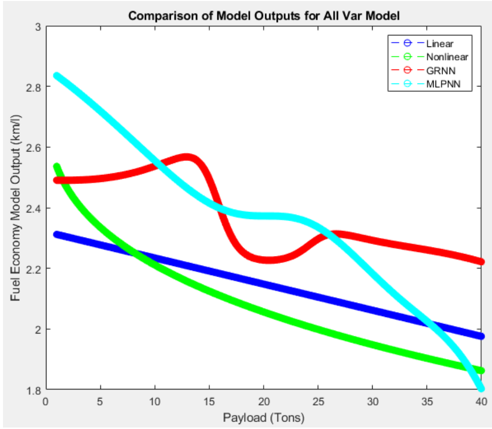

Figure 11: Payload vs Fuel Economy for all four model types, using low levels of regularization for neural models.

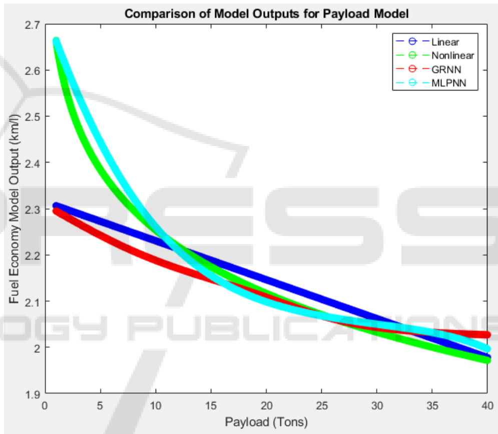

Figure 12: Payload vs Fuel Economy for all four model types, using high levels of regularization for neural models.

Table 4: Regression coefficients for route and payload models.

Input Factor		Linear	Nonlinear
Constant		2,707	4,540
Payload	Coeff	-0,012	-0,104
	Exp	1,000	0,568
Elevation Gain	Coeff	0,000	-0,407
	Exp	1,000	0,243

We investigated the consistency in driver performance over time by correlating both the uncompensated and compensated driver fuel economies between the training and test sets. In Table 10 below it can be seen that the consistency in driver performance is increased by compensating for the impact of route inclination and payload, as the correlation between training and test set performance is higher for compensated compared to uncompensated performance. This confirms that factors like route inclination and payload add variability to driver performance measures that is unrelated to actual driver performance. It is furthermore observed that, after also compensating for driver identify, the correlation of residual driver performance between the training and test sets is almost zero. This is to be expected as most of the driver impact is now present in the driver model output, with the remaining model residual fuel economy being mostly noise.

Table 5: Linear regression coefficients for driver fuel economy models (both uncompensated and compensated for route and payload factors).

Input Factor	Uncompensated	Compensated
Const	4,702	-0,205
Max Speed	-0,001	0,001
Max RPM	-0,012	-0,009
Max Brake	0,019	-0,014

Table 6: Correlation coefficients between fuel economy model outputs and targets for the training set.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
All Var	0,695	0,721	0,856	0,800
Route	0,627	0,660	0,740	0,735
Payload	0,174	0,184	0,221	0,257
Route&Payload	0,671	0,705	0,814	0,783
DriverBeh	0,381	0,381	0,392	0,400
DriverID	0,357	-	0,300	0,327

Table 7: Correlation coefficients between fuel economy model outputs and targets for the test set.

Inputs	LinRegr	NonLinRe	GRNN	MLPNN
All Var	0,592	0,655	0,763	0,741
Route	0,607	0,636	0,710	0,706
Payload	0,180	0,202	0,240	0,282
Route&Payload	0,640	0,678	0,768	0,744
DriverBeh	0,139	0,159	0,315	0,341
DriverID	0,121	-	0,127	0,148

Table 8: Training set correlation coefficients between outputs and targets for models trained on the route and payload residual fuel economy.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
DriverBeh	0,263	0,262	0,271	0,277
DriverID	0,435	0,067	0,368	0,414

Table 9: Test set correlation coefficients between outputs and targets for models trained on the route & payload residual fuel economy.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
DriverBeh	0,024	0,044	0,173	0,200
DriverID	0,134	0,033	0,112	0,131

Table 10: Correlations between driver fuel economy performance measured over the training and test sets.

Fuel Economy Measure	Train vs Test Corr
Uncompensated	0,292
Route&Cargo Compensated	0,326
Driver,Route&Cargo Compensated	0,012

5 ESTIMATING MODEL COMPENSATION IMPACT ON DRIVER PERFORMANCE MEASUREMENTS

One of our stated objectives is to measure driver performance more consistently by compensating for those factors over which the driver has no control. We therefore calculated a compensated fuel economy figure for each trip by subtracting the route & cargo fuel economy model output from the original fuel economy, and then adding the population average fuel economy to this residual to obtain a fuel economy figure that is mostly attributed to driver behaviour:

$$\begin{aligned} &Driver\ fuel\ economy = Original\ fuel\ economy - \\ &Route\&Cargo\ model\ output + \ Population\ average \end{aligned} \quad (2)$$

We expect variations in driving performance to be reduced after compensating for the impact of route and payload. To verify if this is the case we calculated the standard deviation of uncompensated driver fuel economy averages over all drivers, and obtained a figure of 0.192 km/l. The compensated driver fuel economy in equation 2 above was used to calculate compensated driver averages. The standard deviation of compensated driver averages was then calculated as 0.158 km/l, which is indeed somewhat lower than the figure before compensation.

Figure 13 displays histograms of the compensated fuel economy using both the linear and nonlinear route and payload models. When compared against the uncompensated histogram the distributions have clearly changed. In Figure 14 we compare uncompensated versus route and cargo compensated fuel economy histograms for a sample of drivers. The change in distribution is clearly visible; in cases where the average did not change much, as for driver 923, the spread became narrower as expected, due to removal of the impact of varying route inclinations and payloads.

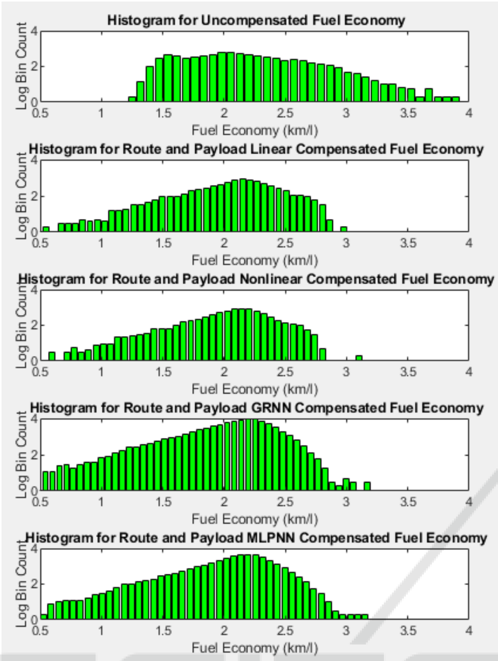

Figure 13: Histograms for route and cargo compensated fuel economy.

To investigate the relationships between uncompensated and compensated driver performance measures, we calculated correlations between driver fuel economy averages and the linear regression model coefficients of the Driver ID based models. Table 11 below displays the correlations between the coefficients of both the uncompensated and route & payload compensated Driver ID models, versus the uncompensated and compensated fuel economies, as observed over both the training and test sets. The correlation between the uncompensated fuel economy and uncompensated driver ID model coefficients is almost 1 for the training set as expected, as the model coefficients were extracted from this data. For the test set it is still significantly positive, confirming that driver ID explains a significant fraction of observed fuel economy. We also observe a large positive correlation between the compensated driver ID model coefficients and compensated fuel economy over the training set.

In contrast the correlations between the route compensated Driver ID model coefficients and uncompensated fuel economy are negative for both the training and test sets; this indicates significant differences between driver performance before and after eliminating the impact of route inclination and payload. It is confirmed by the fact that the route & payload compensated fuel economy is also negatively correlated with the uncompensated Driver ID model coefficients for both the training and test sets. The correlation of -0.729 between driver ID regression coefficients before and after compensation confirms how drastically driver performance assessment is changed by the model correction. This is a very important result, as it provides evidence for the acceptance of our hypothesis that driver performance measures are drastically impacted by the presence of factors that are not identical for all drivers and not within the driver's control.

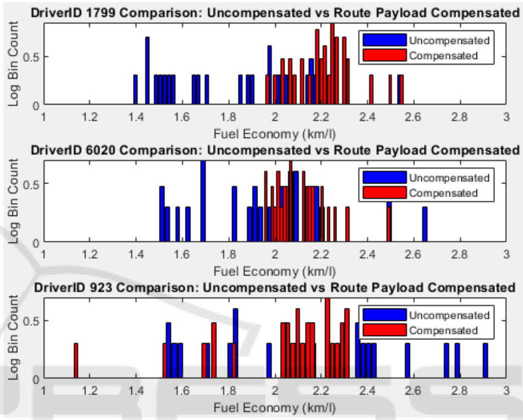

Figure 14: Comparison of uncompensated and route and cargo compensated fuel economy histograms for different drivers.

Table 11: Correlations between driver average fuel economy and Driver ID based model coefficients.

Driver Fuel Economy	Coeff Uncomp	Coeff Route Comp
Uncompensated Train	0,976	-0,594
Uncompensated Test	0,243	-0,066
Route & Payload Comp Train	-0,581	0,525
Route & Payload Comp Test	-0,124	0,082
Driver & Route Comp Train	0,014	0,000
Driver & Route Comp Test	-0,383	0,536
DriverID Coeff Route Comp	-0,729	1

As a further confirmation of these results we calculate correlations between average driver fuel economy performance before and after compensation. Table 12 indicates that driver performance before and after route and payload compensation is negatively correlated. The fact that this is almost equally strong for the training and test sets provides evidence that it is not as a result of model overfitting. We furthermore observe that when also removing the impact of driver ID the remaining correlation for the training set is almost zero, as the remaining model error will now have little resemblance to the original fuel economy. A small positive correlation remains for the test set as the models could not capture all variations present in the data; this is also to be expected as not all factors impacting fuel economy are present in the model (e.g. wind speed and traffic conditions).

Table 12: Correlations between compensated and uncompensated driver fuel economy performance.

Variable	Train	Test
Route&Cargo Compensated	-0,598	-0,554
Driver,Route&Cargo Compensated	0,007	0,240

To quantify the degree to which driver performance measures are impacted by model compensation we calculated each driver's ranking compared to other drivers, firstly based on uncompensated and secondly based on compensated performance averages. For each driver the difference in ranking position was determined before and after model compensation; this change in ranking was normalized by division through the total number of drivers. The average absolute change in ranking differences was then calculated over all drivers to obtain an overall figure of the degree to which ranking was impacted by performance compensation, as indicated in equation 3 below:

$$\text{Ave Relative Ranking Change} = \sum_{k=1}^{N} \text{Abs(Ranking Change)}_k / N \quad (3)$$

where N is the total number of drivers.

For random changes to all driver rankings this figure will be 0.5; for no ranking changes it will be zero. To verify the consistency in driver performance over time, we first calculated the relative change in ranking between the training and test sets for both the uncompensated and compensated fuel economies. We obtained a relative ranking change of 0.27; this indicates that performance does change over time, but that it is not entirely random, with some level of consistency. We then proceeded to compare the ranking of driver performances between the case with no compensation and the case after model compensation. Table 13 and Table 14 displays the relative ranking changes for different compensation models for the training and test sets. It can be seen that the change in driver ranking before and after compensation is bigger than the difference of 0.27 observed between the training and test sets; this indicates that, over and above changes in performance over time, the model based compensation results in a significant difference in driver ranking.

Table 13: Average relative change in driver performance ranking before and after compensation for the training set.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
All Var	0,468	0,468	0,447	0,456
Route	0,477	0,469	0,465	0,466
Payload	0,493	0,489	0,495	0,494
Route&Payload	0,479	0,471	0,472	0,473
DriverBeh	0,460	0,459	0,482	0,458
DriverID	0,343	0,494	0,500	0,411

Table 14: Average relative change in driver performance ranking before and after compensation for the test set.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
All Var	0,471	0,468	0,462	0,462
Route	0,483	0,472	0,471	0,467
Payload	0,493	0,486	0,493	0,493
Route&Payload	0,482	0,464	0,473	0,475
DriverBeh	0,470	0,467	0,477	0,472
DriverID	0,414	0,495	0,499	0,445

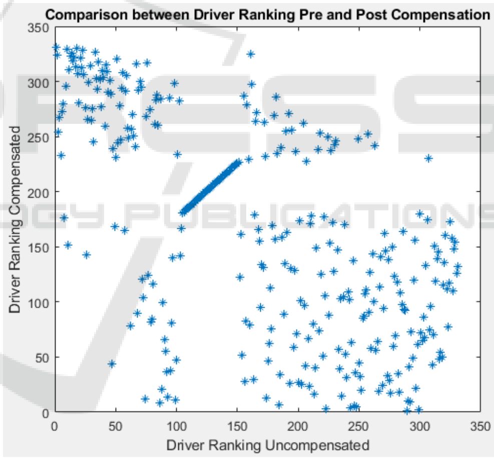

Figure 15: Comparison between driver ranking before and after compensating for route and cargo.

These results are confirmed by the scatterplot of driver rankings before and after compensation as displayed in Figure 15. The series of drivers that seem to have retained the same ranking before and after (straight line in the middle of the graph) are drivers with no trips in the test set and to whom we allocated average performance; they therefore assumed sequential positions in the ranking list.

As a last measure of the impact of model compensation we calculated the fraction of drivers for whom performance relative to the population average changed from positive to negative or vice versa after compensation. If performance before and after model compensation is unrelated (e.g. random performance changes) the total fraction of changes should be 0.5. Table 15 displays the fraction of drivers with reversed relative performance. We observe that for the route & cargo model compensations the relative changes are the biggest. For the driver models the fraction of changes approach 0.5, because the residues from these models are largely unrelated to driver identity and would therefore appear to be random.

To compare the impact of the different models on driver performance after correction, we calculated the differences in average relative change in ranking between the models. The comparison matrix in Table 16 provides evidence that all the models largely agree in terms of the required changes in driver ranking, as these differences are fairly close to zero (in those cases where a model was compared against itself a result of exactly zero was obtained). Lastly we performed a similar comparison between route models and payload models that used the same modelling technique; these results appear in Table 17. The differences are slightly larger than in the previous case, as payload represents a smaller fraction of fuel economy changes compared to route inclination and is therefore less effective when used on its own.

Table 15: Fraction of drivers with reverse in relative performance before and after compensation.

Inputs	LinRegr	NonLinR	GRNN	MLPNN
All Var	0,565	0,565	0,529	0,511
Route	0,577	0,565	0,544	0,532
Payload	0,601	0,592	0,592	0,583
Route&Payload	0,577	0,583	0,544	0,571
DriverBeh	0,565	0,553	0,577	0,562
DriverID	0,363	0,607	0,598	0,447

Table 16: Difference in average relative change in driver performance ranking after compensation between on different route and payload models.

Model Type	LinRegr	NonLinR	GRNN	MLPNN
LinRegress	0,000	0,070	0,091	0,078
NonLinRegr	0,070	0,000	0,109	0,095
GRNN	0,091	0,109	0,000	0,059
MLPNN	0,078	0,095	0,059	0,000

Table 17: Difference in average relative change in driver performance ranking after compensation based on different route vs payload models.

LinRegress	0,082
NonLinRegress	0,123
GRNN	0,100
MLPNN	0,121

6 CONCLUSIONS AND FUTURE WORK

In this paper we derived models for truck fuel economy using four different modelling techniques. We proved that neural models outperform linear and nonlinear regression models, regardless of the set of input factors that are used, and that both radial basis and MLP networks produced satisfactory results. We also demonstrated that selecting the width of the radial basis functions or the number of hidden layer nodes can be used to obtain the required level of accuracy and generalization ability.

The point of departure of our research was a hypothesis that factors beyond the control of a truck driver has a significant impact on fuel economy performance measures. The results reported in this paper provides conclusive evidence that the hypothesis can be accepted. Firstly, we found that factors like route inclination and payload explain a significant fraction of total observed fuel economy deviations. Secondly we observed that variations between averages of driver performance are reduced after compensating for route and payload. Thirdly we found that there is more consistency between driver performance in the training and test sets after compensating for route and payload than before. In the fourth place we proved that average driver performance measured before and after compensating for route and payload are negatively correlated. In the fifth place we observed large changes in driver performance ranking after compensation, and lastly we found that the fuel economy performance of the majority of drivers, relative to the population average, changes in sign after compensating for route and payload.

The default measure currently used for driver fuel performance is the observed average over all completed trips. The new performance measure that we propose, to replace the default measure of average over all completed trips, is to use the residual of the model that predicts fuel economy in terms of route inclinations and payload. The population average for fuel economy is then added to this residual to obtain a realistic fuel economy figure for each driver.

Future work will involve the inclusion of additional input factors not related to driver behaviour, like wind speed and traffic conditions, as factors to be compensated for, as well as the use of more sophisticated neural network techniques, e.g. using clustering techniques to determine the optimal number of radial basis functions.

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