Neural models to implement environmentally friendly best fleet management practices

Alwyn J. Hoffman [1][0000-0003-4909-1073] and Schalk Rabé[1]

[1]School of Electrical, Electronic and Computer Engineering, North-West University, Potchefstroom, South Africa

alwyn.hoffman@nwu.ac.za

Abstract. Fuel cost is of critical importance to the profitability of road transport operators. In addition, the transport industry is a primary contributor towards harmful emissions. Earlier studies identified fuel economy as an important contributor towards fuel cost and found that truck driver behaviour is an important determinant for this phenomenon. We used a representative data set to extract regression and neural models for fuel economy and used these models to remove the impact of factors not controlled by the driver, allowing us to measure driver performance more accurately. All models extracted demonstrated significant out-of-sample predictive ability. Neural models for fuel economy outperformed regression models. We verified the significance of compensating for factors not controlled by the driver by demonstrating large differences in driver fuel economy ranking before and after compensating for route inclination and payload.

Keywords: Green Transport Corridors, Fuel economy, Truck Driver, Performance Benchmarking, Generalized Regression Neural Network, Multilayer Perceptron.

1 Introduction

Road freight transport is an essential element of the global economy. This is specifically relevant in regions with limited availability of rail infrastructure [1]; for example, road transport is responsible for 76% of cargo movement in South Africa; this figure is even higher in other African countries [2]. 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% [3]. Fuel cost is the single biggest contributor to the cost of road transport operations, representing approximately 25-50% of operating costs [4] [5] [6]. Fuel economy is therefore a critical element to be managed by road freight transport operators to ensure continued profitability in a very competitive industry.

The contribution of the transport sector towards greenhouse gas emissions in the US has been widely researched and is estimated at around 29% of all emissions caused by human activities [7]. As of 2010 the global transportation sector accounts for 14.3% of total GHG emission [8]. The transition to clean energy will be 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 [8].

Before proceeding with the main topic of this paper, namely the development of a model to accurately measure the contribution of driving behaviour to truck fuel economy, we will provide some background on the broader topic of Green Transport Corridors.

2 Green transport corridors

Green Transport Corridors (GTC) has been coined by the European Union as being "sustainable logistics solutions for cargo transportation with a shared pool of resources aiming for multimodal trans-shipment routes with a concentration of freight traffic between significant hubs" [9]. After the revision of the EU Transport White paper in 2006, the concept of green corridors was introduced as an initiative of the European Commission, in the Freight Transport Logistics Action Plan [13]. Important stakeholders of green transport corridors are logistics hubs comprising ports and logistic centres, logistic forwarders as well as political institutions on several levels [12].

The relevance of Green Transport Corridors stems from the fact that environmental pollution caused by international trade is becoming more severe with the expansion of global trade and continuous economic growth. According to the "Pollution Haven" hypothesis, the development of trade liberalization in different countries will cause developed countries to lose competitiveness in polluting industries due to strict environmental control. In contrast, developing countries will occupy a larger market share in these industries due to the reduction of environmental control [10]. When environmental regulation is more stringent, international trade can thus improve the welfare of the whole society and eliminate the negative impact on the environment

Different aspects of green transportation have been studied in order to design sustainable and environmentally friendly multi-modal transport solutions. The green transport corridor concept is aimed at the development and implementation of integrated and sustainable transport solutions, based on trans-shipment routes with concentration of freight traffic over long distances between major hubs, and characterised by reduced environmental and climate impact. Common topics recognised by all green corridor initiatives include co-modality, which enables the choice of environmentally friendly transport along the transport route, as reduced emissions are one of the obvious objectives of a greener transportation [11].

When discussing the impact of transport infrastructure on the environment, existing research mainly focus on a single mode of transport and pays little attention to multi-modal transport mode composed of multiple traffic tools. Multimodal transportation may fully use the benefits of diverse traffic technologies to create a transportation system that is low on energy, low on pollution and high on efficiency. Important properties of green corridors are trans-nationality, multi-modality, public – private partnerships and multi – level stakeholder structures requiring new governance models to safeguard efficient management, sustainable corridor development and strong alignment of transport policies at various administrative levels [12]. The implications for Africa of these factors impacting green transport corridors can be summarised as follows:

- Trans-nationality: Most African transport corridors are inherently multi- or trans-national in nature, as they link land-locked countries and regions to regional ports. Examples include the Djibouti-Addis Ababa corridor linking Ethiopia to the port of Djibouti, the Northern Corridor linking Uganda and Rwanda to the port of Mombasa, the Dar es Salaam corridor linking Burundi, Zambia and the Eastern DRC to the port of Dar es Salaam, and Beira corridor linking Zimbabwe and Malawi to the port of Beira. Measures that are implemented to make these corridors greener will need the support of all countries served by the corridors. This implies a need for the harmonization of regulations between all countries linked to the corridor, not only regarding matters like load control but also regarding environmental regulations.
- Multi-modality: To optimize the environmental friendliness of transport corridors, it is necessary to choose the transport mode that is the most environmentally friendly for the type of cargo and the distances over which it is transported. For the maritime leg it requires comparative analysis between the different shipping lines serving the same routes, to allow clients to select service providers not only based on cost or transport time but also based on environmental criteria. For the land-based leg it is essential to expand the role of rail vs road, as it is widely known that rail is a more environmentally friendly mode of transport compared to road for bulk cargo like coal. Due to the demise of most rail operations on the African continents, around 80% of cargo is however transported by road; this not only reduces the lifetime of the road infrastructure but also add to the carbon footprint of the African transport industry.
- Public – private partnerships: Due to legacy reasons many elements of transport corridors on the African continent are operated by state-owned monopolies. This is associated by low levels of productivity and lack of options from which cargo owners from the private sector can choose. An approach that can find a balance between public and private sector involvement is that of public – private partnerships, which have already found a foothold on the African continent in the form of concessions given to the private sector to operate ports, rail and road networks. A new criterion for the formation of such partnerships should be the environmental criteria to be satisfied by the respective operations, measured against international standards aimed at the reduction of greenhouse gas emissions.
- Multi – level stakeholder structures: Transport corridors involve stakeholders at multiple levels, from local operators serving short term routes and markets, to multi-national operators, individual governments and regional bodies like SADC, EAC and COMESA. The objectives of green transport corridors can only be achieved if environmental objectives are integrated into the long-term goals and strategies of these bodies, and if the deployment of green transport concepts can benefit from international donor funding. While strategic level decisions about environmental objectives can be made at regional level, practical differences will only be observed once the consequences have trickled down to grass-roots level, by incentivising large and small role players to operate in more environmentally friendly manners. Regional and governmental structures must therefore actively liaise with industry associations at local level to promote

environmental objectives and to explain new criteria that are enforced, as well as the associated incentives awarded to compliant operators.

- New governance models: The issue of good governance has always presented challenges on the African continent. Objectives and strategies that on the surface appear to require substantial costs without immediate benefits may be difficult to promote and enforce if there is no transparency in the way that compliance is measured, and credits are awarded. Enforcement of environmental compliance will require a combined carrot-and-stick approach, where practical compliance levels are accurately measured through the collection of field data, where non-compliant operators are held accountable, e.g. by withholding of permit to operate cross-border, and where there is a clear link between the level of compliance and the incentives that are awarded, both to private operators and public sector officials.

Recent studies considered the impact of the heterogeneity of factor endowments in different cities on green development and found that operating multi-modal corridors between economic regions can improve regional green economic efficiency (GEE). The impact mechanism test showed that promoting regional innovation and reducing urban energy intensity are two effective ways for multi-modal corridors to improve regional GEE [14].

Against this background the further sections of this paper will study the fuel efficiency of long-haul trucking operations as an important element of green transport corridors. More specifically we will illustrate how the environmental and economic impact of truck driver behaviour can be accurately measured, aimed at incentivising fuel efficient driving behaviour.

3 Modelling truck and driver fuel economy

Driver proficiency, payload and route inclinations are known to be the primary factors that influence truck fuel consumption [15] [16] [17]. Engine characteristics and driving style have also been found to play a major role [18] [19]. Another study applied a Big Data approach to large vehicle fleets driving on flat roads and at constant speeds [20], while further research investigated the use of telematics solutions to improve truck fuel consumption [21].

Various historical studies applied neural networks to model the fuel economy of trucks with the aim to find the most accurate for fuel economy in terms of the input factors mentioned above [22] [23] [24] [25]. A critical aspect that has been overlooked is to accurately quantify the contribution of the driver. The behavior of the driver is the only factor that can be readily influenced to reduce emissions and fuel costs without negatively impacting the economic function fulfilled by transport. This will however only be possible if the impact of factors like route inclinations and payload are removed before assessing the performance of the driver.

To achieve the objective of accurate driver assessment, we will re-use the linear and nonlinear regression and neural techniques that model fuel economy for long haul freight trucks in terms of route inclination, payload and driver identity [26]. We will use these models to evaluate driver fuel economy performance after compensating for factors not controlled by the driver [26].

The focus of this work is to investigate the hypothesis that the presence of factors not under the control of the truck driver, like route inclinations and payload differences, significantly influence the performance outcomes for truck drivers if not properly compensated for. To test this hypothesis, we use regression and neural models that quantify the impact on fuel economy of factors not controlled by drivers, to remove the impact of such factors in order to arrive at a residual fuel economy that is mainly determined by driver behavior. This approach should produce more reliable driver performance measures than simple averages of performance over all driver trips and should therefore enable objective assessment of driver performance.

The rest of the paper is structured as follows: the collection of a representative set of fuel consumption data and the different routes that were covered by the available data set is described in section 4. Statistical measures of fuel economy for the population as well as per route and driver are extracted in section 5, to provide evidence of the need for a driver performance model. The extraction of empirical models that will allow the isolation of the impact of the driver on fuel consumption is covered in section 6**Error! Reference source not found.**. Section 7 estimates the impact of model compensation on driver performance measurement. In section 8 we conclude and make recommendations for future research work.

4 Collection of fuel consumption and input factor data

In order to develop reliable models it is necessary to generate representative fuel usage statistics on routes that include widely ranging inclinations. For this purpose, we collected data over a period of two calendar years from a fleet of 468 vehicles that cover most of the major routes in Southern Africa, as displayed in Figure 1 below.

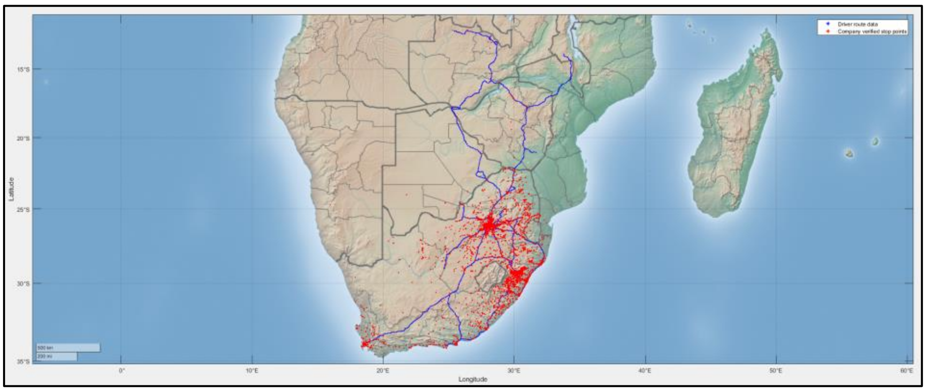

Figure 1GPS crumb trail data of a typical truck from the data set

We identified categorical variables that have been proven to influence fuel economy (including driver ID and route) and categorized the data according to these variables. The collected data included GPS location, time and date and the total amount of fuel used by the engine for the duration of a trip (defined as from switch on to switch off). We filtered out all trips with a trip distance of shorter than 100 km as very short trips have much lower fuel economy (measured in km/l) compared to the long haul trips that is the focus of this study. The dataset furthermore included the payload per trip.

To identify occurrences of fuel theft we calculated the discrepancies between the amounts dispensed after each trip compared to the amounts of consumed fuel according to the on-board computer of the trucks for the same calendar period. As trucks were not always fully refuelled, it resulted in some invalid comparisons; we therefore removed those observations where significant negative discrepancy values were obtained.

https://www.sciencedirect.com/science/article/pii/S2210539522001298

https://journals.sagepub.com/doi/10.3141/2478-13?icid=int.sj-abstract.similar-articles.3

5 Extracting statistics for route and driver fuel economy

The statistics for the variables related to fuel economy measured across 7,332 observations were described in detail in earlier work [26]; we will only repeat the most important results in this paper. 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 2 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 3 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 because of route inclination and payload variations.

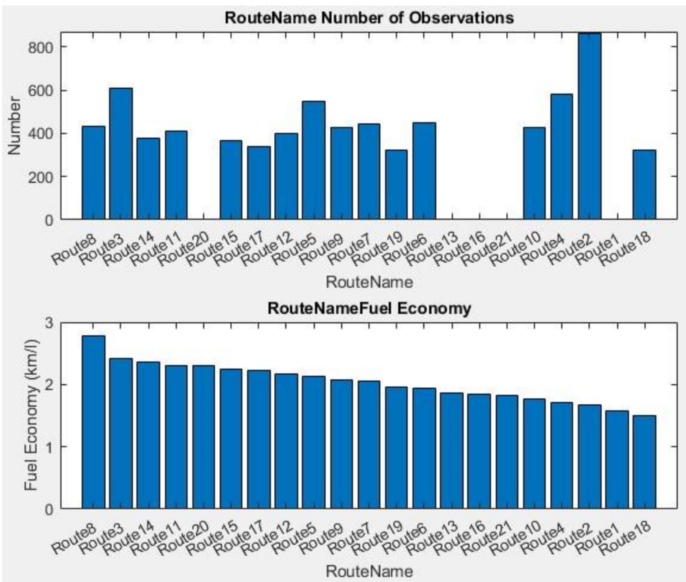

Figure 2 Number of trips and average fuel economy per route [26]

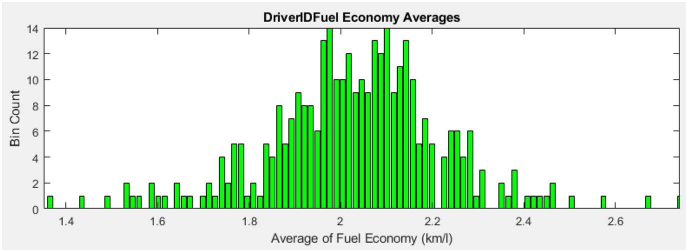

Figure 3 Histogram of average fuel economy per driver for all routes [26]

As could be expected, the variation in performance between drivers within a specific route is not quite as big as across all routes, as can be seen by studying the histograms of driver average fuel economy for a few individual routes in Figure 4. By first removing the impact of the route, we can quantify the potential for fuel economy improvement, should all drivers perform at the same level. From these histograms of average driver performance on the same routes, it can already be seen that, should all drivers perform at the same level as the best drivers, fuel usage would be reduced by more than 30%.

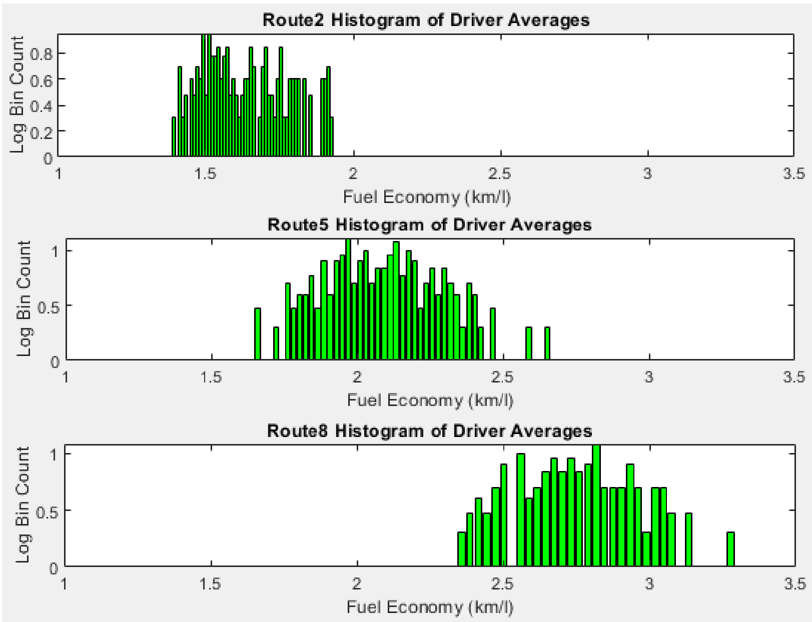

Figure 4 Histograms of average fuel economy per driver for individual routes [26]

6 Extracting empirical fuel economy models

In a previous article [26] we described the extraction of linear fuel economy regression models, nonlinear regression models as well as various neural network models. Thia included a generalized regression neural network, which is a type of radial basis function network, as well as multi-layer perceptrons. 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.

We first extracted models using driver, route and payload factors as inputs to allow comparison of our results with results from previous research. We selected input factors by ranking potential inputs based on absolute value of linear correlations between inputs and fuel economy, and 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. The list of model parameters selected on this basis included Elevation 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 scatterplots of Target vs Output for the regression and neural models respectively, as displayed in Figure 5 and Figure 6, show that the model fits for the test sets are very similar to that for the training sets. This indicates that the models have good generalization capability. The neural models provide a superior fit of output to target compared to the regression models, while the GR neural network seem to be slightly superior to the MLP network. We will confirm these observations using correlation analysis.

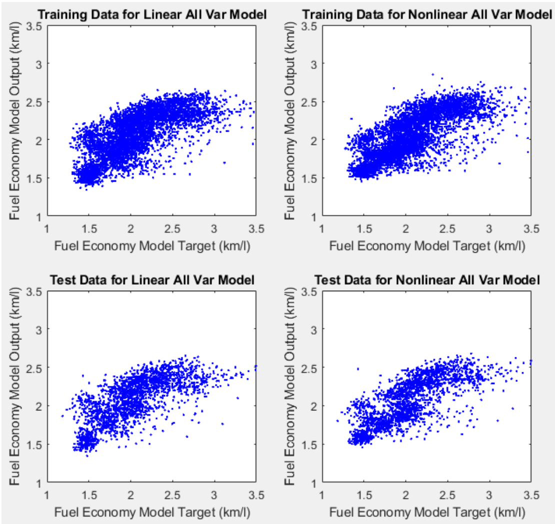

Figure 5 Scatterplots for linear and nonlinear regression Targets and Outputs [26]

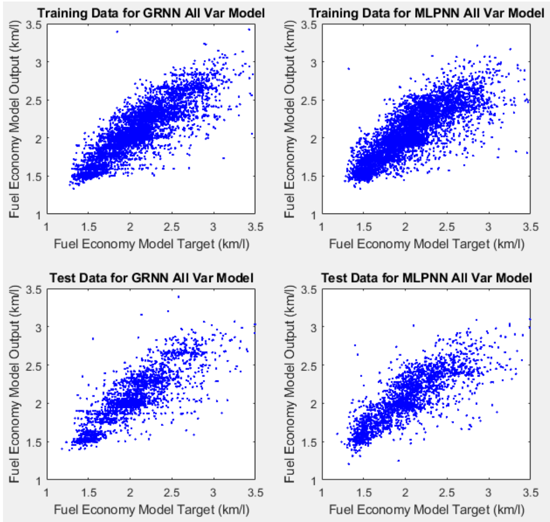

Figure 6 Scatterplots for GRNN and MLP neural network Targets and Outputs [26]

We calculated the correlations between model outputs and target variables for both the training and test sets, as displayed in Table 1 and Table 2 below, to assess model accuracy. As expected, the models that include driver, route and payload inputs have the biggest correlations between output and target. The observed relationships between fuel economy and the respective explanatory variables are strong and consistent, as most of the correlation obtained in the training set is still present in the test set. 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 behavioral model that uses Max RPM, Max Brake and Max Speed as inputs, slightly outperforms the driver ID model that uses driver identity as input.

Table 1 Correlation coefficients between fuel economy model outputs and targets for the training set [26]

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&Pay-	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 2 Correlation coefficients between fuel economy model outputs and targets for the test set [26]

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&Pay-	0,640	0,678	0,768	0,744
DriverBeh	0,139	0,159	0,315	0,341
DriverID	0,121	-	0,127	0,148

7 Estimating model compensation impact on driver performance measurements

To measure driver performance more consistently we have to compensate for those factors that the driver cannot control. For this reason, we calculated a compensated fuel economy figure for each trip by subtracting the route and payload fuel economy model output from the original fuel economy. We then added the population average fuel economy to this residual to obtain a fuel economy figure that is mostly attributed to driver behavior:

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

Table 3 and Table 4 displays correlations obtained between outputs and targets for the various models. As before we observe that neural models slightly outperform linear regression models, and that for neural models a significant fraction of the correlation between output and target is retained in the test set.

Table 3 Training set correlation coefficients between outputs and targets for models trained on the route & payload residual fuel economy [26]

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

Table 4 Test set correlation coefficients between outputs and targets for models trained on the route & payload residual fuel economy [26]

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

To verify if variations in performance for the same driver are reduced after compensating for the impact of route and payload, 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; as expected this is indeed lower than the figure before compensation.

In Figure 7 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 the removal of the impact of varying route inclinations and payloads.

To verify the impact of compensating for route and payload we calculate correlations between average driver fuel economy performance before and after compensation. Table 5 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).

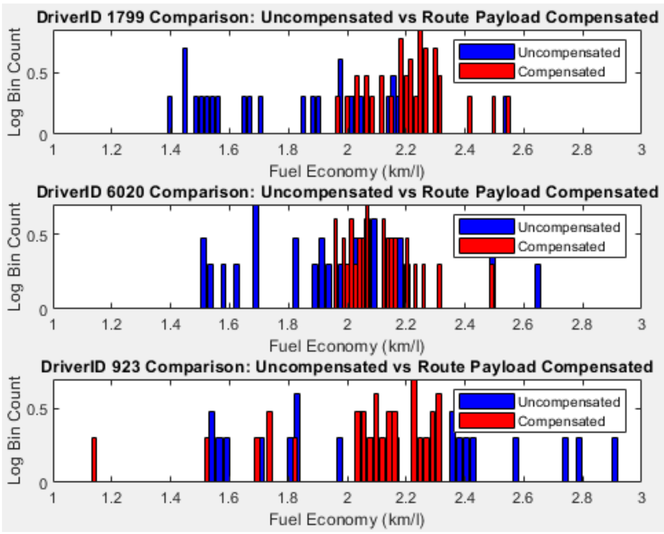

Figure 7 Comparison of uncompensated and route and cargo compensated fuel economy histograms for different drivers [26]

Table 5 Correlations between compensated and uncompensated driver fuel economy performance [26]

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

To quantify the degree to which model compensation influences driver performance measures 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; we normalized this change in ranking by division through the total number of drivers. We then calculated the average absolute change in ranking differences 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. This figure will be zero for no ranking changes and 0.5 for random changes to all driver rankings. 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 and 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 6 and Table 7 displays the relative ranking changes for different compensation models for the training and test sets. The fact 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, indicates that, over and above changes in performance over time, the model-based compensation results in a significant difference in driver ranking.

Table 6 Average relative change in driver performance ranking before and after compensation for the training set [26]

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&Pay-	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 7 Average relative change in driver performance ranking before and after compensation for the test set [26]

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&Pay-	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

These scatterplots of driver rankings before and after compensation as displayed in Figure 8 confirmed these results. The straight line in the middle of the graph may seem to indicate that a series of drivers have retained the same ranking before and after compensation. In fact, these 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.

We then calculated the fraction of drivers for whom performance relative to the population average changed from positive to negative or vice versa after compensation. The total fraction of changes should be 0.5 if performance before and after model compensation is unrelated (e.g. random performance changes). In Table 8 we observe that for route and cargo model compensations the fraction of drivers with reversed relative performance 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.

We calculated the differences in average relative change in ranking between the models, to allow comparison of the impact of the different models on driver performance after correction. As these differences are close to zero, displayed in Table 9, it provides evidence that all the models largely agree in terms of the required changes in driver ranking. In those cases where a model was compared against itself a result of exactly zero was obtained. Table 10 displays the results of a similar comparison between route models and payload models that used the same modelling technique. As payload represents a smaller fraction of fuel economy changes compared to route inclination, it is less effective when used on its own. The differences are therefore slightly larger than in the previous case.

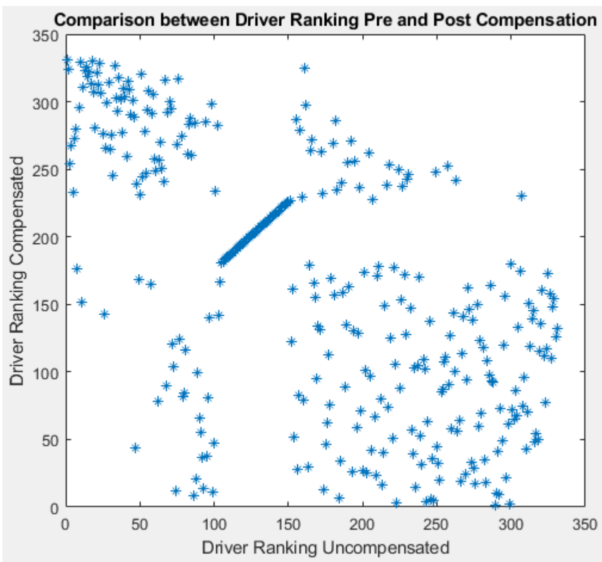

Figure 8 Comparison between driver ranking before and after compensating for route and cargo [26]

Table 8 Fraction of drivers with reverse in relative performance before and after compensation [26]

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&Pay-	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 9 Comparing different route & payload models based on difference in driver performance ranking after compensation [26]

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 10 Comparison between route and payload models based on difference in driver performance ranking after compensation [26]

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

8 Conclusions and future work

The objective of this paper was to determine the impact of truck drivers on truck fuel economy. More specifically, we investigated the impact on driver performance ranking of compensation for factors not controlled by the driver. We stated a hypothesis that factors beyond the control of a truck driver have a significant impact on methods to measure driver fuel economy performance. The results reported in this paper provides conclusive evidence that we can accept this hypothesis.

Based on our analysis of fuel economy, we found that route inclination and payload explain a significant fraction of total observed fuel economy deviations. We observed that compensating for route and payload reduced variations between average performance levels of different drivers. We furthermore found that there is more consistency between driver performance in the training and test sets after compensating for route and payload than before. We also found that driver fuel economy performance, measured before and after compensating for route and payload, are negatively correlated. In line with this finding, we observed large changes in driver performance ranking after compensation. Lastly we found that, for the majority of drivers, the fuel economy performance relative to the population average changes in sign after compensating for route and payload.

The above findings provide convincing evidence that the default measure currently used for driver fuel economy performance, namely the observed average performance over all completed trips, is not reliable. We therefore propose a new performance measure, based on the residual of the model that predicts fuel economy in terms of route inclinations and payload. By adding the population average for fuel economy to this residual one can obtain a realistic fuel economy performance assessment for each driver.

Based on feedback from road transport operators and operators of truck parking facilities, we believe that fuel theft activities are not only restricted to refuel depots, but also occur in locations like truck parks, where drivers receive bribes in exchange for allowing fuel to be siphoned from their trucks. We can investigate the prevalence of this phenomenon by monitoring average fuel tank levels before and after trucks visited such locations, where no formal refuel facilities are located. Momentary samples of fuel tank levels tend to be an unreliable indication of the volume of fuel currently in the tank, due to movements in the fuel surface while driving and the high thermal expansion coefficient of diesel. By filtering out short term fluctuations and linking such measurements to temperature readings, it should however be possible to provide indicators of estimated changes in fuel tank volumes before and after suspicious events while the truck is in transit.

Future work will involve the inclusion of additional input factors not related to driver behavior, like wind speed and traffic conditions, as factors to be compensated for in the fuel economy model. We will also consider the use of more sophisticated neural network techniques, e.g. using recurrent neural networks to apply temporal filtering to real time measurements of fuel tank levels. We furthermore plan to extend the study to include vehicle fleets from other parts of Africa, including the rest of SADC region and East Africa.

References

[1] A. J. Hoffman, "The use of technology for trade corridor management in Africa," in *NEPAD Transport Summit*, Sandton, Johannesburg, South Africa, 2010.

[2] J. Havenga, "10th Annual State of Logistics Survey for South Africa, ISBN number: 978-0-7988-5616-4, p. 9.," Stellenbosch, South Africa, 2013.

[3] "Stopping the flow of illegal black gold," *Transport World Africa,* p. Vol. 12 No. 3, June 2014.

[4] J. Naidoo, "Transport White Paper: The South African Cross-Border Industry, THRIP Research Report," North-West University, Potchefstroom, South Africa, 2013.

[5] G. Kelly, "African Business Quarterly: Fuel price increase – what it means from a road freight logistics perspective," February 2024. [Online]. Available: https://www.abizq.co.za/fuel-price-increase-what-it-means-from-

a-road-freight-logistics-perspective/#:~:text=Fuel%20is%20fast%20crossing%20the,staging%2Fdistribution%2Fretail%20operations.. [Accessed 2 October 2024].

[6] L. Perrin, "How the Rising Costs of Fuel Affect Your Freight Charges," [Online]. Available: https://www.hemisphere-freight.com/how-the-rising-costs-of-fuel-affect-your-freight-charges/. [Accessed 2 October 2024].

[7] United States Environmental Protection Agency, "Sources of Greenhouse Gas Emissions," 26 April 2019. [Online]. Available: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

[8] United States Environmental Protection Agency, "Transportation and Climate Change," 26 April 2019. [Online]. Available: https://www.epa.gov/transportation-air-pollution-and-climate-change/carbon-pollution-transportation.

[9] G. Prause and T. Hoffmann, "Innovative management of common-pool resources by smart contracts," *Marketing & Management of Innovations,* no. 1, pp. 265-275, 2020.

[10] Y. Duan and X. J., "Pollution Haven or Pollution Halo? A Re-Evaluation on the Role of Multinational Enterprises in Global CO2 Emissions," *Energy Economics,* vol. 97, 2021.

[11] K. Hunke and G. Prause, "Hub Development along Green Transport Corridors in Baltic Sea Region," Hamburg: University of Technology, Hamburg, 2012.

[12] G. Prause, "Governance of green transport corridors," in *Wismar Business School Conference*, Tallin, Estonia, 2014.

[13] FTLAP, "Freight Transport Logistics Action Plan," Commission of European Communities, Brussels, 2007.

[14] Y. Maoa, Y. Xiea and C. Zhuo, "How does International Transport Corridor affect regional green development: evidence from the China-Europe Railway Express," *Journal of Environmental Planning and Management,* Vols. Vol. 67, No. 7, p. 1602–1627, 2024.

[15] J. d. Weille, "Quantification of Road User Savings," *World Bank Occasional Papers No. 2, World Bank, Washington D.C.,* 1966.

[16] D. Biggs, "ARFCOM - Models For Estimating Light to Heavy Vehicle Fuel Consumption, Research Report ARR 152," Australian Road Research Board, Nunawading, 1988.

[17] I. G. C. Bennett, "HDM-4 Fuel Consumption Modelling, Preliminary Draft Report to the International Study of Highway Development and Management Tools," University of Birmingham., Birmingham, 1995.

[18] J. Rakha and H. Wang, "Fuel consumption model for heavy duty diesel trucks: Model development and testing," *Transportation Research Part D,* pp. pp. 127 - 141, 2017.

[19] O. Delgado, N. Clark and G. Thompson, "Modeling Transit Bus Fuel Consumption on the Basis of Cycle Properties," *Journal of the Air & Waste Management Association*, pp. 443 - 452, 2011.

[20] F. Perrottaa, T. Parrya, L. Neves, T. Buckland, E. Benbow and M. Mesgarpourd, "Verification of the HDM-4 fuel consumption model using a Big data approach: A UK case study," *Transportation Research Part D*, pp. 109 - 118, 2019.

[21] A. J. Hoffman and M. Van der Westhuizen, "An Investigation into the Economics of Fuel Management in the Freight Logistics Industry," in *IEEE Intelligent Transportation Systems Proceedings*, Qingdao, PRC, 2014.

[22] X. Zhigang, W. Tao, E. Said and Z. Xiangmo, "Modeling Relationship between Truck Fuel Consumption and Driving Behavior Using Data from Internet of Vehicles," *Computer-Aided Civil and Infrastructure Engineering Vol 33,* p. 209–219, 2018.

[23] W. Jian-Da and L. Jun-Ching, "A forecasting system for car fuel consumption using a radial basis function neural network," *Expert Systems with Applications Vol 39*, p. 1883–1888, 2012.

[24] E. Siami-Irdemoosa and S. R. Dindarloo, "Prediction of fuel consumption of mining dump trucks: A neural networks approach," *Applied Energy 151*, p. 77–84, 2015.

[25] H. S. Jassim, W. Lu and T. Olofsson, "Assessing energy consumption and carbon dioxide emissions of off-highway trucks in earthwork operations: An artificial neural network model," *Journal of Cleaner Production 198*, pp. 364-380, 2018.

[26] A. J. Hoffman, "Neural models for benchmarking of truck driver fuel economy performance," in *11th International Conference on Neural Computation Theory and Applications*, Vienna, Austria, 2019.

[27] L. Gong, T. Morikawa, T. Yamamoto and H. Sato, "Deriving Personal Trip Data from GPS Data: A Literature Review on the Existing Methodologies," in *The 9th International Conference on Traffic & Transportation Studies*, Beijing, China, 2014.

[28] M. van der Westhuizen, "The characterization of automotive fuel consumption in the freight logistics sector," North West University, Potchefstroom, 2017.