DEVELOPMENT OF A MODEL FOR ROAD TRANSPORT FUEL MANAGEMENT

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ABSTRACT [1] [2] [3]

Road transport is responsible for 76% of cargo movement in South Africa; at the same time transport cost in Sub-Sahara Africa forms a much higher fraction of the total cost of landed goods compared to the rest of the world. Fuel represents the single biggest operational cost for road transport operators; efforts towards improved fuel efficiency are therefore a priority within this sector. As fuel usage depends on many factors, including engine size, vehicle fabrication, driver behaviour, payload, traffic conditions and route inclinations, it is not a trivial exercise to create accurate consumption benchmarks for a specific operation. This paper investigates various factors that are known to impact fuel utilization with the aim of quantifying the relative importance of the contribution of each. Fuel usage data was collected for a representative set of trucks covering all major routes in South Africa and for various cargo categories over a 3 year period. This data was filtered based on different criteria, including driver identity, route and vehicle model. Comparisons were drawn between consumption figures derived from manually recorded refuel events and figures derived from measurements that are automatically performed by on-board vehicle sensors. It was concluded that driver behaviour and the possible siphoning of fuel from vehicles seem to be a major factor and would justify further actions towards curbing fuel losses. At the same time route inclination, payload and vehicle model also play an important role and should be incorporated into costing models used to determine how different routes and trips are priced.

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1. INTRODUCTION

Road transport forms a backbone of the African economy, due to the limited availability of rail infrastructure [1]. Road transport is responsible for 76% of cargo movement in South Africa [2]. Compared to the rest of the world the cost of transport in Africa is however much higher as a fraction of the total cost of delivered goods - transport represents as much as 18% of GDP in many African countries, compared to a global average of less than 10%. Fuel cost is the single biggest contributor to the cost of road transport operations, not only due to the high price of diesel but also due to unacceptable levels of fuel theft experienced by transporters: practical figures obtained from industry players indicate that this figure may be as high as 15 to 20 % of total fuel consumption if not more [4] [3]. At the same time those factors that cannot be avoided, like payload and route inclinations, must be properly accounted for when costing specific routes and trips to ensure that all routes and customers are serviced on a profitable basis; the alternative would be that some customers are unknowingly subsidizing others. Previous research in the field of fuel consumption modelling identified the primary factors that impact on consumption [5] [6] [7]. In order to restore the competitiveness of the African road transport industry it is therefore essential to find solutions, not only for efficient fuel management, but also for the effective prevention of fuel theft.

Figure 1 below displays a histogram of fuel consumption collected over more than 280,000 trips undertaken within the boundaries of South Africa. It can be seen that the consumption varies quite widely, from around 0.5 km/l up to more than 5 km/l. It is furthermore noticed that the statistical distribution seems to contain more than one mode, which is indicative of more than one independent underlying cause for the observed variations. The first mode centres around 2 km/l, which is generally regarded as the average consumption rate that should be expected for long haul road transport; the other is much higher at around 4 km/k, which seems unlikely to be caused only by normal factors. This provides additional motivation for a study of this nature.

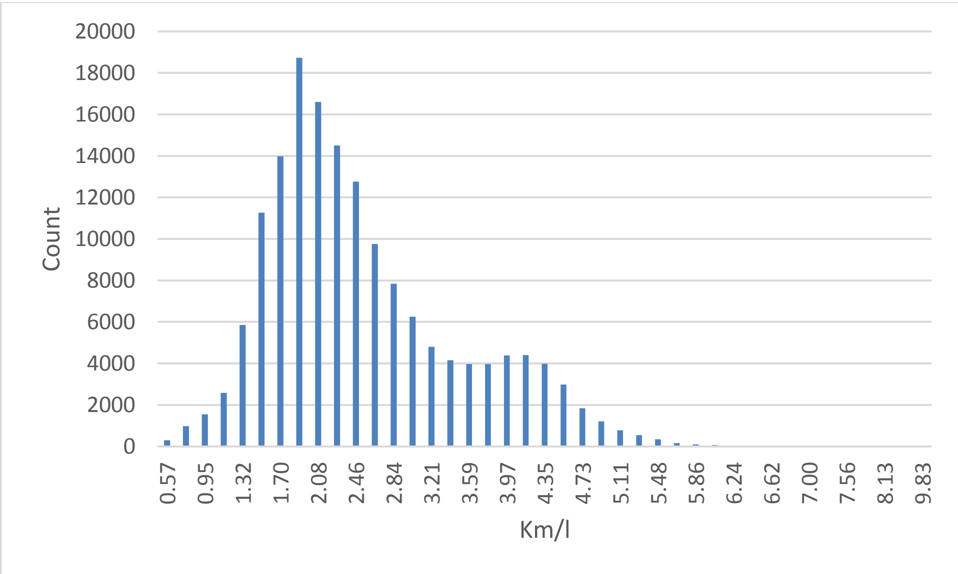


Figure 1 Histogram of fuel consumption over approximately 280,000 vehicle trips

Effective fuel management requires a system solution that can operate at different tiers: tier 1 comprises of sensing capabilities reflecting the current status of the vehicle and its fuel (e.g. GPS coordinates, valve open status, fuel tank level, etc.); tier 2 consists of local intelligence on the vehicle to collect and interpret sensor data and communicate with the home base if necessary (typically in the form of a tracking unit with different communications capabilities); tier 3 will be the management system that collects data from a number of vehicles and provides supervisory functions (e.g. for fuel consumption benchmarking).

In a previous paper we demonstrated that it is possible to deploy a telematics solution for improved road freight transport fuel management, and that with limited savings achieved (typically 1% of current fuel consumption) such a system will generate a positive return on investment, even if it requires the installation of new hardware for that purpose [8]. The obvious question from the perspective of a road freight transport operator is what level of improvement, compared against current fuel costs, can realistically be achieved should additional measures be imposed. The answer to this question will largely depend on the underlying causes for currently excessive consumption, and whether such causes could be eliminated. A variety of underlying reasons contribute towards non-ideal fuel consumption; these include driving practices (e.g. speeding), fuel theft, deviating from prescribed routes, excessive idling at points of loading and offloading, spending significant time in congested traffic and others. The identification of the actual reasons for excessive consumption and the quantification of the contribution of each is not a trivial problem to solve; even if a telematics system is in place that captures raw data related to fuel consumption the answers are typically hidden within stacks of collected data that still requires detailed interpretation.

The focus of our current research work is to create relevant benchmarks for fuel consumption that can be used by road freight transport operators to evaluate their own fuel performance. To achieve this objective we need to firstly quantify the actual fuel consumption for a sufficiently large number of trips over a representative set of routes within Southern Africa. This data set must include observations that cover all of the suspected primary determinants of fuel consumption as listed above. Secondly we must develop a methodology that can be applied to mine large sets of consumption data in order to identify the primary factors that explain differences in fuel consumption between different trips and to quantify the contribution of each. This will allow the realistically achievable improvements to be quantified and benchmarks to be created at levels that will challenge the status quo but that will still be practically achievable.

In this paper we describe the process that was followed to create a fuel consumption database and to categorize fuel consumption for different scenarios that represent the impact of some of the primary determinants of fuel consumption. We identify the obstacles that were encountered and that complicated the correct interpretation of the data, and describe the approaches and methods that we developed in order to overcome these. We then proceed to illustrate typical results that were obtained in terms of average consumption within specific categories, the difference in consumption between categories and the relative contribution made by each of a number of explanatory variables that impact upon fuel consumption.

The rest of the paper is structured as follows: section 2 details existing literature with relevance to our study, whilst section 3 provides an overview of the process that was followed to collect a representative set of fuel consumption data and section 4 describes the different routes that were covered by the available data set. In section 5 we draw a comparison between manually recorded refuelling figures and the consumption figures as collected by on-board vehicle sensors. We then proceed to investigate the impact of driver behaviour in section 6. Section 7 focuses on the impact of vehicle model on consumption, while section 8 describes a case study that investigates the impact of route inclination and payload. In section 9 we conclude and make recommendations for future research work.

2. LITERATURE STUDY

An investigation into fuel consumption in the commercial vehicle industry will be of value to both the logistics sector (from a cost reduction and performance management perspective) as well as for environmental agencies (from an emissions control perspective). It has been found that road transport is responsible for as much as 93% of carbon emissions in urban areas, while at the same time fuel costs represent between 25 and 40% of overall logistics transport costs [9]. From both perspectives the primary objective is to reduce the amount of fuel that is required to achieve a specific economic objective; in the case of the freight logistics industry this is the transportation of goods from points of production to points of consumption.

In order to pursue the above objective it is necessary to firstly identify the primary determinants of the fuel consumption of commercial freight vehicles (mostly trucks) when engaged in economic activities; the activities of all vehicles in the population must be sufficiently similar to those of other vehicles in the population to allow comparisons and the generation of performance benchmarks. Once all the primary determinants have been identified and their relationships with fuel consumption and emissions have been characterized it will be possible to develop a mathematical model that can be used in scenario analysis to study various possibilities towards improvement of the status quo. Previous research in the field of fuel consumption modelling identified the primary factors that impact on consumption [5] [6] [7]. These include vehicle engine type and size, payload, road inclination, wind strength and several others. In this study we focus on those factors that can be extracted from the available set of data reflecting the trip plans for a fleet of vehicles as well as their GPS tracking coordinates and fuel consumption per trip.

The determinants of fuel consumption can be broadly divided into three categories: vehicle specific attributes (those that determine the fuel efficiency of a specific model), the characteristics of the assignment to be completed (the route distances and inclinations and the times of day of week when goods must be delivered), and driver specific attributes (how effectively the vehicle is controlled by the driver and the accuracy of execution of the assignment by the driver). While each of these categories of factors have been studied separately before we could find no literature where factors from all three categories were studied collectively.

The first set of factors is fairly well understood as explained by [6] and many other research papers that focus on the fuel efficiency of different vehicle makes and models. The second set of factors have been studied from the perspective of characterizing the nature of commercial vehicle movements through the national and provincial road networks [10] [11]. It has furthermore been demonstrated that freight traffic can be simulated under different traffic conditions and policy measures [12]; such results can be combined with a fuel usage model to predict the amount of fuel that vehicles will use under different circumstances.

Other studies [13] derived personal trip data from GPS devices embedded into Smartphones; these techniques are however limited to the characterization of the movements of different sectors in the population without knowing the mode of transport that was used or the impact of behaviour on fuel consumption. While focusing on the establishment of models for vehicle movements in order to support traffic simulation models, the above studies did not address the impact of vehicle activity chains on fuel usage.

The third set of factors relate to the behaviour of truck drivers from a fuel efficiency perspective. Previous studies [8] have shown that within the African context not only inefficient driving styles but also illegal practices like the siphoning of fuel play a large role in determining the overall cost of fuel to the transport operator. While only some of these behaviours, like speeding and excessive idling, directly impact emission level they all add to the overall cost of the logistics operation, hence contributing towards the cost of goods delivered to the consumer [1][4].

3. OVERVIEW OF THE COLLECTION OF FUEL CONSUMPTION AND RELATED 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. In order to simplify the process we started off with a fleet of approximately 400 vehicles that covers most of the major routes in South Africa. This would allow 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 passes over the Drakensberg range have to be crossed). This fleet also includes more than one vehicle make, allowing consumption of different engine designs to be compared.

As the primary long term objective of our research is the creation of a reliable set of fuel consumption performance benchmarks, it is important to collect data in a manner that support direct comparisons between different sets of data. This requires the available data to be subdivided into subsets per major routes that are 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 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 section 4 below.

Our initial focus was to reconcile fuel dispensed to vehicles according to refuelling records and fuel actually used by vehicles based on on-board sensing devices. For this reason we collected the refuelling records per truck over a period of one calendar year that covers all seasons, which is important as the road transport industry tends to be cyclic with peaks reached in the months leading up to the Christmas season, and a slump in business early in the new year. As the vehicles involved in the study are not always refuelled once per trip but as needed, we had to reconcile fuel dispensed with fuel used over periods of time than covered more than a specific trip.

The GPS tracking system used by these vehicles collects fuel usage data via the CAN bus system. While fuel usage is measured almost 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. The actual fuel usage reports were matched with the fuel dispensed reports by using the vehicle registration numbers that were present as vehicle identifiers in both lists.

It is important to also match trips with drivers, as driver behaviour is one of the primary determinants of effective fuel consumption, both in terms of driving skills and the tendency toward fuel shrinkage. In this case drivers were identified in two ways: in the trips plans drivers should be identified; this field was however missing for 44.8% of recorded trips. In addition drivers have to identify themselves by way of an ID tag that is inserted before a truck is started; this field was available for a larger fraction of trips (76.7%). The missing 23.3% may be ascribed to the fact that driver identification is not enforced on some vehicles, or can be overridden by a manager.

Another important aspect to take into consideration is the impact of route inclination on fuel usage. As could be expected fuel consumption is much higher on inclines compared to flat portions of the route; given the limit on the speed of a truck on downhill stretches this increased consumption level is not all made up on the downhill sections. In order to quantify the impact of inclines integrated over the entire route the inclines were extracted from Google maps by using the route descriptions as defined by the set of GPS coordinates representing each route [9]. While there may be other sources of inclination data the inclines obtained from Google maps were sufficiently accurate for the purpose of this work.

The final determinant of fuel usage that was investigated is payload. The load carried by a vessel has a major impact on its fuel usage over a specific route, specifically for routes that include steep inclines. The vehicles that were available for this study were however not always weighed before departure; we therefore had to use another approach to characterize the impact of payload for at least a subset of the total data set. For this purpose we analysed data on a two-way trip from a depot to a sugar mill where trucks travelled empty in one direction and full in the other. This allowed us to measure the impact of payload for the same set of vehicles.

4. IDENTIFICATION OF MAJOR ROUTES TO BE USED FOR COMPARISON PURPOSES

In order to achieve the objectives of this study it was necessary to identify routes that were regularly travelled by a significant number of vehicles and that would reflect the impact of all the major determinants of fuel consumption as identified above. As the number of locations where weigh bridges are present is quite limited it was decided to use the availability of a frequently visited static scale as one of the primary considerations in this choice. This would allow us to incorporate payload as determinant for fuel usage in the analysis, at least for a subset of vehicles that visited the weighbridge during the trip.

Table 1 below lists the Sanral weighbridges where vehicle from the fleet were observed from time to time; this list was compiled by searching the entire database of weighbridge data for the list of vehicle registration numbers present in the fleet. The most frequently visited weighbridge by fleet vehicles is Heidelberg just south of Gauteng on the N3 on the road corridor between Durban and Johannesburg; this is also known to be the busiest road freight corridor in South Africa. We therefore decided to firstly consider vehicles that use this route.

Table 1 Sanral weighbridges where fleet vehicles were observed

Site identifier	Name	Number of Occurrences
GAUTHEID	Heidelberg	1463
MPUMFARR	Farrefontein	700
KZNLMIDW	Midway	561
MPUMMDLE	Mid-East	555
MPUMMACH	Machado	523
KZNLMKON	Mkondeni	276
MPUMMDLW	Mid-West	138
MPUMKOMA	Komati	54
GAUTDONK	Donkerhoek	48
MPUMMDWT	Polokwane Zebediela	9

Figure 2 below displays the trip start positions for all trips included in the available data set. It can be seen that many of these are present along the N3 between Johannesburg and Durban, which confirms our choice. Figure 3 below displays the map for the N3 route as well as the elevation profile. It can be clearly seen that several steep inclines have to be mounted from Durban to Johannesburg; once the route has passed Harrismith it is relatively flat till the final destination is reached. For this route it will therefore be possible to characterize the fuel consumption over a relatively large sample of vehicles of which a percentage were weighed en route and that travelled across upwards and downwards inclines as well as flat sections.

We proceeded to refine the search for the most commonly used route by listing the loading and offloading points. Firstly we listed the most frequent loading points and selected from the list those that were in close proximity to the N3. For this most frequently visited loading point the list of most frequent offloading points were determined. In this way we identified the most frequently travelled single route from Redhill, Durban to Illovo, Johannesburg for which 323 trips were available within the available data set. We also identified the list of vehicles that had planned journeys between these points; 14 vehicles were identified that complete this route at least twice during the period covered by the data set.

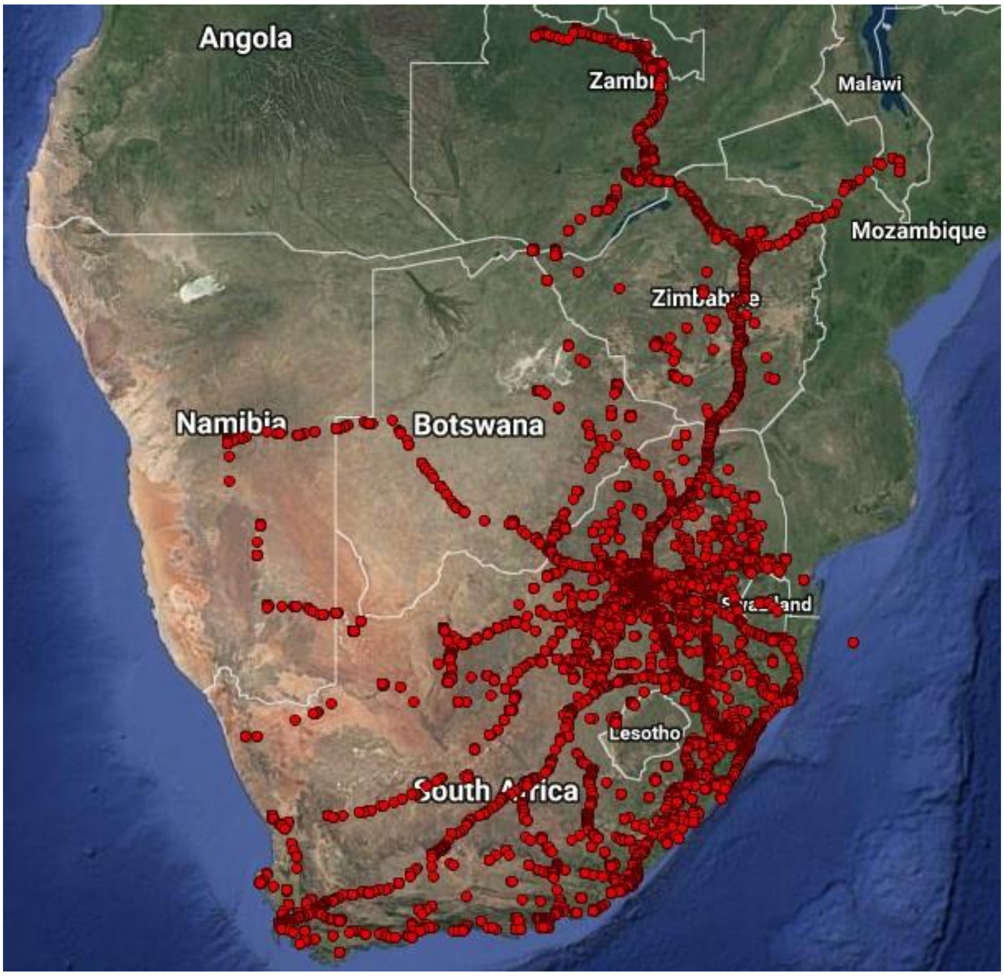


Figure 2 Trip start positions for all trips in the study

5. COMPARISON BETWEEN REFUELING AND FUEL CONSUMED FIGURES

As mentioned above, one of the primary objectives of the study was to compare fuel dispensed to vehicles against fuel actually used by the engine. This part of the investigation would serve several purposes:

- It can be used to calibrate the fuel flow gauges used inside the engines. It is quite possible that these gauges may have a calibration error which need to be corrected before the results can be used for comparison purposes. It can be expected that for a significant fraction of trips the fuel dispensed is correctly recorded. In such a case the fuel dispensed vs fuel consumed can be used to verify if the fuel usage gauge produced accurate results.
- It would indicate what fraction of fuel dispensed to a vehicle was not used in the engine – if both measurements were accurate it would imply that the remaining fuel was removed (in all likelihood stolen). Once it is known during which trips most fuel disappeared in this way it could be determined where trucks made unplanned stops that could potentially be associated with efforts towards fuel theft.
- It would indicate how accurately fuel dispensing records were maintained – if there are many cases where the engine used more fuel than what was dispensed to the vehicle based on fuel records it would imply that some records of fuel dispensed are not accounted for – this can potentially be correlated with the responsible driver to determine whether negligence played a role.
- If however the general tendency is for fuel dispensed to exceed the amount of fuel used by vehicles, and at the same time manually recorded distances exceed distances based on the automatically sensed odometer reading, it may imply that these records are deliberately manipulated to hide the fact that fuel is siphoned from the system and that recorded distances are overstated to show acceptable consumption figures.

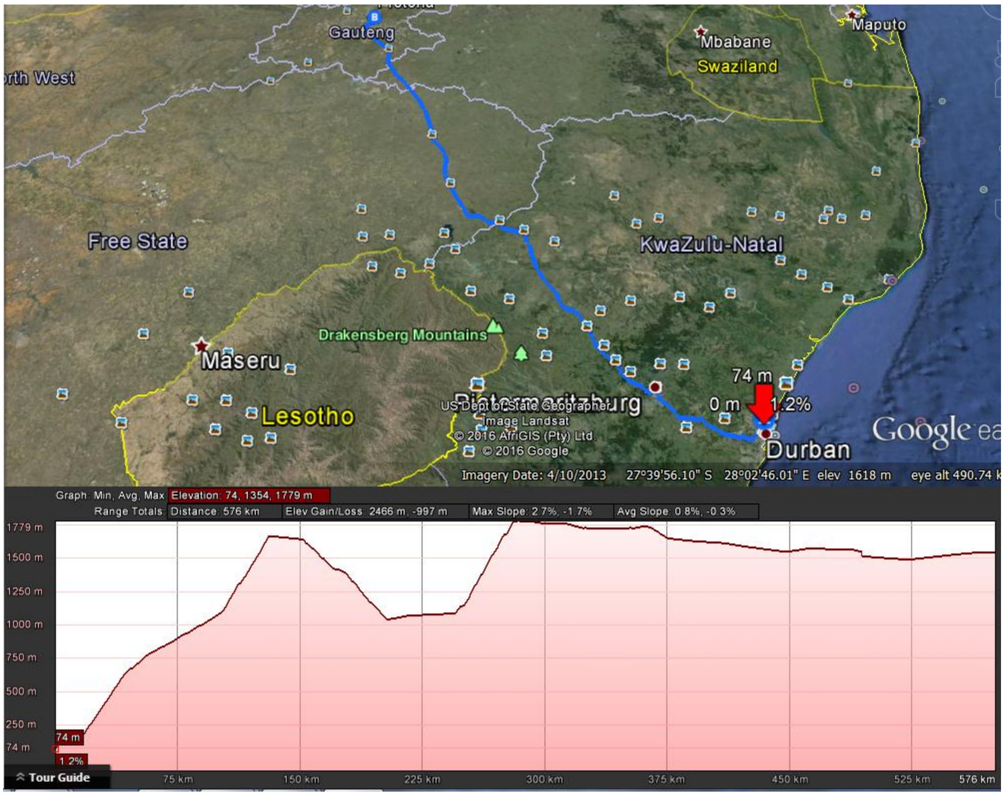


Figure 3 Map and elevation profile of the N3 Johannesburg-Durban route

The fuel records show that for the majority of trips vehicles are refuelled at the main fleet depot and that vehicles are most of the time filled up rather than partially refuelled. E.g. for one specific vehicle it was refuelled 137 times during the course of a year, 89 times at the main fleet depot with only 5 partial refuels. From the fuel records, which provide the date and time of the activity, and the GPS tracking data, it can be determined exactly where the fuel pump was located, as the vehicle had to be stationary for a period of time at this location.

In order to allow direct comparison between refuel and fuel consumption records we selected calendar periods during which vehicles always refuelled only at the main fleet depot, as this also corresponded with the end of the current trip and start of a new trip. Some instances of such comparison displayed discrepancies of up to 15% where the fuel dispensed was less than the fuel consumed – this indicated missing refuel records; this was confirmed by comparison of the distance logs as in the same case the vehicle odometer recorded a 19% longer distance covered compared to the distance extracted from the refuel records.

Two further case studies are displayed in Table 2 below for vehicles that were refuelled only at the main depot. OBC refers to information available from the on-board computer based on measurement of distance and fuel consumed made available via the CAN bus system of the vehicle [8] [9] [10], while manual corresponds to records maintained during refuelling of the vehicles.

Table 2 Case studies: refuel vs fuel consumed records

Item	Trip 1	Trip 2
Start date / time	2016-02-02 22:29:25	2016-02-01 09:55
End date / time	2016-02-04 14:44:21	2016-02-02 22:19
Distance travelled	905 km	1221 km
Fuel consumed	450 l	640 l
OBC distance / manual distance	99.8%	99.84%
OBC fuel / manual fuel	88.8%	100.82%

From the above experiment we can make the following conclusions:

- In all likelihood the good correspondence between distance covered and fuel consumed for Trip 2 provides proof of the fact that the OBC measurements are very accurate and that discrepancies due to faulty gauges are limited to a fraction of 1%.
- In the case of Trip 1 there is accurate correspondence between the distances but 11.2% less fuel was consumed than dispensed – in all likelihood this represents a case of fuel theft.

We performed a more complete comparison between fuel dispensed and consumed for a particular vehicle. In order to make accurate comparisons we excluded data where there were suspected missing refuel records. While some partial refuel records were encountered, this would average out over a sufficiently large number of observations. Table 3 below displays a comparison between OBC and manually recorded data over a full year of data.

Table 3 Comparison between OBC and manual fuel records over one year

Vehicle FMID	Refuel distance travelled (Km)	OBC distance travelled (Km)	Refuel fuel dispensed after trip (L)	OBC fuel consumed (L)	OBC Km / Refuel KM %	OBC L / Refuel L %	OBC vs Refuel accuracy %
1340	86 891.00	84 937.70	43 415.07	42 312.74	97.75	97.46	99.70

As can be seen from the above table, the refuel logs indicate that the vehicle travelled slightly further that the OBC recorded and that slightly more fuel was dispensed than consumed. This may indicate that some trips were not properly logged by the OBC, which will be investigated further. However, taking the ratio between the fuel dispensed based consumption rate and OBC fuel consumed based consumption rate (both in km/l) yields 99.70% correlation, indicating that good accuracy is being achieved in the fuel dispensed and fuel consumed categories.

Extending this to all vehicles, the average results over 148 vehicles are shown in Table 4 below. A few further conclusions can be drawn from this comparison:

- In general manually recorded distances are overstated; this may be to try and make up for dispensed fuel that was not consumed by the vehicle but stolen.
- Significantly more fuel is dispensed to vehicles than actually consumed by the engines; this difference is close to 20%.
- Even when accepting the possibly overstated distance travelled there is still a discrepancy of almost 10% between the fuel consumption rate in l/km between OBC and manually recorded fuel levels – this can be accepted as the minimum estimate for fuel shrinkage.

Table 4 Averages of comparisons between OBC and manual fuel records over 148 vehicles

Total refuel distance travelled (Km)	Total OBC distance travelled (Km)	Total refuel fuel dispensed after trip (L)	Total OBC fuel consumed (L)	OBC Km / Refuel KM %	OBC L / Refuel L %	OBC vs Refuel accuracy %
69 432.92	63 524.19	35 985.61	30 161.00	90.6	82.9	91.3

6. IMPACT OF DRIVER BEHAVIOUR

The results from the previous section show that major discrepancies exist between distances and volumes of fuel consumed as measured by the vehicle sensors and similar figures as recorded by drivers and fuel pump attendants during refuelling of vehicles. It confirms that driver behaviour, and more specifically manipulation of recorded figures by drivers, most likely in order to hide the siphoning of fuel, justifies more in-depth investigation.

For this purpose we calculated the following figures across all drivers and all routes:

1. The fuel consumption rate in km/l based purely on OBC measurements calculated over the full calendar year for each vehicle.
2. The fuel consumption rate in km/l based on manually recorded figures during refuelling events, for the same calendar period.
3. The fuel consumption rate in km/l calculated as OBC distance divided by dispensed fuel – this is a figure that in many cases will be used by transporters to determine their average fuel efficiency levels, should they use the aggregate odometer readings for the entire fleet over a year as well as the total fuel expense of the company.
4. OBC distance as fraction of recorded aggregate distance during refuel events, to provide an indication of the overstating of actual travel distances as recorded by drivers.
5. OBC fuel consumed as fraction of fuel dispensed, to provide an indication of the fraction of fuel dispensed but not consumed by the vehicle, i.e. the best estimate of the level of fuel theft.
6. Standard deviations for all of the above, to provide an indication if larger deviations occur within the manually recorded figures compared with the OBC recorded figures – if the manually recorded figures were manipulated it could be expected that larger deviations would occur within those sets of figures opposed to the OBC based figures, as it would be difficult to always siphon the same proportion of fuel between each refuel event.

These figures were calculated both as normal averages over all drivers as well as by weighting the contribution of each driver based on the OBC distance associated with that driver. The use of weighted averages will prevent large deviations that may occur within the figures for drivers that drove only small distances, from skewing the overall figures. We furthermore removed outliers that were beyond the 3 sigma limits and where the distance driven by that driver was very low, as it could be assumed that, in the case of drivers for whom only a few refuel events are available, one unintentional mistake in the recording of a refuel event can result in a totally unreliable figure. Amongst the 203 drivers 10 observations were removed for this reason; this represented approximately 5% of the total distance travelled by all drivers.

Table 5 Comparisons between OBC and manual fuel records over 193 drivers

	OBC Km / Refuel km %	OBC l / Refuel l %	Refuel based km/l	OBC based km/l	OBC km / Refuel l	Refuel km/l vs OBC km/l %
Average	86.027	81.516	2.010	2.117	1.723	95.211
Weighted Average	90.574	82.251	1.942	2.156	1.754	90.828
Standard Deviation	18.384	20.637	0.389	0.241	0.463	15.500
Variance	337.958	425.889	0.151	0.058	0.214	240.243

From the above set of figures we derive the following conclusions:

1. Distances travelled are overstated by approximately 10%, in all likelihood to hide the fact that fuel is siphoned.
2. Consumption in km/l based on recorded figures is 5% lower than actual consumption based on OBC figures - drivers claim, based on their own recordings, to achieve approximately 1.94 km/l, whereas the OBC average is 2.16 km/l. The trucks therefore actually perform better than claimed by drivers, the latter figures once again manipulated to hide the fact that fuel is removed from the system.
3. The consumption figure that the fleet owner will arrive at by only using overall distance travelled based on odometer readings and overall fuel paid for is even worse (1.75 km/l) than what is effectively claimed by drivers.
4. The argument that manually recorded figures are manipulated is strengthened by the standard deviation figures: for the OBC based consumption, which is mainly impacted by factors like route inclination,

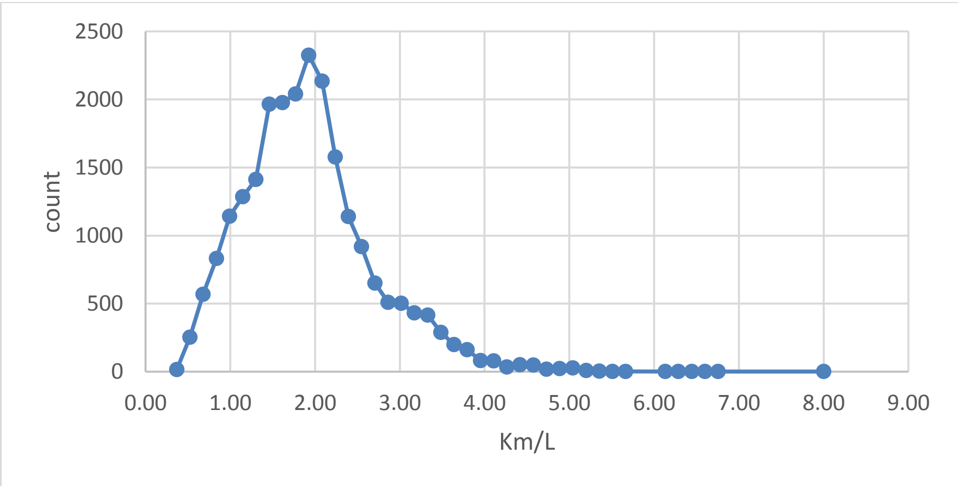
payload and idling times, the standard deviation is 0.24 km/l, whereas for the figure based on OBC distances and dispensed fuel the standard deviation is 0.46 km/l. For stochastic processes where different independent causes contribute to the same outcome, the relative importance of each are normally measured in terms of variances, as for normally distributed processes the total variance can be calculated as the sum of the variances caused by the contributing factors. If we therefore compare the variance within the OBC only km/l set with the variance where dispensed fuel is used, the latter has a variance that is between 3 and 4 times larger; differently stated the factors that should explain variance in fuel consumption in a system that is not manipulated (inclinations, payload, etc.) explain only 27% of the observed variation – the remaining 73% is caused by inaccurate recording and/or fuel theft.

5. For both normal and weighted averages the OBC fuel consumed is approximately 18% less than recorded fuel dispensed – this confirms that fuel theft is a significant problem, and that it is most likely the single biggest determinant of deviation between actual and ideal fuel cost.

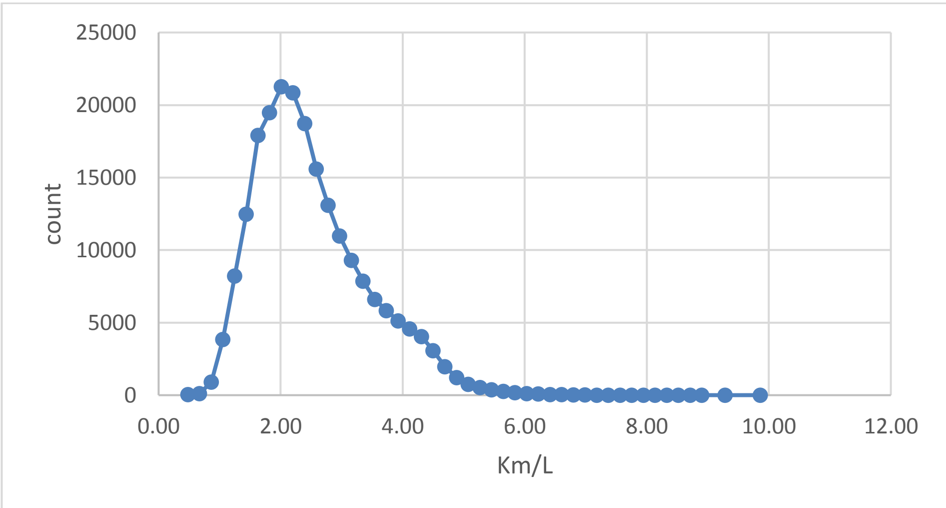
7. IMPACT OF VEHICLE MODEL ON FUEL CONSUMPTION

The choice of vehicle model is a further important consideration for transport operators as it is known that not all models perform equally well in all conditions. For this reason we separately calculated the average OBC based consumption of each vehicle model over all routes and all drivers. In Error! Reference source not found. **below we show the histograms of fuel consumptions for two different vehicle models. The average figures for a larger number of models appear in**

Table 6 below; we also show the number of trips over which the calculations were performed. A large difference can be seen for different models; this may be partly explained by the fact that different vehicle models may be used over different routes, a factor that has not yet been removed from these figures.



(a) Fuel consumption for Model 1



(b) Fuel consumption for Model 3

Figure 4 Histograms of fuel consumption for different vehicle models

Table 6 Fuel consumption for different vehicle models

	Number of trips	Weighted Average km/l
Model 1	23140	1.76
Model 2	19876	2.53
Model 3	215611	2.51
Model 4	10206	3.07
Model 5	17952	2.62

8. CASE STUDY: IMPACT OF INCLINATION AND PAYLOAD FOR A SPECIFIC ROUTE

Section 6 and 7 provided evidence that factors that can be managed to reduce overall fuel consumption indeed play a very significant role. This does however not mean that other factors, including route inclinations and payload, should not be further investigated. In a system where the unwanted phenomena have been largely eliminated, these factors should be the primary determinants of fuel cost, and should therefore be used not only to measure the performance of vehicle models and driver proficiency, but also to correctly price each route and each trip based on actual cost.

In order to investigate the impact of inclination and payload a route was selected that displays large difference between inclinations between the two directions of travel, and where the payload also differed significantly as trucks travelled empty in one direction and fully loaded in the other. The route selected was the Pietermaritzburg – Noodsberg route where trucks moved between a sugar refinery and an offloading point for processed sugar. In Figure 5 below the inclination of the route is displayed, showing on average uphill from Pietermaritzburg to Noodsberg but with mostly empty trucks and downhill the other way but with loaded trucks.

When studying the routes travelled by trucks between these destinations is was observed that for a portion of the journey two different routes were used; for the purpose of the analysis only trips that took the most travelled route were included. When the average OBC based consumption was calculated for the two direction the rather surprising result was obtained that the unloaded trucks traveling mostly uphill on average achieved a figure of 2.14 km/l, while the loaded trucks traveling mostly downhill could only achieve 1.59 km/l – a difference of more than 25%. As these figures were not based on recording of fuel dispensed but purely on OBC measurements it could be assumed that they reflect the true average performance of trucks on these routes.

This provides evidence that factors such as inclination and payload do play a very significant role in fuel consumption and should be incorporated into a pricing model on a per trip basis. Should in this case different customers be serviced in each direction, and should the uphill leg have involved a larger payload compared to the downhill leg the applicable fuel consumption for each leg would have differed by an even larger amount than the 25% recorded above. Given that fuel cost represent approximately 40% of the overall cost of a road transport operation, and that margins are often only a few percent, the implication is that the differential fuel cost for each customer specific trip can make the difference between running at a healthy profit or a significant loss.

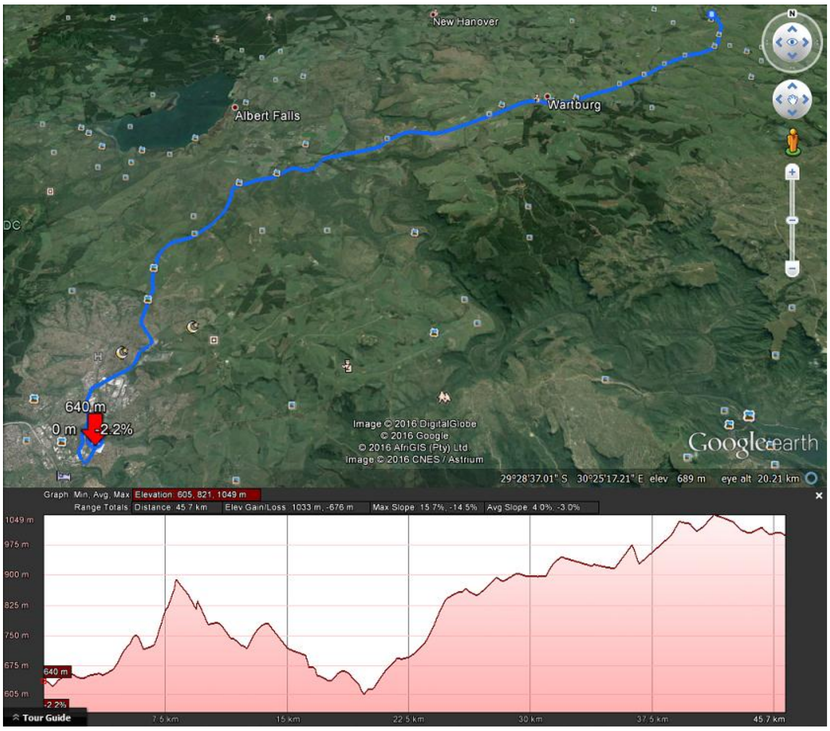


Figure 5 Map and elevation profile of the Pietermaritzburg - Noodsberg route

9. CONCLUSION

In this paper we investigated different factors that impact upon fuel consumption of trucks operated on a variety of routes around South Africa. Fuel consumption and related data was collected from a fleet of approximately 400 vehicles over a calendar year during which more than 280,000 trips were completed. We found that large discrepancies exist between distances travelled and amounts of fuel consumed as recorded by the on-board sensors of the vehicles versus those that were manually recorded. While some of these may be due to negligence, the errors are mostly skewed towards larger amounts dispensed than what the vehicles actually consumed. More detailed investigations into cases where deliberately introduced mistakes were most likely absent indicates that the on-board sensors produce errors of less than 1%, leaving us with the conclusion that in most cases where significant discrepancies occur the manually recorded figures are manipulated in order to hide the levels of fuel siphoning that appear to be present. Based on a comparison between fuel dispensed and fuel consumed it would appear that the level of fuel theft is approximately 18%, in line with estimated figures that were obtained from various industry players. This finding suggest the need to improve the level of control over the way in which fuel figures are recorded as well as improved measures to physically prevent fuel theft from vehicles. If these figures are calculated and reported to managers on a per trip basis it should be possible to act against the offenders immediately after the completion of a trip.

We further investigated other factors that influence fuel consumption, and found that vehicle model also has a significant impact, justifying current practices to select specific vehicle models for specific types of routes based on average inclination. It was also demonstrated that payload and inclination plays a big role and should be incorporated into costing models to determine suitable pricing for specific routes and for vehicles carrying specific payloads. The primary application areas for the results of this work would be the evaluation of the performance of truck drivers and of different truck models, as well as the accurate costing of trips based on a combination of the distance to be covered, the characteristics of the route in terms of inclination and rural vs urban, as well as the payload to be carried.

Further work will refine this study by determining the trips and geographical locations where most fuel siphoning appears to occur, and to match these incidents with suspicious stops that are made in unauthorized locations along such trips. This can provide further evidence of the prevalence of fuel theft and provide motivation for the implementation of additional preventative measures. Weights obtained from Sanral weighing scales will be combined with vehicle GPS and consumption data to determine the impact of payload on consumption for similar vehicle models on similar routes. Routes will furthermore be characterized in terms of their average inclinations and the results incorporated into a fuel consumption model that can estimate the expected consumption per route, supporting more accurate benchmarking of fuel efficiency and assisting efforts towards more accurate costing of specific routes.

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

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

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

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

[7] I. G. a. 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.

[8] M. v. d. Westhuizen and A. J. Hoffman, "An Investigation into the Economics of Fuel Management in the Freight Logistics Industry," in *IEEE Intelligent Transportation System Conference Proceedings*, Qingdao, PRC, 2014.

[9] J. M. Francke and P. Wouters, "Policy options for carbon efficient heavy vehicles".

[10] Q. van Heerden and J. W. Joubert, "Commercial vehicle behaviour: analysing GPS records," in *CIE42 Proceedings*, Cape Town, South Africa, 2012.

[11] Q. van Heerden and J. W. Joubert, "Generating intra and inter-provincial commercial vehicle activity chains," *Procedia - Social and Behavioural Sciences,* vol. 125, pp. 136-146, 2014.

[12] S. Schroeder, M. Zilske, G. Liedtke and K. Nagel, "Towards a multi-agent logistics and commercial transport model: the transport service provider view," *Procedia - Social and Behavioral Sciences,* vol. 39, pp. 649-663, 2012.

[13] 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.

[14] "SAE J1939-21 Data Link Layer, Surface Vehicle Recommended Practice," April 2001.

[15] "SAE J1939-71 Vehicle Application Layer, Surface Vehicle Recommended Practice," December 2003.

[16] "FMS-Standard," 19- June 2014. [Online]. Available: http://www.fms-standard.com.