VAN FUEL EFFICIENCY MEASUREMENT: A SUCCESSFUL APPLICATION OF DATA ENVELOPMENT ANALYSIS

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Introduction

The transport industry is a very competitive environment constrained by ever complex regulations and smaller margins. In such environments, measuring performance is essential in order to ensure resources are best used so that the organisation can stay competitive. Due to fleets' complex operations, fleets' performance can be improved in many different ways. Freight Best Practice (FBP, 2005) mentioned that fuel costs for commercial vehicles operators could be as high as 30 to 40% of all their expenditure. Furthermore, fuel has been shown to be a highly variable budget on which improvements are generally possible (Wilson, 1987). The use of fuel is also intrinsic to any industry using vehicles. In addition, and as mentioned by McKinnon (1993), fuel consumption can be improved in many different ways. Consequently, it seems potentially easier and more beneficial to concentrate first on improving companies' fuel efficiency rather than on other operational areas. Finally, because vans have a bigger market share than HGVs (68.1 billion vehicle kilometres for the former and 28.7 for the latter in 2008 - DfT, 2009, p.130) and that van fuel efficiency measurement is rather different from HGV's, this study will primarily focus fuel efficiency improvement in the van industry.

Improving the design of a supply chain can for example have huge repercussions on fuel consumption although potential savings on fuel might be outweighed by other costs thus this approach would not be ideal. Conversely, many different fuel saving interventions exist. Amongst these are diesel or oil additives, energy efficient tyres and aerodynamic kits. Technologies like CANbus (Controlled Area Network Bus, a bus on the vehicle which allows different electronic units to share information such as wheel speed or fuel used) can provide an accurate driver's mpg along with detailed information on each driver's behaviour. Although this cannot alone lead to improvement in fuel efficiency, more accurate information and measurement can help fleet managers making better informed decision which could ultimately lead to improvements in fuel efficiency. Yet, even though most of these interventions can demonstrate a Return On Investment (ROI), they all represent an investment which some companies might not be able to afford.

On the other hand, because fuel cards are omnipresent in the industry, improving fuel efficiency measurement based on fuel card data could indirectly improve fuel efficiency without requiring this extra investment. Besides, mpg, the industry-standard fuel efficiency measure, has several limitations which should be addressed (these will be detailed in the next section). This study will consequently concentrate on improving fuel efficiency measurement based on fuel card data.

Background

As seen above, mpg suffers from several limitations. These are detailed below:

- The measure does not include parameters necessary to its interpretation (e.g. 'vehicle weight', 'vehicle age').
- The measure does not reflect pence per mile (ppm) efficiency.
- The measure is often misused in the industry. This happens when mpg is calculated per period (e.g. monthly) when not all vehicles refill at the beginning and end of the period.

In order to improve van fuel efficiency measurement, these limitations have to be addressed.
To do so, traditional benchmarking approaches would combine mpg and ppm together through the use of weighted averages. However, average is a measure of a central tendency that is a

representative value only when data demonstrate a low variability which might not always be the case. The choice of the weights is also often open to debate as no entity is likely to be best 'across all areas' (Sharif, 2002). Besides, this method does not provide mechanism to incorporate external parameters such as 'vehicle weight'.

These weighting limitations were addressed by several outranking methods successively developed by Roy and Bouyssou and Pomerol and Barba Romero ((Bouyssou and Roy, 1993), (Barba-Romero and Pomerol, 2000) cited in (Laise, 2004)). However, these methods tend to be best at ranking entities rather than at providing a score or measure.
All these limitations are addressed by another benchmarking method called Data Envelopment Analysis (DEA) first introduced by Charnes Cooper and Rhodes (Charnes et al., 1978). DEA evaluates an entity's performance by calculating its respective score. This score is determined by comparing the entity's weighted input to weighted output efficiency ratio against all the other entities' efficiency ratio values. This concept of efficiency ratio is illustrated below:

$$Total\ Productivity\ Ratio = \frac{\sum_{j=1}^{s} output_j \times\ weight_j}{\sum_{i=1}^{m} input_i\ \times\ weight_i}$$

where s is the number of outputs and m the number of inputs,

$weight_j$ is the weight of $output_j$, and

$weight_i$ is the weight of $input_i$.

Figure 1: Total factor productivity ratio

A linear mathematical process is then carried out for each entity. This process optimises the performance ratio by finding the best set of weights whilst being constrained by the all the other entities' inputs and outputs values. Following this process, DEA determines the following:

- Whether the unit is efficient, i.e. a best in class (the set of efficient units define the efficient frontier, the line which represent best empirically observed performance).
- If not efficient, how much input reduction (whilst keeping output levels constant) is necessary in order to reach efficiency (or vice versa. This is called the 'technical or radial inefficiency').
- Any potential slack on all input or outputs (this is called the 'mix inefficiency').
- For inefficient units, the list of all the efficient units that represent the local best practices.

This study uses DEA to improve van fuel efficiency measurement as this technique can address the first two limitations of mpg as listed above. The last limitation, in regards to the misuse of mpg will be addressed by a separate smoothing algorithm detailed in the following section.

Data Cleansing and Volume Smoothing

Three companies participated in this study. Their fuel card data was collected for the same period (April to June 2009) along with information regarding their vehicles (e.g. amongst others vehicle registration, vehicle make, model and description, type of operations, vehicle gross weight). The three companies use telematics services thus the distance used in the models was obtained from the tracking units. As DEA is sensitive to measurement error and exogenous influence (Avkiran and Thoraneenitiyan, 2009), a study was independently conducted for each company to avoid having a company's environmental factors biasing the results.

An algorithm was developed to cleanse the fuel card data. This algorithm tried to match fleet registrations details with registrations found on the fuel card file. The algorithm first tried to match the registrations discarded from any space. If unsuccessful, a series of phonetic mismatch were then considered. For example FO08 FNX could be misspelled as F008 FNX or FOO8 FNX based on the mispronunciation of ‘0’ as ‘O’. Because the companies all used telematics services, telematics information was also used to further cleanse the results (e.g. check whether the vehicle was at a petrol station at the time of refill). Finally, mpg performance was calculated between transactions so that any vehicle showing an unrealistic mpg was individually appraised and potentially discarded from the dataset (if missing a fuel transaction for example).

When measuring fuel efficiency based on fuel card data, fuel consumption can only be accurately measured between refills and only if refills are always made up to the top of the tank. This way, the fuel consumption can be calculated because the distance between the two refills is known (using telematics or odometer readings), and the volume of fuel used to cover this distance corresponds to the volume of the second refill. However, most fleet managers need to compare fuel efficiency performance for all vehicles/drivers during the same period (generally a week or a month). Yet, it is hardly ever possible to have all vehicles filled up at the exact beginning and end of the measurement period and many would simply use the volume refilled during the period as the volume used – even though this is sometimes blatantly inaccurate.

In order to address this issue, this study developed another algorithm which calculates the volume of fuel used during the period. This is illustrated by the figure below:

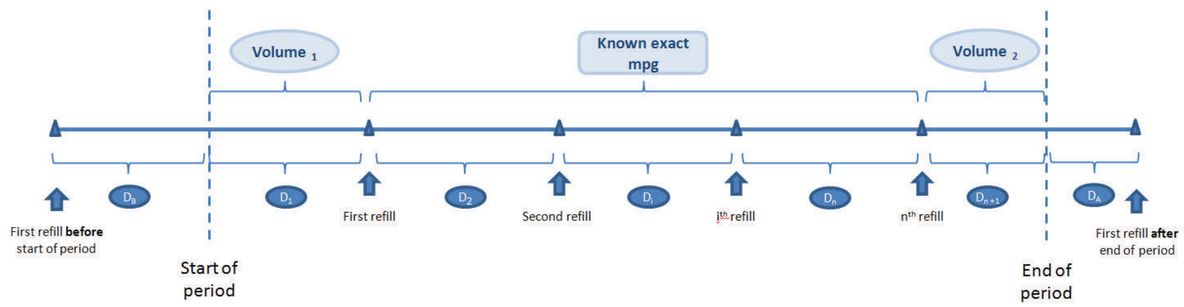

Figure 2: Measuring fuel efficiency over a period of time

The ‘Smoothed volume’ is the sum of the exact volume used between the first refill and the last refill within the period, and an estimation of the volume used between the beginning of the period and the first refill and of the volume used between the last refill and the end of the period. These last two volumes are estimated with the mpg calculated between the first and last refill. This is illustrated below:

$$Smoothed\ Volume = \sum_{i=2}^{n} Volume\ of\ refill_i \times \left(1 + \frac{D_1 + D_{n+1}}{\sum_{i=2}^{n} D_i}\right)$$

Figure 3: Formula for the smoothed volume

This smoothed volume corrects inaccuracies created by advantageous refills (i.e. just before the beginning or straight after the end), resulting in an artificially high mpg, or disadvantageous refills resulting in an artificially poor mpg performance. This is illustrated below:

VehCode *	Bad MPG *	Smoothed MPG *	Fuel Drawn *	Fuel Used *
1	53.671	49.49	285.26	309.356
2	53.025	51.211	248.76	257.569
3	51.452	51.963	433.45	429.187
4	43.252	42.999	121.39	122.104
5	50.554	50.124	248.74	250.876
6	42.361	43.726	170.45	165.129
7	29.653	30.826	251.71	242.128
8	63.313	58.901	283.14	304.351
9	44.121	46.169	333.12	318.34
10	59.164	49.354	182.66	218.967

Figure 4: Results of the smoothing algorithm

This smoothed volume is used in the fuel efficiency model described below and this addresses the last limitation aforementioned of 'misused measure'. It is important to observe that without telematics distance information, this algorithm also requires the odometer reading to be taken at the beginning and end of the period (not just at the refills).

Fuel Efficiency Model

In order to address the two other limitations (i.e. that mpg does not incorporate the cost dimension and does not include parameters necessary to its interpretation), the fuel efficiency DEA model was originally designed with the following inputs and outputs:

Figure 5: Fuel efficiency model

This model relates to the mpg measure as it stills uses 'fuel used' as an input and the corresponding 'mileage' as outputs. 'Fuel cost' is added to the model as an input (so that vehicles could be mpg efficient but ppm inefficient and vice versa). Similarly categorical variables such as 'vehicle weight' and 'vehicle age' are also added as inputs of the model.

This model is tested independently with each company's data using a step by step approach. This implies the first model solely consists of 'fuel used' and 'miles travelled' as this simple model can be easily compared to mpg. To allow an accurate measurement of the impact each variable has on fuel efficiency, 'vehicle weight' and 'vehicle age' are added one variable at a time.

Because each variable in the fuel efficiency model should be free to change independently from the others (or more precisely in what is called a non-radial manner), the Slack Based Model model (Tone, 2001) was retained for this study. However, since 'vehicle weight' and 'vehicle age' are 'non-modifiable' variables (known as non-discretionary), a specific non-discretionary adaptation of the SBM was developed for this study (named SBM-ND-I for Slack Based Model Non-Discretionary Input oriented). This adaptation allows slacks on all variables but only the slacks corresponding to the discretionary variables enter in the calculation of efficiency.

Results

The results of the basic model with ‘fuel used’ and miles travelled were highly correlated with the mpg measure (the very small discrepancies were only due to rounding operations in the DEA model calculations). This suggested that DEA could effectively be a relevant alternative to fuel efficiency measurement with mpg.

Adding the cost to the model did not significantly impact the results both in terms of efficiency status or ranking position. Furthermore, the results of the ‘fuel cost’ and ‘miles travelled’ model were similar to both those of the ‘fuel used’ and ‘miles travelled’ model and to the ‘fuel used’, ‘fuel cost’ and ‘miles travelled’ model. As there was no change in the efficiency status between all these models, and that the ranking position was not significantly affected, this suggests no vehicle was simultaneously mpg efficient and ppm inefficient or vice versa. There is consequently no interest in adding ‘fuel cost’ to the fuel efficiency model and only the ‘fuel used’ variable was retained in the model.

Incorporating the vehicle gross weight in the fuel efficiency model required further data processing as for the model to behave logically in relation to ‘vehicle weight’, the ratio ‘vehicle weight’ to ‘miles travelled’ had to be unique within a ‘vehicle weight’ category. This was essential as otherwise the impact of ‘weight’ for vehicles within the same weight category would be different in regards to the number of miles travelled – which is logically not a desired characteristic. Consequently ‘fuel used’ was normalised in regards to number of miles travelled so that each vehicle had virtually travelled 1,000 miles and used a proportional amount of fuel to cover this distance. However, vehicle weight was left untouched so that the ratio ‘vehicle weight’ to ‘miles travelled’ was effectively unique within a ‘vehicle weight’ category. Finally, the weight was also transformed into an isotonic variable by subtracting the ‘vehicle weight’ variable to a bigger number K (Dyson et al., 2001). This is because in DEA it is assumed that an increase in inputs should result in an increase in outputs (and a heavier vehicle would logically demonstrate a worse mpg performance thus the weight ‘direction’ needs to be reverted).

This model results were consistent and logical as within each weight category, vehicles with the best mpg performance demonstrated the best DEA scores. This is illustrated in the figure below where the vehicle weight was made isotonic using K = 3,501 and the mpg and score column highlighted with a R.A.G. colouring (green represents good performance, red poor performance):

VehCode	Normalised Fuel Used	Isotonic Weight (3501)	Distance Travelled	mpg	Score
8	77.18	1316	1000	58.90246022	1
20	83.3	1316	1000	54.57493253	0.926530612
3	87.49	1316	1000	51.9612742	0.882157961
14	87.96	1316	1000	51.68362756	0.877444293
2	88.77	1316	1000	51.21202974	0.869437873
5	90.7	1316	1000	50.12229195	0.850937156
21	91.35	1316	1000	49.76564729	0.844882321
1	91.86	1316	1000	49.48935206	0.840191596
10	92.11	1316	1000	49.35503072	0.837911193
17	93.83	1316	1000	48.45030246	0.822551423
18	97.35	1316	1000	46.69842712	0.79280945
9	98.47	1316	1000	46.16727816	0.783792018
19	99.42	1316	1000	45.72613036	0.776302555
15	99.81	1316	1000	45.54745897	0.773269212
11	99.98	1316	1000	45.4700128	0.771954391
13	100.61	1316	1000	45.18528854	0.767120565
6	103.97	1316	1000	43.72503491	0.742329518
4	105.73	1316	1000	42.99718037	0.729972572
16	112.56	1316	1000	40.38816525	0.685678749
12	115.83	1316	1000	39.24796581	0.666321333
7	147.48	1316	1000	30.82514158	0.523325197
28	87.9	640	1000	51.71890648	1
33	88.12	640	1000	51.58978529	0.997503404
31	90.58	640	1000	50.18869375	0.970412895
23	101.39	640	1000	44.83767512	0.866949403
42	108.8	640	1000	41.78393272	0.807904412
26	115.1	640	1000	39.49688862	0.763683753

Figure 6: Model results with ‘fuel used’, ‘vehicle weight’ and ‘miles travelled’

It is essential to observe that in some cases, some vehicles can be best in class (in regards to mpg) in their respective weight category but are nonetheless evaluated inefficient. This is because the model uses data from all weight categories when evaluating any vehicle's efficiency. In this specific case, some vehicles in different weight categories demonstrated a better performance than these best in class vehicles. Thus, despite the fact these vehicles are best in class in their weight category; the model evaluated them as inefficient. This concept is illustrated in figure 7 with the two vehicles 66 and 68. These vehicles are the best in class in their respective weight categories and in relation to mpg but not evaluated efficient by the model (thus not on the efficiency frontier represented by the blue line). This is illustrated in the figure below where best fuel performance is represented by a smaller number on the x axis and heavier vehicles are at the bottom of the graph:

Figure 7: graphical representation of the results

Finally, adding 'vehicle age' to the model further segmented the results in such a way that the fleet managers mistrusted and were confused by the results. For this reason, and although it seems logical from a theoretical point of view to include 'vehicle age' in fuel efficiency, this variable was discarded from the fuel efficiency model.

Conclusion

As explained earlier, the fuel information used in this study was collected from fuel card data. Although this was ideal for this proof of concept – fuel cards are nearly omnipresent in the industry – there are a few limitations attached to it. For example, this model is of limited use if the fuel efficiency measure cannot be related to a driver which is case if several drivers share the same vehicles during the measurement period. This limitation can however be addressed if driver fuel information is retrieved directly from the engine electronic systems.

Further research could focus on applying this method to the HGV segment. As the vehicle's load weight will need to be taken into account, it might be possible to look at scoring each journey or using an average load weight during small periods instead of using the vehicle gross weight. The smoothing algorithm can also be improved and more exception rules could be developed in order to increase its robustness (e.g. like appraising the likeliness of the refill to be up to the top of the tank).

This study demonstrated it is possible to improve van fuel efficiency measurement based on fuel cards through the use of the cleansing and smoothing algorithms and of the SBM-ND-I DEA model. The companies' fleet managers appreciated this model and the fact the efficiency scores provided by the model could be compared across all their van fleet without having to know each vehicle's weight.

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