A Mixed Integer Programming Model for Fuel Efficiency with Logistics Uncertainties Impact

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Abstract

Total supply chain management cost has always been the interest of many companies in these recent economies. The aim to survive and sustain is important these days. Sustainability in road transport operation can be measured by how the transport company manages the fuel consumption for its vehicles or trucks. Fuel efficiency is one of the key points to measure the success of road transport operation. It can be achieved by controlling the right variables such as speed, weight or volume of transported good, travelled distance and other related variables. However, all the variables are highly affected by the logistics uncertainties such road congestion, faulty vehicles, error in information and many more. In this study, a fuel namely diesel usage optimization model that consider the effect of the logistics uncertainties is proposed. The mixed integer programming model that considers truck tonnage, its age, model and travelled distance as the controlled variables while delay, wrong information and changes in demand volume (carried volume) as the constraints is adapted using a 3-month data from a freight forwarding company. The model is solved using Excel Solver and shows that different models at different age are losing the fuel efficient, but the difference is not significant. At the same time, delay and wrong information do not have effect on fuel efficient but changes in demand volume largely affect the fuel efficiency by 20.4 percent for the three-month data. The sensitivity analysis for the upcoming months are also done.

Keywords— Diesel Usage, Fuel Efficiency, cost control

1. Introduction

Fuel accounts for a large share of operating costs in the freight transport sector and is the source of virtually all freight-related emissions. Hence it is of no doubt can be used as the performance metric to measure the effectiveness of transportation operation management. The metric itself is a productivity measure showing the efficiency with which energy is converted into the movement of freight which is very much application to measure the road transport operation management. In the road sector, performance can be measured from several different perspectives and for several reasons (Ajanovic and Haas, 2012). Firstly, is the amount of freight movement can be a good indicator of the level of economic activity. There has traditionally been a close correlation between freight tonne-kms and GDP, though the ratio of these variables can decline as an economy develops and services increase their share of total output. Knowing how much freight is being moved also indicates the related transport demands for infrastructural capacity, fuel, labour, and vehicles (Mahlia et al, 2012;Mc Kinnon, 2015).

Sustainable transportation refers to any means of transportation that is 'green' and has low impact on the environment. Sustainable transportation is also about balancing our current and future needs, and sustainability in road transport operation can contribute to sustainable transportation as well as ensure sustainable business to the road transport operators. In Malaysia, there are a lot of logistics uncertainties that have significant impact in road transport operation that can slow and interrupt the business (Iqkhmal et al, 2020). Delay and Wrong information top up the list of uncertainties that affect Malaysian road transport operations.

Most of the latter studies suggest that the energy efficiency of the road freight sector is improving relative to both trucks-kms and tonne-kms. Eom et al (2012), however, found wide variations in both the average energy intensity of trucking across the eleven developed countries they examined and 'their overall trends mixed'. In much of the developing world, data are too limited to make similar assessments. Clean Air Asia (2012), however, were able to compile average fuel efficiency data for light- and heavy-commercial vehicles in thirteen Far Eastern countries. Statistics are also available on the average energy intensity of rail freight operations in many countries. The most recent set of figures assembled by IEA / CER (2012) suggest that the average energy intensity of moving freight by rail declined by 19% between 1990 and 2009 from 234 kilojoules per tonne-km to 191. Macro-level analysis of energy efficiency trends in freight transport has been quite a fertile field of research in recent years, particularly in the trucking sector. Kamakate and Schipper (2009), Eom et al (2012) and Liimantainen et al (2014), for example, have undertaken multi-country reviews of these trends while other studies have focused on individual countries: e.g. United States (Langer, 2004), UK (Sorrell et al, 2009), Finland (Liimatainen and Pollanen, 2010) and China (Li et al, 2013) .

Compiling data on the fuel used by trucks can be challenging. In many countries no records are kept of the proportions of diesel fuel going into different types of vehicle at the point of sale. Splitting this fuel by trucks, vans, cars and buses must therefore be done by other means. This usually entails measuring vehicle-kms travelled by these vehicles and multiplying this by an average fuel efficiency measure (litres per 100km) derived from operator surveys or drive cycle testing. Research has found, however, that there can be significant discrepancies in government estimates of both truck-kms and average fuel efficiency derived in different ways (McKinnon and Piecyk, 2010). One must therefore exercise caution in interpreting national level fuel economy data. As a first approach, an extensive literature review has been performed, showing that the most important in-use factors affecting the difference between real-world and certification performance are the use of air conditioning devices, ambient temperature and environmental conditions, roof add-ons, driving style, tyre pressure and the increase of vehicle weight.

The elasticities of the type of approval (TA) test have also been identified as highly influential and were analysed separately due to their nature. Summarising the findings of the literature review and the subsequent analysis performed, the real world- certification difference could range between 25-45 %, depending on the combination of factors and conditions. It should be noted that most of the parameters examined can be influenced directly by the driver, except for ambient and road conditions (Basalim et al.,2017).

Fuel management are also important in keeping costs down and maximizing profits. Fuel accounts for a large share of operating costs in the freight transport sector and is the source of virtually all freight-related emissions. Policy-makers therefore need little convincing of the importance of fuel efficiency as a performance metric. The metric itself is a productivity measure showing the efficiency with which energy is converted into the movement of freight. This can either be done with respect to vehicle-kms (fuel efficiency) or to a denominator that takes account of the weight or volume of goods transported (often called 'energy intensity'). Vehicle specifications such as age, tonnage, types will be included as constraint in an optimization of fuel consumption or namely diesel optimization in road transportation operations. Fuel usage should be emphasized because it can bring major impact to the company if the usage is not properly managed. Hence, in this study, the said variables are analysed and considered in modelling the fuel optimization for road transport operation. The uncertainties are included as the constraints in the proposed model.

2. Methodology

Model building

The fuel efficiency can be controlled if traffic volumes can be estimated. Several ways can be implied from drivers and trucks specification in order to achieve effective fuel consumptions. Fuel efficiency can be calculated by taking the total volume of fuel consumption divided by total distance travelled as defined as Z.

$$Z = \text{Fuel Efficiency (KM/Liter)} = \frac{\text{Distance Travelled (KM)}}{\text{Fuel Consumption (Litre)}}$$

In a road transport company, maximizing the fuel efficiency will be the objectives. Hence the model can be rewritten in a mixed integer linear model as follows:

Maximize $Z = aX_1 + bX_2 + cX_3$
Subject to
Delay <= l hours
Percentage of wrong information < 0.1
Percentage of changes in demand < 0.1

And
$X_{1,}, X_2, X_3 \geq 0$ for integrality constraints

Where Delay = l hours follows normal distribution, l~N(average, variance)

$X_{1,}$ is the truck tonnage; $X_1 = \{3, 5, 7.5, 10, 40\text{ft}\}$
X_2 is the truck age on the road; $X_2 = \{3,4,5,6,7,8,10,11,13\}$
X_3 is the truck model; $X_3 = \{\text{Hino, Fuso, Nissan}\}$

Data were collected from the GPS system attached in truck. The fuel report software shows the total distance travelled by truck in daily basis. The total distance was calculated in Kilometre Unit. (KM). The fuel consumption is calculated by total fuel before truck moving in morning and after truck finish moving. Additional fuel fills up were also added in the calculation. The date was collected from 26 units of truck. Each truck has different class tonnage, age, and model. The data collected for 3 month and sort according to each category.

Table 1 summarised the initial data used for calculating the parameter values l (delay hours), percentage of wrong information and percentage of change in demand.

Table 1: A Three-way table for average fuel efficiency based on tonnage, age and models

Age (years)	Tonnage					Model			Average (km/lt)
	40 ft	10	7.5	5	3	Hino	Fuso	Nissan	
3	2.72					2.72			2.72
4			5.87				5.87		5.87
5				3.76				3.76	3.76
6		2.97				2.97			2.97
7					4.59	4.59			4.59
8	2.51				5.05	5.05			4.20
10		3.04			4.68	4.27			4.00
11	2.38	3.31				3.00			2.90
13		3.49				3.49			3.49
Average	2.54	3.20	5.87	3.76	4.77	3.73	5.87	3.76	

Data Collection

The 3-months data from May 2020 until July 2020 were collected and analyzed. Figure 1 shows the actual GPS System Fuel Report from the GPS software. The total miles and fuel consumption were provided. Total numbers of fills up is also shown together with the location of trucks.

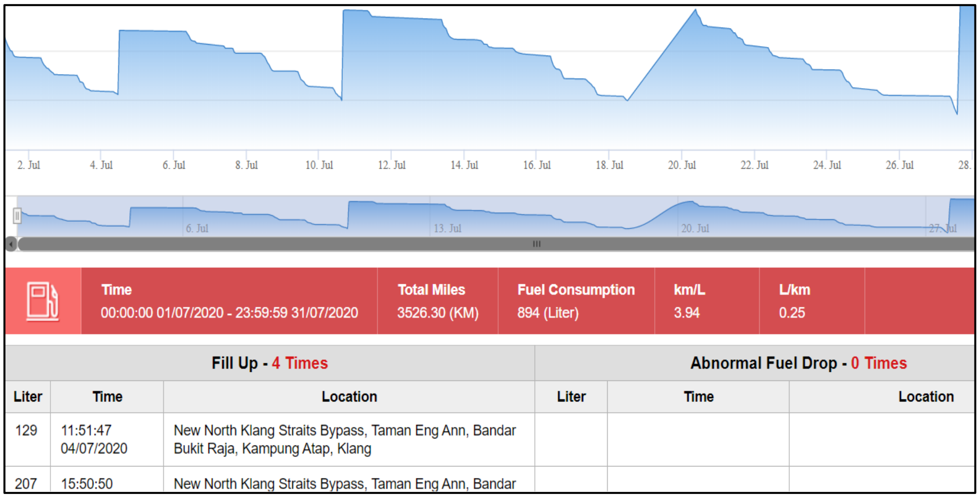

Fig.1: Sample of report of uncertainty sources

Methods of Analysis

The analysis is divided into two phases:

1. Data setting and model validation
2. Comparison of the fuel efficiency of each truck versus the efficiency value based on the proposed model.

Data setting

A three-month daily operations data was accumulated. Three main variables are considered which are size of truck (in tonnage), age of truck used on the road, and models of truck. From the data, there are 7 units of 3 tons truck, 2 units of 5 tons truck, 3 units of 7.5 tons truck, 7 units of 10 tons truck and 7 units of 40-footer trucks. The age of truck disperses from 3 years to 13 years. Truck was sort according to each of trucks used on the road. The models are also considered in which there are 3 types of models (Hino, Fuso, and Nissan) were considered. A total of 19 units of truck from Hino models, 5 units from Fuso and 2 units from Nissan.

Based on Cost Risk Score Analysis in Table 2, (Iqkhmal et al, 2020), Delays has the highest risk score, followed by Delivery Constraint, Demand Changes and Information Error. Since Delivery Constraints are usually resulted from changes in demand and error in information, its is dropped from the model.

Table 2: Cost Risk Score (based on expert views)

Uncertainty Cluster	Cost Risk Score					
	Responses	Impact	Cost	Risk Score	Mean	Std Dev
Delays	54	5	270	100.00	39.63	32.17
Delivery Constraint	34	5	170	62.96	31.01	22.65
Demand	34	4	136	50.37	25.68	19.42
Information Error	32	4	128	47.41	20.74	16.99
System Error	25	3	75	27.78	14.07	9.41
Returns	11	3	33	12.22	9.51	2.78
Complexity	13	2	26	9.63	8.15	2.10
Legislation	9	2	18	6.67	6.67	#DIV/0!

3. Results and Discussion

The parameter values are set based on the historical data. Hence the initial results are in form of descriptive statistics. The relation between fuel consumption and tonnage, age and models are described.

Figure 2 shows the fuel consumption based on tonnage. There are 5 groups in which is 3 tons, 5 tons, 7.5 tons, 10 tons, and 40ft. The lowest fuel efficiency goes to 40ft where the 3-month data shows that it has the lowest average value at 2.45 km/litre compared to the other smaller tonnage. The 10-tonnage truck follows in 2nd lowest place at 3.25 km/litre. The best tonnage in fuel efficiency is 7.5-tonnage trucks with the average for 3 months is 5.86 km/l.

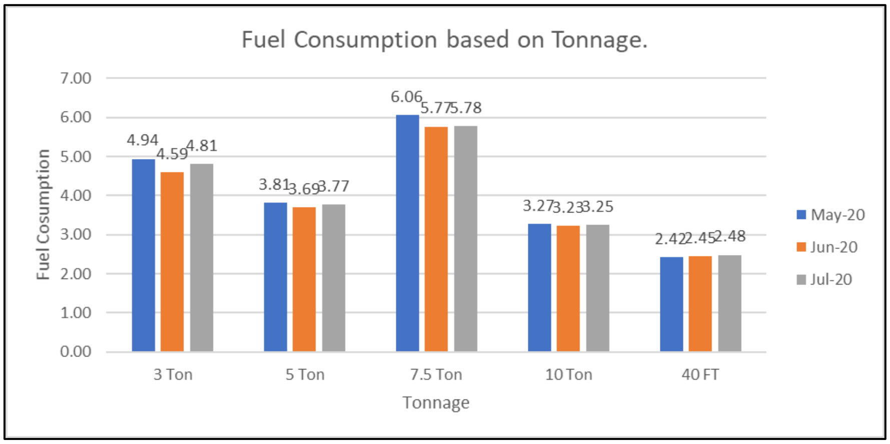

Fig.2: Fuel Consumption based on Truck Tonnage

This shows that the weight of truck has effect on the fuel consumption. Table 3 shows the ANOVA table of tonnage and 3-month fuel efficient average values assuming that both data sets are distributed normally. Since p-value is very small, hence it can be concluded that there is at least one tonnage has different fuel-efficient value. The higher tonnage of the truck could be significantly resulted in the higher the fuel consumption and the lower the fuel efficiency.

Table 3: ANOVA for tonnage and 3-month average fuel efficiency

SUMMARY of ANOVA

Groups	*Count*	*Sum*	*Average*	*Variance*
Tonnage	31	603.5	19.46774	281.0989
3 Month Average Fuel Efficiency	31	110.0833	3.551075	1.499462

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	***P-value***	*F crit*
Between Groups	3926.774	1	3926.774	27.79049	**1.94E-06**	4.001191
Within Groups	8477.952	60	141.2992			
Total	12404.73	61				

From Figure 2, the 7.5 tonnage truck shows a better fuel-efficient performance compared to the 3 tons and 5 tons, this shows that there are some other factors that can affect the fuel efficiency. Figure 3 shows the pattern for 3 months fuel efficiency in relation to age of the trucks. It shows that the fuel efficiency based on age of truck used has mixed results. For the month of May 2020, the 3 years truck has average of 3.8 km/l, the 4 years has higher fuel efficiency at 2.89km/l. Meanwhile for the 5 year shows a better fuel efficiency at a higher value of 5.04km/l, however for the 7-year truck, it has the worst fuel efficiency ats 2.08km/l.

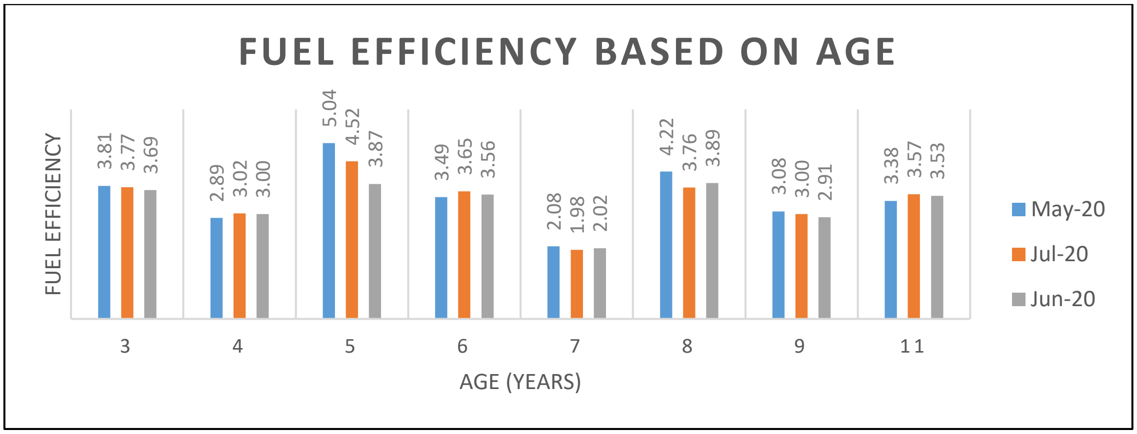

Fig.3: Fuel Efficiency based on Truck Age

Based on the data, it can be concluded that the age of truck does not give much impact to fuel efficiency. The data has shown the 11 years and 9 years truck has better fuel efficiency compared to 7 years truck. This is because of the other factor that affect such as how the truck was taken care of, for example having it taken for maintenance as per scheduled and how many times did truck breakdown. Table 4 shows results of ANOVA test on the variation in the fuel efficiency and age. The p-value is also smaller than the level of confidence 0.05, hence it can be concluded that there is at least one group of age that vary from the rest. Meaning that there is some evidence to conclude that age also affect the fuel efficiency.

Table 4: ANOVA for age and 3-month average fuel efficiency

SUMMARY of ANOVA

Groups	*Count*	*Sum*	*Average*	*Variance*
Age	31	247	7.967742	8.298925
3 Month Average	31	110.0833	3.551075	1.499462

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	***P-value***	*F crit*
Between Groups	302.3576	1	302.3576	61.7158	**8.63E-11**	4.001191
Within Groups	293.9516	60	4.899193			
Total	596.3092	61				

Figure 4 shows the fuel efficiency calculated based on model. It shows that based on three (3) models considered, Nissan model has highest fuel efficiency for the 3 months at 3.81km/l, 3.69km/l, and 3.77km/l respectively. The lowest fuel efficiency is Hino model which are 3.58km/l, 3.43km/l and 3.54km/l for 3 months. The truck model or brand did have effect on fuel consumption because of the different types of engine used will give different performance to the truck. Besides that, each brand has different price, the higher quality truck performance will affect the truck price. Hence, there is a need of truck model price analysis in order to get the precise results.

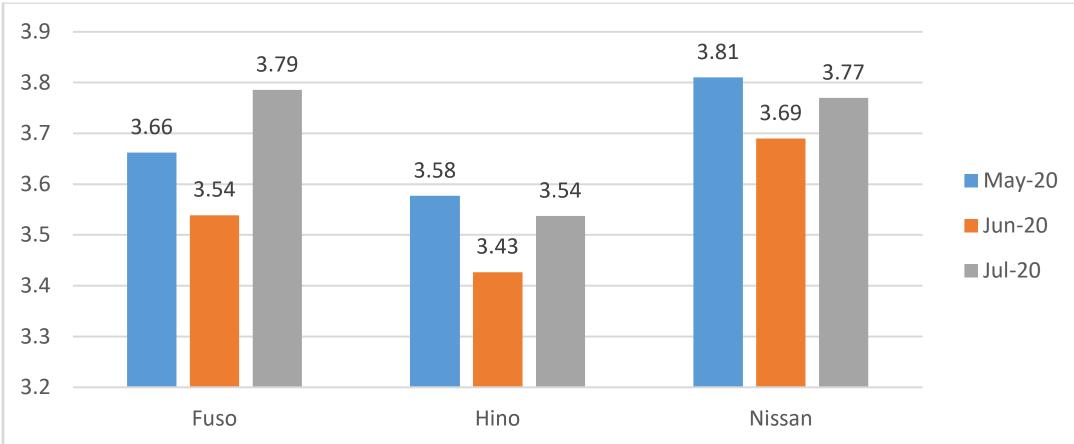

Fig.4: Fuel Efficiency based on Truck Model

From the collected data, the performance of delivery operations is measured against the target benchmark values which are calculated based on the standard operation values. Figure 5 shows that only the 40ft vehicles are close to the target values.

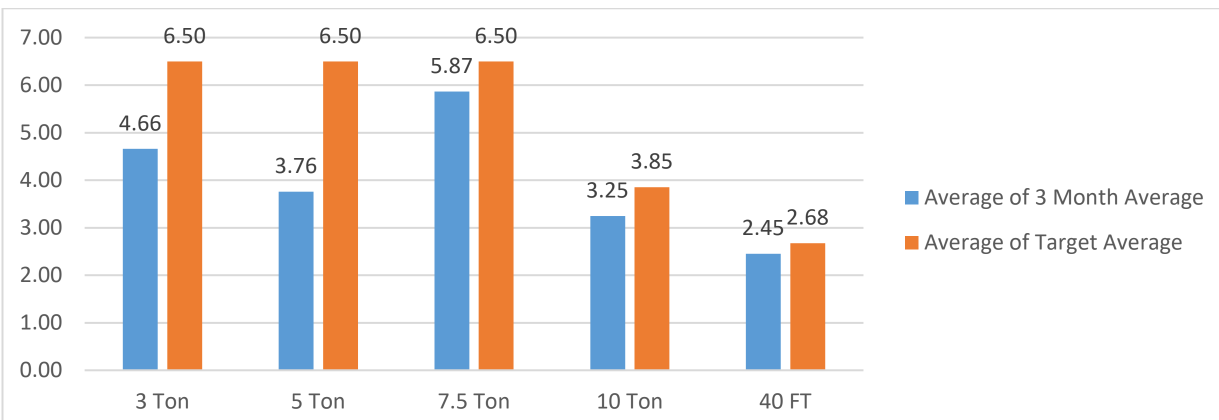

Fig.5: Target Fuel Efficiency based on Tonnage

4. Conclusion and Recommendation

The study concludes that incorporating the uncertainties in road transport operations can result in less fuel efficiency and some variables (tonnage, age and model of vehicles) can be managed for better efficiency. To control the fuel consumption, road plan is needed to get better fuel efficiency. For example, choose the route which has less road congestion, plan the delivery early before the peak hour because truck might get stucked in heavy traffic thus led to unnecessary idling. The important things are to optimize the cargo for truck to reduce the overweight loads.

Besides that, there are some other factor could affect the fuel consumption such as driver behaviors such as aggressively driving, speeding, and harsh braking. The unnecessarily idling while waiting for cargo to load ls have effect in fuel consumption. Based on this factor, fuel efficiency can be controlled and monitored by transport manager and operation to sustain road transport operation. Further analysis using several other formulations in measuring the fuel efficiency need to be done while incorporating the uncertainties into the calculation. The best practice in fuel management will prevent or at least we can predict the uncertainty that might occur.

Acknowledgment

We would like to thank Malaysia Institute of Transport (MITRANS) UiTM for funding this publication.

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