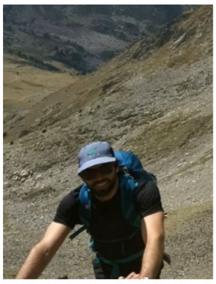
Fuel Consumption of Heavy-Duty Trucks at in Signalized Intersections: Potential Savings



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Abstract

Fuel consumption and CO_2 emissions have been a topic of interest in the last decades. Not only environmentalists but also governments are taking rapid action to reduce emissions of pollutants. The measures imposed by governments involve, naturally, all stakeholders in the logistics sector, from road authorities and logistic operators to truck manufacturers.
The improvement of traffic conditions is one of the perspectives in which the reduction of emissions is being addressed is. Optimization of traffic flow, avoidance of unnecessary stops, control of the cruise speed and coordination of trips in an energy efficient way are necessary steps to remain compliant with the upcoming regulations. In this study we measured the fuel consumption in heavy-duty vehicles while traversing signalized intersections and we examined the differences between various scenarios. We found that in good traffic conditions avoiding a stop translates to a 0.12 l fuel saving.

Keywords: Fuel Consumption, Greenhouse Gases, Heavy Vehicles, Freight Transport, C-ITS, traffic control

1. Introduction

Road transportation is not only one of the main causes of CO_2 emissions, but it is also the main component of the logistic costs. Furthermore, a large percentage of it takes place in specific corridors where most of the freight traffic takes place. Aiming to reduce the emissions and fuel-usage in these specific corridors can have a huge economic and environmental impact.

1.1 Fuel Consumption and CO_2

Depending on the degree of development of the country, domestic logistics costs account for 5% to 20% of a country's GDP of which about 60% are transportation costs (Havenga and Pienaar [2012], Ittmann and King [2010]). Although the global road to rail modal split ratio is estimated to be 60:40, this varies significantly from one country to another. Specifically, in Latin America and China, the percentage of rail transport is below 25% and it is under 40% for the United States (Kaack et al. [2018]). The European Union is more heterogeneous and the estimations of the road-rail modal split vary between 17% (Blauwens et al. [2006]) and 34% (Kaack et al. [2018]). Rail dominates in a few countries that share certain characteristics, i.e. they span large areas with a very irregular population distribution, such as Australia, Russia and Canada. Furthermore, in the last ten years the share of road freight activity has been shown to be increasing compared to rail freight worldwide (Kaack et al. [2018]). At the same time, the transport industry is a significant source of greenhouse gas emissions such as CO_2. As of 2015, the transportation sector was responsible for 7% of the total CO_2 energy related emissions (Kaack et al. [2018]). Furthermore, freight transport which is highly dominated by trucks, constitutes 25% of U.S. total CO_2 emissions (Ang-Olson and Ostria [2005], Hwang and Ouyang [2013]). Altogether, these figures call for urgent action in road transportation so that logistics can expand to allow for economic growth with smaller impact on air quality, as described in the emissions goals of the European Union. The last two decades have shown a shift in freight transport research towards sustainability and safety, affecting heavy-duty transport vehicles in a number of ways. Different options have been and are being explored at different levels, ranging from different energy sources to automation and coordination. The changes in the transport of goods could be classified as follows: vehicle energy consumption and efficiency, control of emissions, and finally automation and coordination both between vehicles and with the network infrastructure.

1.2 Emissions and Traffic Control

Reducing the number of stops made by vehicles can lead to a drop in travel times, fuel consumption and undesired CO_2 emissions, while at the same time increasing safety on road (see Peters et al. [2009] and the references therein, for example: Barth and Boriboonsomsin [2008]). Although initially aimed at reducing travel time rather than increasing sustainability, methods to maintain a steady flow in main roads have been around since the implementation of the green waves, which have been studied since the late 1910s (Guberinic et al. [2008], Tully [1976]). Further steps in this direction were green waves influenced by induction loops where the fixed or manually adjustable schedule was replaced by a dynamic algorithm with the traffic flow at specific points as input. The application of induction loops for traffic control was introduced in the 1960s (Klein et al. [2006]) and has been under development since then. Some traffic controllers based on induction loops that are widely used are SCOOT (Robertson and Bretherton [1991]) and SCAT (Sims and Dobinson [1980]). In the Netherlands these systems are known as VECOM and VETAG and have been in use since the 1970s (Meyer [1975], Middleham [1976], Ros [1986]). Since then, diverse efforts have been put into developing communication systems between vehicles, infrastructure and traffic management centers. These technologies are now widely referred to as intelligent transport systems (ITS). PROMETHEUS, probably the first European research program on ITS, dates back to the 1980s (Festag [2014]). It was around the same time that the Interstate Surface Transportation Efficiency Act (ISTEA) in the United States issued the theme of ITS (Roess [2011]). In the early 2000s, the ubiquitous availability of Global Positioning System (GPS) devices and wireless communication boosted ITS technology developments and resulted in Cooperative-ITS (C-ITS) systems such as the intelligent traffic light control systems (iTLC). On the one hand, iTLCs receive information about the traffic in advance, both from induction loops and from cell-phone applications, allowing to coordinate the traffic reducing the number of stops.On the other hand these systems also communicate bidirectionally, sending back information to the vehicle or the driver, being able to concede priority and determine the optimal speed based on real time data. iTLC systems provide with an opportunity to contribute to achieving the environmental goals by optimizing traffic while minimizing emissions.

2. Methods

The current study employed physical measurements of emissions, fuel consumption, speed and position of a group of the vehicles. After identifying the location of the traffic lights, the data around the crossing was selected to study the different speed and emission profiles and in particular, the differences in emissions of different approaches. Furthermore, the data were subjected to a process of filtering, analysis and enrichment. The following subsections are dedicated to explaining the data; first, the physical measurements and the properties of the vehicles employed; second, the pre-processing and enrichment of the data acquired and third, the analysis which includes filtering and reference to the statistical methods used.

2.1 Setup

The measurements have been done on five Euro VI DAF trucks with engines with power between 320 kW and 355 kW. The acquisition of the data took place during the Integrator project [URSA MAJOR neo – Integrator Connected Truck Trials]. The total weight of the vehicles was also estimated by means of the truck features and their kinematics over all the dataset. The mean and standard deviation of the weight of the vehicles including all trips were 25.75 t and 9.05 t, respectively. The data were acquired during 2019, while the trucks realized their normal operations (naturalistic behavior) in The Netherlands.

2.2 SEMS system

On board measurements have been done by means of the Smart Emissions Measurement System (SEMS) developed by TNO. This system provides a simple and easy to-use yet robust and reliable emissions monitoring solution. It has been tested extensively since its development in 2012 (see for example, Kadijk et al. [2015, 2017], Vermeulen et al. [2012]) and there is an ongoing project to develop its industrialization and large-scale deployment (Heepen and Yu [2019]). SEMS consists of a variety of measurement sensors that are installed in the vehicles which is supplemented with data that is obtained from the existing vehicle electronic and communication system. The first group encompasses a GPS receiver as well as sensors to measure NO_x concentrations, O_2 concentrations, NH_3 concentrations, and exhaust gas temperature and pressure. The sensors were mounted near the end of the exhaust line, in threaded bushes welded through the wall of the tailpipe. Regarding the second group, data from CAN-bus was acquired, such as velocity, throttle position and rotational speed of the engine. All data thus acquired was gathered in a data logger located in the cabin. This small computer was set up to start (stop) acquisition when the ignition was turned on (off). A built-in data transmitter uploaded the data periodically to a server. A computer running a scheduled pre-processing task picked up the data from the server, performed checks, corrections and calculations on the data and wrote it in a dedicated SEMS database.

Data as collected from sensors generally needs pre-processing to remove illogical values and spikes that cannot be explained by the conditions. Furthermore some signals need calibration based corrections. The CAN-bus signal implementation variation among manufacturers is another reason to perform checks and corrections.

The pre-processing of the SEMS data is preformed automatically on a server, although some pre-emptive checks have been done already within the SEMS itself.

The following tasks are performed during pre-processing:

- Calibration; sensor data are corrected using a function based on calibration of the particular sensor in the lab.
- Speed signals from GPS and vehicle are compared and combined to produce a good and continuous signal.
- Raw cleaning; check for negative values, filter some signals for spikes, remove signals when the engine is not running, and to fill small gaps in the data if possible.
- Time alignment; align signals related to emissions to signals related to the engine.
- Ammonia correction; correction of NO_x concentration signal for ammonia, based on ammonia sensor values. This is necessary, because the NO_x sensor is cross sensitive for NH_3.
- Mass flow calculation; emissions in grams are calculated by calculating the flow of exhaust gas, and multiplying it with the concentrations observed.

The result is a set of clean 1 Hz signals that can be used for further calculations, e.g. of emissions per km.

2.3 GPS Data Preprocessing

In order to enrich the data with information from the infrastructure, the time series of the GPS data needed to be connected to the road network. For each trip the trajectory was map-matched using the Open Source Routing Machine (OSRM) (Luxen and Vetter [2011]). The result of this is a new time series where each point is a node on Open Street Maps (OSM) (OpenStreetMap contributors [2020]) from where any information present on it can be added to the original data.

2.4 Data Enrichment and Selection

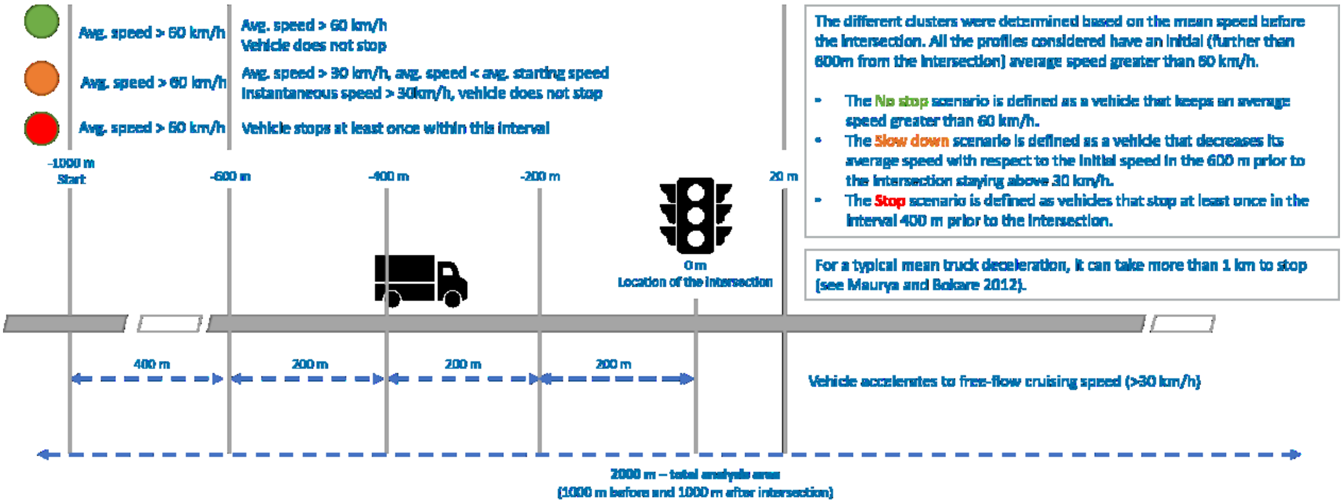
Once the data were linked to the map, we could identify all the points in the data in which a vehicle is crossing a signalized traffic light (based on traffic light locations as in OSM) and the respective segment of the road of equal length before and after the intersection. In this study only intersection passages at provincial roads (80 km/h) were considered. We identified the start and end point of segments of 2 km length centered on the intersection crossing and also the vehicle action on the intersection i.e., the maneuver. This 1000 m has been chosen based on the typical deceleration of a heavy-duty vehicle that can take up to 1 km (Ligterink [2016], Maurya and Bokare [2012]). The result is a series of N intersection passages. The total number of passages measures and identified in the analysis was N = 11087, from which only those with straight maneuver were picked, resulting in a smaller set with N = 4972. Taking into account the correlation between turn radius and vehicles' velocity, the analysis of the turns is significantly more laborious and the interpretation of the results is cumbersome; hence it was not carried out in this work and remains to be explored in future research.

2.5 Analysis

Three different clusters were defined from the speed profiles with a set of simple rules. These clusters represent different scenarios to be analyzed, a scenario in which the vehicle does not stop at the intersection and does not change its speed significantly; a scenario in which the vehicle has to stop completely at the intersection; and an intermediate scenario in which the vehicle significantly decreases its speed before the intersection but does not stop. Throughout the rest of the paper, we refer to these clusters as **non-stop**, **stop**, and **slow-down**; and we associate them with the colors green, red and amber, respectively. The clusters are based on the mean velocity of the vehicle in two main subsegments; the immediate 600 m before the intersection and the 400 m section between 1000 m and 600 m from the intersection. A detailed graphical representation of the rules that define the clusters is shown in Figure 1. The clustering defines disjoint sets that do not necessarily include all the passages, as is the case in our current work, where the number of passages included after the clustering was further reduced to N = 902 distributed as shown in the table 1.

Table 1 Number of clusters in each passage.

Cluster	*Number of passages*
no-stop	378
slow-down	349
stop	175



The different clusters were determined based on the mean speed before the intersection. All the profiles considered have an initial (further than 600m from the intersection) average speed greater than 60 km/h.

- The No stop scenario is defined as a vehicle that keeps an average speed greater than 60 km/h.
- The Slow down scenario is defined as a vehicle that decreases its average speed with respect to the initial speed in the 600 m prior to the intersection staying above 30 km/h.
- The Stop scenario is defined as vehicles that stop at least once in the interval 400 m prior to the intersection.

For a typical mean truck deceleration, it can take more than 1 km to stop (see Maurya and Bokare 2012).

Figure 1 Graphical explanation of the definition of the different clusters. The approach to the intersection is split in several parts: the first 400 m and the remaining 600 m o the approach are split in 200 m segments. All the clusters need to have a mean speed in the first 400 m greater than 60km/h. On the next 600 m, for a vehicle to be included in the stop cluster it needs to stop at least once in the segment; keep the average speed on each subsegment of 200 m greater than 60km/h to be included in the non-stop; and to be included in the slow-down cluster, the vehicle mean speed in at least one of these 200 m subsegments needs to be smaller than the mean speed computer in the first 400 m, but should always keep an instantaneous speed greater than 30 km/h.

3. Results

The results of the clustering are shown in Figure 2. The solid lines represent the median speed of each cluster along the 2000 m segment whereas the shaded areas represent the standard deviation. In green the non-stop cluster seems to keep a constant speed with relatively small deviation, in amber, the slow-down cluster decreases its speed when approaching the intersection but does not stop. Finally, on the median of the stop cluster it can be observed that the speed of the vehicles decreases significantly at the intersection. The reason why the median speed does not reach a value of 0 km/h is because the vehicles do not all stop exactly at 0 m. Because of queues, many vehicles stop before the zero point (somewhere along the approach lane). It is also worth noting that the standard deviations for all the clusters are smaller on the

approach than after the intersection. This can be explained by the way the clusters are defined, where the rules apply to the approach but not to the segment after the intersection. The final speeds of the clusters also differ, which we will address this point in the Discussion section.
In Figure 3 the instantaneous fuel consumption over the entire 2 km passage can be seen. We note that stop and slow-down clusters look similar. The slopes immediately after the stop are close to each other, which is to be expected if we assume that both vehicles accelerate at full throttle after the intersection. For the slow-down cluster, the peak is smaller: if the target speeds are the same, this cluster of vehicles has a higher initial speed and then, need to accelerate for a shorter time. Finally, the green curve represents the non-stop cluster. Its median, although more constant than those of the other two clusters is not as flat as we might have expected. We will discuss this further in the Discussion section.

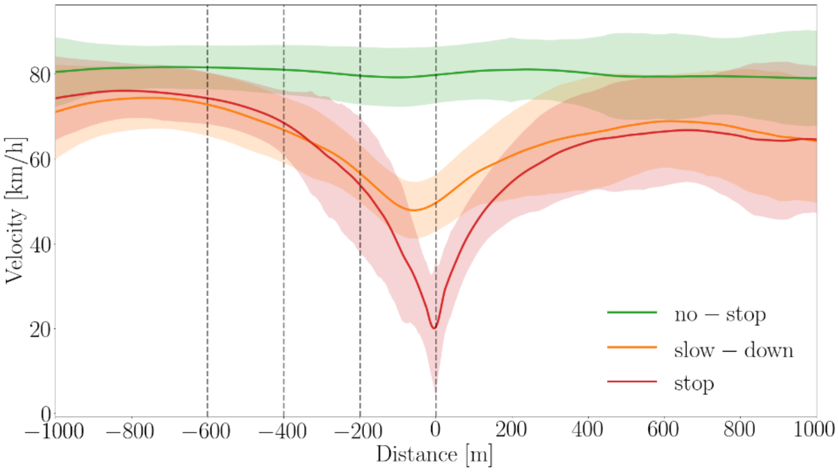


Figure 2 Solid lines represent the median instantaneous speed of each cluster and the shaded area its standard deviation. As indicated in the legend, green represents the non-stop cluster, amber the slow-down and red the stop one.

Finally, in Figure 4 we show the box plots for the median fuel consumption of each of the clusters. The big difference emerges for the stop cluster as compared to either of the other two clusters, and the differences are statistically significant for p-value = 0.01. The difference of the medians between the stop and non-stop is 0.12 l of fuel or 0.32 kg of CO_2.

4. Discussion

The results show that avoiding stops can save an average of 0.12 l of fuel at each intersection, without taking into account traffic, as the two clusters (stop and non-stop) are two cases in which the vehicles approach and leave the intersection without being affected by traffic. In cases where traffic plays a role, the difference can only increase as we found when analyzing the fuel consumption for all the passages that have been excluded in the clustering. This is an important result in times where reducing CO_2 emissions while also keeping logistics costs low is key to achieving emission reduction goals and at the same time not having a negative impact on economy. In a time of emerging C-ITS, this offers a flexible and low-cost option for the governments to improve the efficiency of freight transport and to reduce the forthcoming emissions.

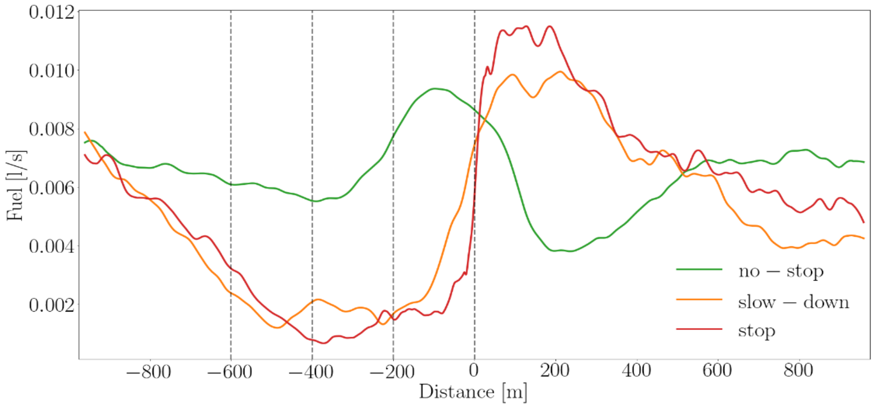


Figure 3 Median fuel consumption in [l/s] for the three scenarios. In green the non-stop scenario, in amber the slow-down and in red the stop scenario. For the sake of clarity, the standard deviation regions were not included.

The results have been obtained using a large dataset and the results are statistically significant, for the equipped DAF trucks in The Netherlands, where gradients on the routes are few and of a very small degree. Naturally, several things remain to be improved and further explored. In our analysis, the clustering focused only on the approach to the intersection. This results in deviations of the speed profiles after the intersection to be relatively high and furthermore, the final median speed for the different clusters is not the same. This introduces a bias in our results, making the difference between the clusters smaller. We performed an analysis of this last part of the segments, and we found that the difference did not increase more than 0.01 l (i.e., the 0.12 l difference could be 0.13 l) which does not affect the main message of our work.

Another important point to consider are the variations of the fuel consumption prior to traversing the intersection. We propose that this increase in fuel consumption (preceded by a small decrease) is of a behavioral nature. Drivers might release throttle when approaching the interaction up until the point in which they are certain that they are able to pass the traffic light in the green phase and then accelerate again. This is particularly relevant because this is a behavior that can be avoided with C-ITS technology that provides priority at the traffic light and/or a speed advise, enabling them to keep a constant speed.

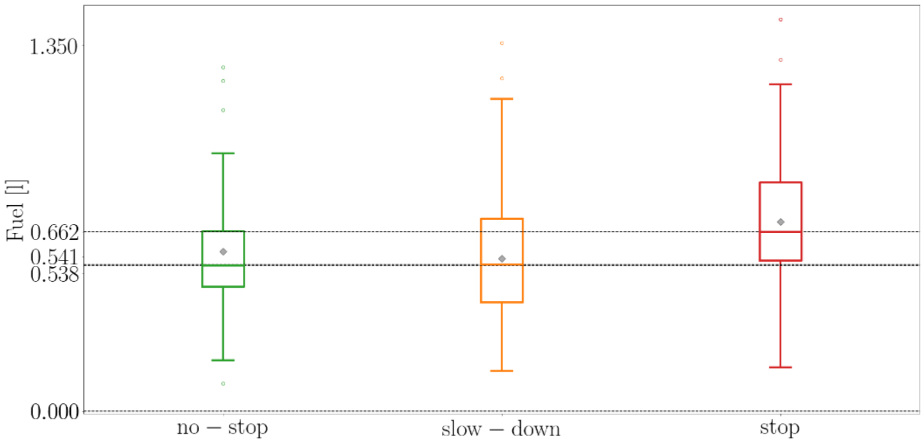


Figure 4 Median fuel consumption for the three clusters. As in the rest of the paper, green indicates the non-stop cluster, amber the slow-down and red the stop cluster. The difference between the medians of stop and non-stop clusters is 0.12 l.

Funding

This study was sponsored by the MRDH as part of the CATALYST Living Lab.

5. References

- Oberg, Kristina L. Nilsson, and Charlotta Johansson. Major transport corridors: the concept of sustainability in EU documents. Transportation Research Procedia, 25:3694–3702, 2017. doi:10.1016/j.trpro.2017.05.339.
- Erica Bickford. Emissions and air quality impacts of freight transportation. PhD thesis, The University of Wisconsin-Madison, 2012.
- Gust Blauwens, Nico Vandaele, Eddy Van de Voorde, Bert Vernimmen, and Frank Witlox. Towards a modal shift in freight transport? a business logistics analysis of some policy measures. Transport Reviews, 26(2):239–251, mar 2006. doi: 10.1080/01441640500335565.
- Rommert Dekker, Jacqueline Bloemhof, and Ioannis Mallidis. Operations research for green logistics – an overview of aspects, issues, contributions and challenges. European Journal of Operational Research, 219(3):671–679, Jun 2012. doi: 10.1016/j.ejor.2011.11.010.
- European Union. Infrastructure - TEN-T - connecting Europe. URL https://ec.europa.eu/transport/node/2443. European Union. Legislative act regarding union guidelines for the development of the TEN-T (EU regulation no. 1315/2013, 2013. URL http://data.europa.eu/eli/reg/2013/1315/oj.
- URSA MAJOR neo – Integrator Connected Truck Trials. http://resolver.tudelft.nl/uuid:7bd21500-957a-492d-ad42-4d3c22d55a37
- Andreas Festag. Cooperative intelligent transport systems standards in Europe. IEEE Communications Magazine, 52(12): 166–172, Dec 2014. doi:10.1109/mcom.2014.6979970.
- Slobodan Guberinic, Gordana Senborn, and Bratislav Lazic. Optimal Traffic Control: Urban Intersections. CRC Press, Boca Raton, FL, 2008. ISBN 9781420062687.
- J.H. Havenga and W.J. Pienaar. Quantifying freight transport volumes in developing regions: Lessons learnt from south Africa's experience during the 20th century. 2012.

- Frank Heepen and Weilin Yu. SEMS for individual trip reports and long-time measurement. In SAE Technical Paper Series. SAE International, apr 2019. doi:10.4271/2019-01-0752.
- Taesung Hwang and Yanfeng Ouyang. Freight shipment modal split and its environmental impacts: An exploratory study. Journal of the Air & Waste Management Association, 64(1):2–12, aug 2013. doi:10.1080/10962247.2013.831799.
- Hans W Ittmann and David King. State of logistics–an overview of logistics in south Africa. 2010.
- Lynn H Kaack, Parth Vaishnav, M Granger Morgan, Ines L Azevedo, and Srijana Rai. Decarbonizing intraregional freight systems with a focus on modal shift. Environmental Research Letters, 13(8):083001, aug 2018. doi:10.1088/1748-9326/aad56c.
- Gerrit Kadijk, Norbert Ligterink, and Jordy Spreen. On-road NOx and co2 investigations of euro 5 light commercial vehicles. R10192, March 2015.
- Gerrit Kadijk, Robin Vermeulen, Edo Buskermolen, Mitch Elstgeest, Declan van Heesen, Veerle Heijne, Norbert Ligterink, and Peter van der Mark. NOx emissions of eighteen diesel light commercial vehicles: Results of the Dutch light-duty road vehicle emission testing programme 2017. R11473, Dec 2017.
- Lawrence A Klein, Milton K Mills, and David RP Gibson. Traffic detector handbook. US Department of Transportation, Federal Highway Administration, 2006. URL https://www.fhwa.dot.gov/publications/research/operations/its/06108/02.cfm.
- Norbert E. Ligterink. On-board determination of average Dutch driving behavior for vehicle emissions. R10188, February 2016.
- Dennis Luxen and Christian Vetter. Real-time routing with OpenStreetMap data. In Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, GIS ’11, pages 513–516, New York, NY, USA, 2011. ACM. ISBN 978-1-4503-1031-4. doi:10.1145/2093973.2094062. URL http://doi.acm.org/10.1145/2093973.2094062.
- Akhilesh Kumar Maurya and Prashant Shridhar Bokare. Study of and deceleration behavior and of different and vehicle and types. International Journal for Traffic & Transport Engineering, 2(3):253 – 270, 2012.
- F Meyer. Points and traffic lights under common control using vetag. Railway Gazette International, 131(5), 1975.
- F Middleham. Vetag-test. Technical report, 1976.
- MIRT. Mirt study of freight transport corridors. URL https://www.topcorridors.com/documenten/HandlerDownloadFiles.
- ashx?idnv=1042154.
- OpenStreetMap contributors. Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org, 2020.
- Jim Peters, Randy McCourt, and Renee Hurtado. Reducing carbon emissions and congestion by coordinating traffic signals. Institute of Transportation Engineers. ITE Journal, 79(4):25, 2009.
- Mark Roberts, Martin Melecky, Theophile Bougna, and Yan (Sarah) Xu. Transport corridors and their wider economic benefits: A quantitative review of the literature. Journal of Regional Science, 60(2):207–248, oct 2019. doi:10.1111/jors.12467.
- D.I. Robertson and R.D. Bretherton. Optimizing networks of traffic signals in real time-the SCOOT method. IEEE Transactions on Vehicular Technology, 40(1):11–15, Feb 1991. doi:10.1109/25.69966.
- Roger Roess. Traffic engineering. Pearson, Upper Saddle River, NJ, 2011. ISBN 978-0-13-613573-9.
- W Ros. Vecom: A powerful local communication channel between vehicle-borne and roadside systems. LMSS, pages 23–25, 1986.
- A.G. Sims and K.W. Dobinson. The Sydney coordinated adaptive traffic (SCAT) system philosophy and benefits. IEEE Transactions on Vehicular Technology, 29(2):130–137, May 1980. doi:10.1109/tvt.1980.23833.
- Isabel M. S. N. Z. Tully. Synthesis of Sequences for Traffic Signal Controllers Using Techniques of the Theory of Graphs. OUEL report. University of Oxford, Department of Engineering Science, Engineering Laboratory, 1976.
- R. J. Vermeulen, N. E. Ligterink, W. A. Vonk, and H. L. Baarbe. A smart and robust NO_x emission evaluation tool for the environmental screening of heavy-duty vehicles. 2012.