# A study on co-modality and eco-driving mobility

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**Abstract**

The last decade has brought on a revolution in the private automotive sector, whereby more and more location-based information has become available. All these big data sets open up a huge potential for advanced data mining and enrichment activities. Based on mobility data stemming from a large private vehicle fleet (300 users, 60 car types, 20 second GPS traces, 9 months, over 110,000 recorded trips), we assessed the modal shift potential by coupling these data with available public transportation data in the region around Brussels, Belgium. Our results indicate that less than 8% of all trips have a suitable public transport alternative. We furthermore concluded that the potential $CO_2$ reduction in city centres is very limited, and by itself not enough to reach either of the presented $CO_2$ reduction targets. In contrast, there is a high potential on motorways as the majority of kilometres were driven there. Public transportation in itself has great difficulty in reaching the emission reduction targets. Finally, there are future business opportunities for the automotive sector in order to remain competitive by having a relevant and realistic outlook on the future mobility market.

*Keywords:* Co-modality; $CO_2$ emission reductions; modal shift potential; new vehicle technologies.

**Résumé**

La dernière décennie a apporté une révolution dans le secteur privé automobile, pour lequel  de plus en plus d'information basés sur la localisation sont devenus disponibles. Tous les grands ensembles de données ouvrent un énorme potentiel pour l'exploration de données de pointe et des activités d'enrichissement. Basé sur l' enregistrement de la mobilité d'une grande flotte de véhicules privés (300 utilisateurs, 60 types de voiture, 20 secondes traces GPS, 9 mois, plus de 110.000 voyages enregistrées), nous avons évalué le potentiel de transfert modal en couplant les données avec les données disponibles de transport en commun dans le région autour de Bruxelles, en Belgique. Nos résultats indiquent que moins de 8% de tous les voyages ont une alternative de transport public approprié. Nous avons aussi conclu que le potentiel de réduction du CO2 dans les centres-villes est très limitée, et par elle-même ne suffit pas à atteindre l'un des objectifs de réduction de CO2 présentées. En tout cas, il existe un fort potentiel sur les autoroutes comme la majorité des kilomètres ont été conduits là. Le transport en commun en lui-même a beaucoup de mal à atteindre les objectifs de réduction des émissions. Enfin, il ya des occasions d'affaires futures pour l'industrie automobile afin de rester compétitive en ayant une vision pertinente et réaliste sur le marché de la mobilité du futur.

*Mots-clé:* Potentiel de transfert modal; nouvelles technologies de véhicules; co-modalité; réduction des émissions de $CO_2$.

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**Nomenclature**

EV electric vehicle
GPS global positioning system
PT public transport
TCO total cost of ownership
TME Toyota Motor Europe

## 1. Introduction

The last decade has brought on a revolution in the private automotive sector, whereby more and more location-based information has become available. Both private companies and governmental bodies are using GPS tracked ‘n traced vehicles in order to optimise their own fleets, or even develop and increase the performance of traffic management systems. As all these big data sets are growing, it opens up a huge potential for advanced data mining and enrichment activities. Our study was in particular concerned with a huge dataset made available by Toyota Motor Europe (TME). By using and developing the necessary computational tools, we analysed this data in such a way that an understanding of the underlying structures emerged (i.e., extraction of trip legs and trip chains). In the following sections, we first detail how we collected and processed the relevant mobility data. We then explain how these data were coupled with a custom-developed model with the available public transportation data (bus, metro, and train) in the region around Brussels, Belgium. The coupling allowed us to assess the modal shift potential, by calculating how many trips could be replaced with the available public transportation, both from an optimistic and realistic point of view. Finally, we present a quick-scan of promising technologies and services within the different modal shift scenarios that we previously created. We then identified the most important consequences for personal mobility, linking them to modal and/or technological choices that are necessary to obtain the target proposed by the European Commission. All details of this study are reported in (Akkermans et al., 2012).

## 2. Analysing the GPS-based mobility data

In the next sections, we first describe the general structure of the available GPS-based mobility data, after which we explain how the mobility patterns were extracted by means of trip legs and trip chains. We finally show how we calculated the $CO_2$ emissions per trip.

### *2.1. General information*

All available GPS-based data stemmed from an internal TME testproject that followed 295 unique users (with their consent, guaranteeing their anonimity by means of propre privacy and security measures), covering a fleet of some 60 different vehicle types. The latter top 10 included Toyota Prius, Avensis, Yaro, Aygo, Corolla Verso, Rav4, Auris, and IQ with engine sizes ranging from 1400 over 1800 to 2000 and 2200 cc. Most of these were diesel cars, some of them petrols and hybrids. The data spanned a time period of approximately one year between September 2010 and July 2011, which in total made up some 324 days. The database was converted into MySQL (Ora), whereby each entry corresponded to a 20-second GPS measurement of one vehicle. After elimination of duplicate and malformed records, the database contained 10,213,297 valid 20-seconds GPS records in Belgium. All the records were a priori map-matched by TME onto four NAVTEQ-based layers. These latter corresponded to different road types, going from motorways to local roads and city centres. Considering the locations of all trips, they all departed (and arrived) in the same regions around Brussels. The top departure location is Brussels as TME’s office location clearly stands out. Only few departures and arrivals originated and ended in the Walloon region, with the majority of the departures stemming from Antwerp, Brussels, and Flemish-Brabant.

Looking at the spatio-temporal structure of the data, we can see how various congestion patterns arise on the road network. There is a clear distinction between morning and evening rush hours, and the night and daytime off-peak periods. By plotting a sequence of all recorded GPS positions, coloured according to their speed, and time-dependent, we got an qualititative view on the congestion throughout the day. Figure 1 gives examples of these phenomena by means of successive hourly time lapses; all GPS records were taken from all Thursdays in the dataset, and plotted on top of each other. The dots are coloured according to the median speed, with red dots slower than 30 km/h, orange to yellow between 30 km/h and 60 km/h, green between 60 km/h and 90 km/h, light blue between 90 km/h and 110 km/h, and dark blue faster than 110 km/h.

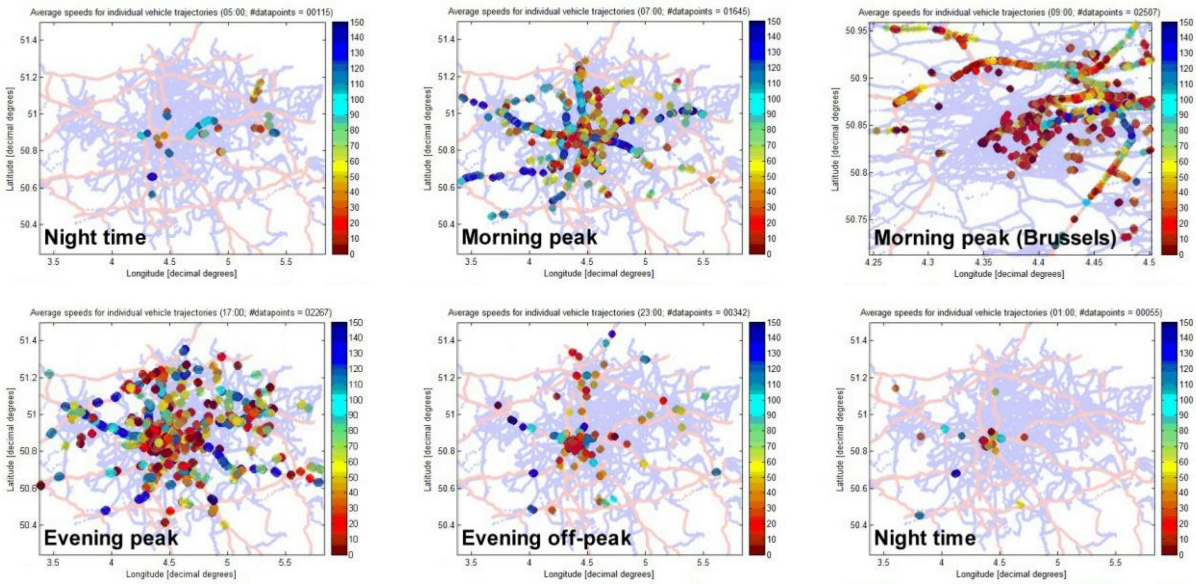


Fig. 1. Examples of spatio-temporal congestion patterns during the off-peak periods and morning and evening rush hours. Blue colours denote high average speeds, green colours medium speeds, and red colours indicate slower speeds (which on motorways are most likely attributed to congestion).

We also analysed the spatio-temporal spread of the different vehicles according to their fuel type, split among the morning peak (defined from 06:00 – 09:00) and the evening peak (defined from 16:00 – 19:00). The results are presented in Table 1.

Table 1. Total distances driven over all 20-second GPS records [procentual].

| | **Diesel** | | | **Petrol** | | | **Hybrid** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Road type** | **On-peak** | **Off-peak** | **Total** | **On-peak** | **Off-peak** | **Total** | **On-peak** | **Off-peak** | **Total** |
| **RT 1** | 27% | 24% | 51% | 29% | 23% | 52% | 22% | 27% | 49% |
| **RT 2** | 7% | 9% | 16% | 6% | 7% | 14% | 7% | 10% | 17% |
| **RT 3** | 11% | 12% | 23% | 12% | 12% | 24% | 11% | 13% | 24% |
| **RT 4** | 5% | 5% | 10% | 6% | 5% | 11% | 5% | 5% | 10% |

For the table we see how diesel cars typically drove 51% of all their distances on motorways (road type 1), and 10% of their distances within city centres (road type 4). Comparing these numbers between fuel types, we observed that the usage patterns of hybrids were typically the same as diesel or petrol cars. As such, we concluded that hybrids as a technology did not cause a change in behaviour.

*2.2. Extraction of mobility patterns as trip legs and trip chains*

In order to determine the mobility patterns contained within the dataset, we extracted trip legs and trip chains. These were based on the following assumptions:

- Trip chains and legs were derived for each user in the database
- Trip chains were complete and began and ended at a user's home location. All (longitude,latitude) locations that lay within a 100 m radius of the user's home location were considered as the home location (because matching home locations on the street level was too complex).

- Trip chains started after 5h00 and ended before 5h00 the day after; they spanned at most 1 complete day.
- A trip chain consisted of 1 or more trip legs.

In order to derive each user's home location, we assumed this location corresponded to the user's point of first departure during the morning commute on working days. Taking for each user the location having the highest number of such departures then gave us his most probable home location. An example of the extraction of home locations near Brussels can be seen in Figure 2. The black dots denote all the locations where a user first departed during the morning, whereas the blue dots denote the calculated users' home locations. The red dots show for each user the average locations of all departures within each city. Note the scatter of the black dots in some regions, implying that users did not always park their vehicles at the same spot or street, but rather stayed in the vicinity.

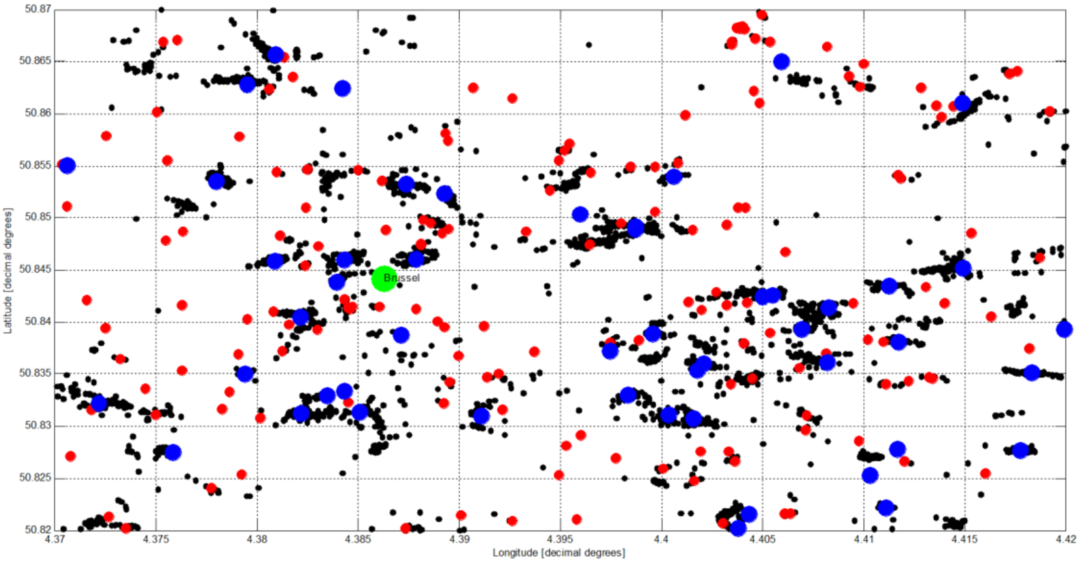


Fig. 2. Determination of users' most probable home locations (blue dots), based on their departures in the early morning.

Once all home locations were known, TME processed all GPS records in order to extract trip legs and trip chains. Most trip chains contained 2 trip legs, with lower probabilities occurring for increasing numbers of trip legs per trip chain. The rationale behind this was that most users travelled directly to and from their work. Based on the distribution of the number of trip legs per trip chain, we estimated that some 80% of all trip chains were composed of 4 trip legs or less. Furthermore, irrespective of the number of trip legs in a trip chain, all trip chains typically consisted of 2 long trip legs (mostly from home to work and vice versa), and were interspersed with some smaller trip legs that covered a significantly lesser distance. As the number of trip legs per trip chain increased, we estimated that the distances of the short legs did no change as there were more or less legs in a trip chain. We also believed that the amount of short trip legs remained the same, because people tended to shop, … either in the neighbourhood of their home location, or of their work location. A possible explanation was the fact that in most cases, people knew these home and work neighbourhoods quite well, and were therefore more keen to have activities there, as opposed to 'somewhere in the middle' of their trip chain.

Most of the trip chains covered distances of less than 100 km. Their distribution had a very long, flat, and low tail, implying that only few users made very long trips. The mean lay around 44.3 km with a standard deviation of 55.7 km; the median lay around 25.4 km.

The distribution of total time spent between departing from and arriving again to a users' home location contained two noticeable peaks, with one for very small times (i.e., less than 2 hours), and one slightly over 10 hours. The former peak was indicative of very short trips, whereas the latter one was indicative of typical home → work → home trips (with optional destinations in between). It also implied that users probably spent some 8 hours at work, with some time travelling to and from, including optional intermediate stopping points in between. When we excluded the time a vehicle is stopped, and only considered the time users spent in their cars driving around, the mean lay around 1.0 h with a standard deviation of 1.0 h; the median lay around 0.8 h. The majority of users were spending around maximum 1 to 2 hours in their cars. There was a very long, flat, and low tail testifying that only few users spent long times driving around in their cars, with some of them driving for a very long time (i.e., over 6 hours).

Consider the distributions of the trip speeds, lead us to a very distinct peak around 34.9 km/h on average with a standard deviation of 19.7 km/h; the maximum at the tail corresponded to some 135.3 km/h. The median lay around 31.2 km/h, corresponding with what we found in literature according to (Maerivoet, 2006).

### *2.3. Calculating $CO_2$ emissions per trip*

Based on all trip legs in the database, we calculated the $CO_2$ emissions and costs of driving.

- The $CO_2$ emissions were derived from the travelled distance for each vehicle, its median speed, the road type travelled on, the vehicle type, and the estimated fuel consumption. The latter was expressed through the emission factors per road type and vehicle speed range, which were adjusted to match the EU27 fleet; the $CO_2$ emissions were then expressed in g/km. TME provided all the speed-dependent $CO_2$ emission factors for the various vehicles in the database. It was based on TME’s default available fuel consumption and $CO_2$ emission cycle data.
- The costs were in turn derived from the travelled distance for each vehicle, the vehicle type, and the cost per kilometre (which TME provided as a total cost of ownership (TCO) per kilometre); they were expressed in euro/km.

The $CO_2$ emissions were dependent on the speeds at which vehicles drove. We split the $CO_2$ calculations out based on different road types, to get a feel of on what roads there is more or less $CO_2$ emitted.

Almost half of all the distances were driven on motorways, contributing to exactly half of all the emissions, implying there is a huge potential to be gained here. From our calculations, we could deduce the average EU27-adjusted $CO_2$ emission of a vehicle in the TME fleet, which corresponded to some 164 g/km. As was expected, the total amount of $CO_2$ emitted increased as the distance per trip leg increased. For shorter distances, there were on the one hand very high $CO_2$ emissions per kilometre, and on the other hand a large spread which decreased with longer trip leg distances. This is because on a long leg there was a higher probability that you would drive on more different types of road, and hence encounter more congestion.

## 3. Assessing modal shift potential

In the next couple of sections we show how we assessed the modal shift potential of the TME fleet, based on the users’ mobility patterns extract in Section 2. We first explain what public transport data we collected, after which we elaborate on the development of a public transport model. The latter was then applied to the mobility patterns from Section 2, yielding the modal shift potential.

### *3.1. Collecting public transport data*

We collected public transport data from the four main public transport companies in Belgium, i.e., De Lijn (Flanders bus and tram), MIVB/STIB (Brussels bus and tram), TEC (Walloon bus and tram), and NMBS/SNCB (Belgium train). The requested data was ‘static’ (i.e., the planned schedules, not the schedules as they were actually driven which would include delays and cancelled trips). From each of the companies a schedule for a regular week was requested. A week was considered ‘regular’ if it was not during the holidays, if there was no high day during the week, and if there were no special services for non-recurring events (like concerts, tourist trains to the coast, …). For our analyses, we used a working day, a Saturday, and a Sunday. The data was comprised of a table with for all the stops including at least the coordinates of its location and its name, as well as information on which service passed by at which stop and at what day of the week and time instant. The locations of all public transport stops in Belgium are shown in Figure 3.

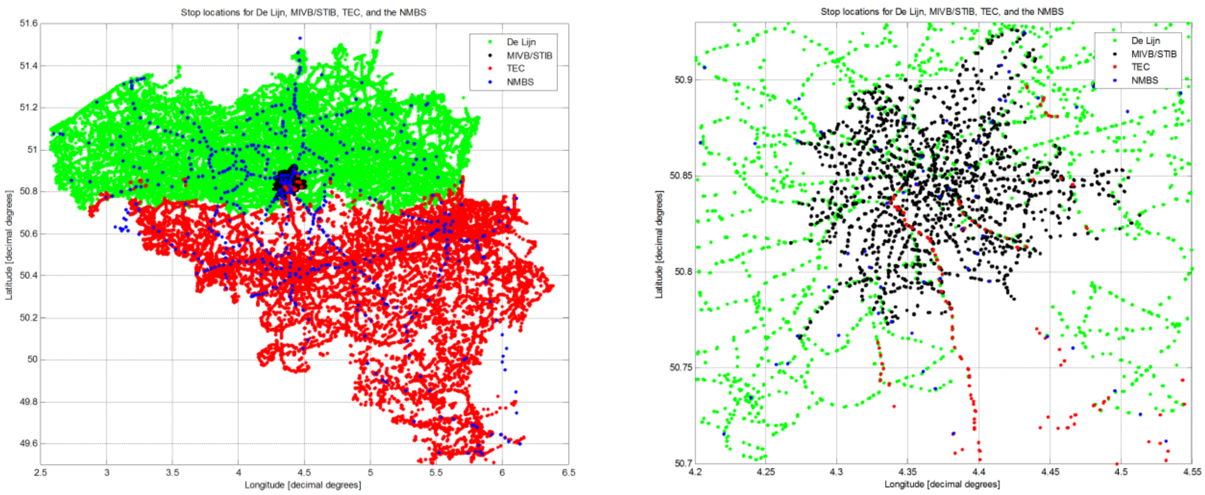


Fig. 3. *Left*: Geographic overview of all public transport stops in Belgium, coloured according to the public transport operator. The blue dots are Belgian trains, which are fewer in number than the total number of busses and trams. *Right*: a closeup of Brussels containing a high density of stops which are operated by the MIVB/STIB.

### *3.2. Development of the public transport model*

The general goal of the public transport (PT) model was to find the best matches between transport modes (taking time and location restrictions into account), given various scenarios and constraints. The results from Section 2 were linked to the public transport data by means of the PT model. In order to investigate for which car trips in TME's dataset a viable public transport alternative was available, we calculated the shortest public transport route for each trip. After such a public transport route was found, it was compared with the original car trip to determine whether or not it was a viable alternative.

The public transport router first generated a 'hypernetwork'. Based on the data in the schedules of the public transport providers, a spatio-temporal network was created, which consisted of:

- Travel links: these were the direct translation of the bus/tram/train services: a link between 2 stops with a departure and arrival time.
- Boarding links: virtual links representing the boarding distance, the boarding travel time (the distance and time to travel from the origin of the trip to the first public transport stop on the shortest route) and a part of the waiting time of the trip (the time the traveller spent waiting at the first stop).
- Egress links: similar to boarding links, but from the last public transport stop to the final destination.
- Transfer links: virtual links that represent the transfer from one public transport service to the next. This can be a transfer between two different lines at the same stop, or at nearby stops. The transfer link represents the waiting time, and – when it's a transfer between different stops – the distance between the stops and the required walking time.

When generating these links, some constraints were immediately applied in order to rule out unrealistic public transport routes and limit the number of boarding, egress, and transfer links:

- Boarding and egress links were generated only to public transport stops within a certain radius around the origin/destination. If less than 3 stops were found within this region, the 3 nearest stops were used.
- Transfer links were generated between stops within a given radius and between services that guaranteed a minimum transfer time (3 minutes plus the time required to walk from the one stop to the other, if any) and did not exceed a maximum transfer time.

The model also took walking and cycling into account in order to access the public transport alternatives. Our model thus simulated a habit in user choice. The final hypernetwork for one day contained about 40 million links. Finally, after the generation of the spatio-temporal hypernetwork, the A* shortest route algorithm was used to find an appropriate public transport route within this network (Hart et al., 1968).

In order to determine the shortest route, not every part of the public transport trip was valued in the same way. Surveys investigating travel behaviour reveal that people's perception of travel time depends on the purpose of their trip and the nature of their actual 'travelling' activity (e.g., driving a car versus waiting at a public transport stop. Our PT model reflected this perception within its travel times.

### *3.3. Modal shift analysis*

In order to assess the modal shift potential, we envisaged three different scenarios for which the PT model was ran:

- **Scenario 1: maximised public transport**
  Here we used the PT model to identify possible public transport alternatives as a replacement for car trips, without very strict practical restraints (access and egress time, number of transfers, …).
- **Scenario 2: emission capping**
  Here we focused solely on the capping of emissions as a result of the (theoretical or practical) implementation of emission targets.
- **Scenario 3: time restrictions (acceptable time losses)**
  Like in Scenario 1, we also made use of the PT model but this time used a more stringent set of practical restraints to mimic more realistic modal choice behaviour.

The constraints within each scenario represented actual policy choices that are currently being considered or already actively implemented by administrations and policy makers. We compiled extensive background policy information and parameterisation to allow for a correct and realistic quantification of the different policies as well as the results of the different modal shift analyses.

For Scenarios 1 and 3, we estimated the modal shift potential within the context of an optimally used, maximally extended public transport system (i.e., it is assumed that there is ample capacity to accommodate all the trips). The concept of a modal shift analysis is depicted illustratively in Figure 4, exhibiting a trip chain that consisted of 5 trip legs. The top picture shows the result for a single user at the trip leg level, whereas the bottom picture shows a different result for the same user but this time at the trip chain level. At the latter level, more stringent constraints apply, e.g., it should be possible to make the various trip legs in succession, within reasonable time frames. From the bottom picture we see how the user could now have only made 2 trip legs by public transport (i.e., the second and the last, coloured green). For the first trip leg, no viable public transport option was found (coloured red). For the third and fourth trip legs, the user might have selected a public transport option, if he would have relaxed some restrictions (coloured yellow).

Note that when calculating the $CO_2$ emissions for public transport, we obtained the emission factors from TREMOVE (Transport & Mobility Leuven, 2011): for busses and trams we used an average of 21.75 g/passengerkm, for trains we used an average of 3.31 g/passengerkm. In order to compare the total cost of ownership, we obtained values from a previous MIRA external costs study (Delhaye et al., 2010): for busses and trams the cost was 26.51 cent/passengerkm, for trains the cost was 6.36 cent/passengerkm (= 6 cent + 6% VAT).

Running the PT model for Scenario 1 (maximised public transport) gave the following comparison with the base case from Section 2.3 in which no trip legs were substituted by public transport:

- A total distance of 1,976,375 km (119%, higher than the base case).
- A total $CO_2$ emission of 186,343,203 gr (68% of the base case).
- A total cost of 461,581 euro (nearly equal to the base case).

When running the PT model for Scenario 3 (time restrictions), we obtained the following comparison with the base case in which no trip legs were substituted by public transport:

- A total distance of 1,780,047 km (107%, higher than the base case).
- A total $CO_2$ emission of 228,941,205 gr (84% of the base case).
- A total cost of 453,481 euro (98% of the base case).

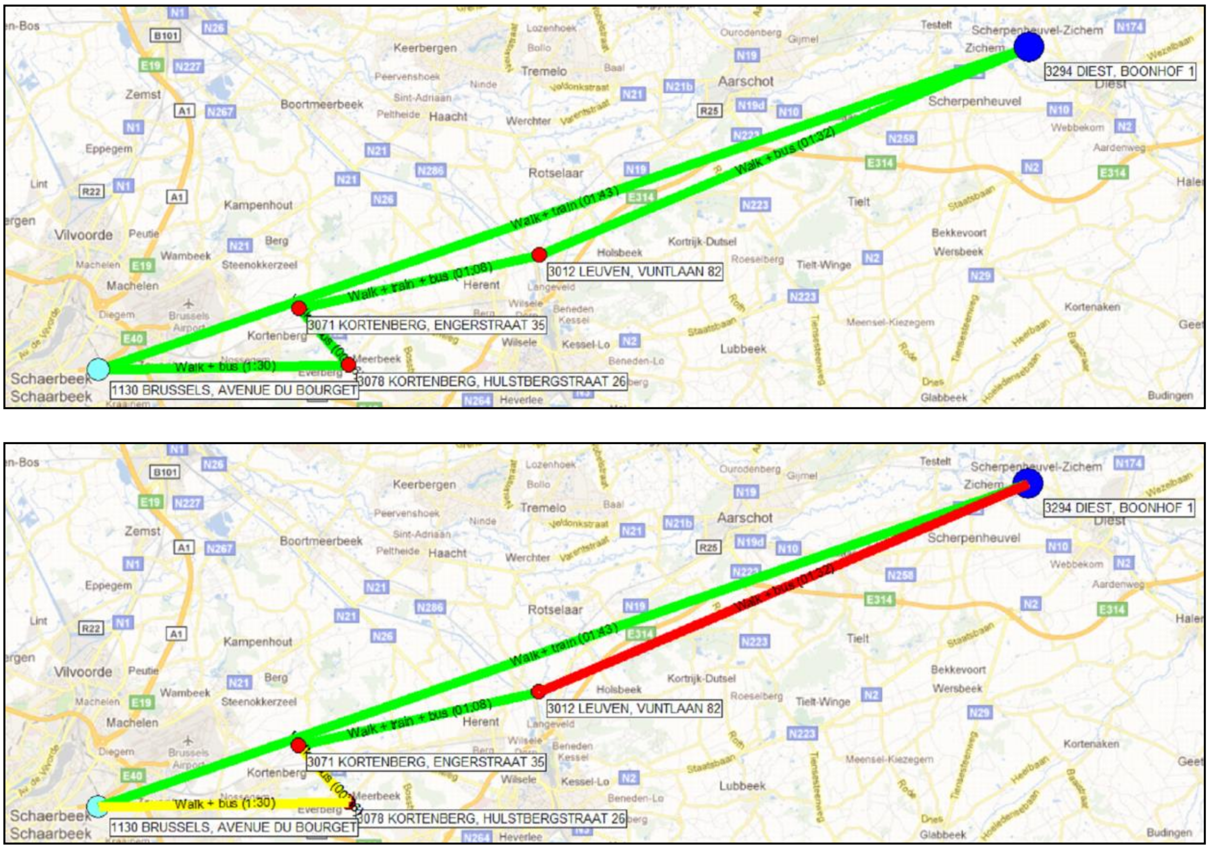


Fig. 4. Illustrative depiction of the modal shift potential for a single user. *Top*: the potential to find a suitable alternative for the car trip for each trip leg separately is high (all green lines). *Bottom*: the potential to find a suitable alternative for the car trip for the entire trip chain is limited (e.g., the red line denotes a trip leg that can not be replaced with a public transport alternative, given a set of constraints).

A more detailed analysis of the amount of trip chains replaced by public transport, yielded following modal shift potential in Table 2, incorporating results from the $CO_2$, travel time and cost impact calculations.

Table 2. Calculated modal shift potential.

| Public transport | Modal shift | $CO_2$ | Travel time | Cost impact |
|---|---|---|---|---|
| **Scenario 1** | 19% | -9% | +52% | none |
| **Scenario 3** | 8% | -3% | +54% | none |

It is clear how the potential drops to 8% when looking at realistic conditions, i.e., Scenario 3 in combination with only trip chains. This leads us to believe that there is a huge benefit to be gained here, as now only 1 out of 13 daily car trips can be replaced by a combination of PT alternatives. Interestingly, the $CO_2$ emissions only drop by 3%, which also leaves a large benefit to be gained here.

One of the often suggested policy options for triggering a modal shift in passenger transport is the capping of emissions related to private transport. In practice however, this intention could be translated in various ways. At the moment, a plethora of emission targets are being discussed, addressed, formulated, implemented, … by different policy makers. In order to maintain a strong link with the EU background, the following targets were considered and discussed with TME: EU White Paper targets and EU “20-20-20” targets (European Commission, 2011). First, the EU stated that “*all transport related emissions need to be reduced with 60% by 2050, compared to 1990*”. Within reasonable boundaries, it was proposed to extrapolate “*a 2020 target of 30% reduction, compared to 1990*”. In a next step, this target was rescaled to represent firstly the Belgian situation and, secondly, the TME fleet in order to make a valid estimation of the effort that would be needed within a fleet that is comparable in usage, but not in technology status. Whether we used the first or second rescaling for further estimations was not of importance due to the relative high level of representation of vehicle use of the TME fleet when compared to Belgian's fleet usage.

We then looked at four different strategies for Scenario 2 (emission capping), which might commonly be considered by administrations of different levels to have a direct or indirect effect on $CO_2$ emissions as a result of passenger car transport:

1) Impose restrictions on locations for the use of conventional internal combustion engines.
2) Introduction of more energy and/or carbon efficient technologies on vehicle or fleet level.
3) Impose restrictions on time periods for the use of conventional internal combustion engines.
4) Impose restrictions on behaviour linked to increased $CO_2$ emissions (speed).

One of the main results here is the $CO_2$ reduction potential for technologies, as shown in Figure 5.

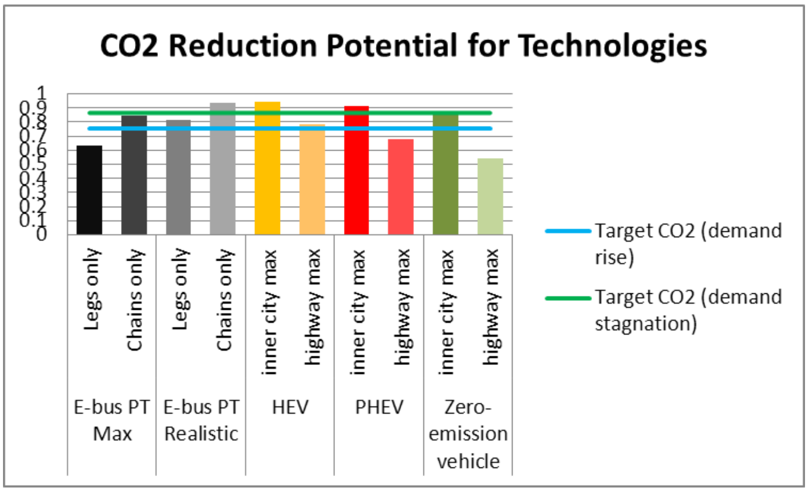


Fig. 5. Overview of the $CO_2$ reduction potential for various engine technologies.

## 4. Vehicle choice, technology, and automotive service

Throughout this study, a number of conditions were constructed to allow for a very broad overview of the costs and results of the implementation of a wide set of public transport policies as well as the introduction of a set of existing technologies. For our quick-scan we looked at different conditions for public transport, going from least over moderate to maximised uptake. In addition, we considered the use of an electric bus as complete replacement for the traditional bus system. Likewise, we introduced four car passenger vehicle technologies, i.e., hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), battery electric vehicles (EV), and hydrogen fuel cell vehicles (HFCV). For each of the vehicle technology applications, costs were estimated based on TCO values. For HEV and PHEV, these costs were provided by TME and validated within the calculation model. For EV and HFCV, two TCO values were used (a low and a high estimation), resulting in separate sub-conditions for these vehicle technologies.

Our quick-scan indicated that the increased implementation of vehicle technologies (HEV, PHEV, EV, and HFCV) allows for reaching the most stringent emission reduction target under specific conditions (motorway usage). Only HEV, PHEV, and EV manage to do this within a reasonable cost increase margin (10%) compared to current costs. However, in the case of, e.g., EVs, the high cost of development should not be underestimated, as this is currently blocking the ramping of EVs on the market.

Most noteworthy within the current analyses were the circumstances wherein a particular technology was applied and had an important effect on the outcome in terms of emissions saved. Measures that focused on reducing emissions in city centres (in general) did not receive the highest emission reduction target, nor would they have reached the lowest. This was because, within a general fleet that was used in the same way as the TME fleet was used, the total amount of $CO_2$ emissions within a built-up area did not account for a sufficiently high portion of the total emissions. Although emissions per vehicle kilometre were relative high, the total vehicle kilometres ran within a city centre was relative low. The opposite was the case when specific attention was given to $CO_2$ emissions levels on the primary road network (motorways). Although individual vehicles tended to perform at their best on higher-speed roads, at least in terms of emissions per vehicle kilometre, it was exactly on these roads that the highest number of kilometres were ran. Because of this, a relative high percentage of the total $CO_2$ emissions took place on these primary roads. Under these conditions, all 4 technologies reached the lowest emission reduction target (HEV, PHEV, EV, and HFCV). 3 technologies reached the highest emission reduction target: PHEV, EV, and HFCV.

Finally, the introduction of automotive services needed to take care of quite a lot of the responsibilities that now fell to the vehicle owners: maintenance, cleaning, insurance, (initial) fuelling, repairs, parking, et cetera. These elements fell well beyond the scope of the current study, but may have warranted further analyses of driving and mobility behaviour.

## 5. Conclusions and recommendations

A comprehensive analysis of the kind presented in this study, i.e. calculating the mobility behaviour based on detailed GPS data and then correlating this with the available public transport schedules, has not been done before. In that sense, our study highlights some of the shortcomings of and opportunities for the current state of public transport in Belgium. Our results indicate that less than 8% of all trips have a suitable public transport alternative, which opens up a lot of room for improvement given that the Belgian government is thinking about road user charging. We furthermore concluded that the potential $CO_2$ reduction in city centres is very limited, and by itself not enough to reach either of the presented $CO_2$ reduction targets. In contrast, there is a high potential on motorways as the majority of kilometres were driven there. Public transportation in itself has great difficulty in reaching the emission reduction targets. Finally, there are future business opportunities for the automotive sector in order to remain competitive by having a relevant and realistic outlook on the future mobility market. One of them is the increased implementation of modern vehicle technologies, by which we can reach the most stringent emission reduction targets within a reasonable cost increase margin (10%) compared to current costs. Nevertheless, in the case of EVs, the high cost of development should not be underestimated, as this is currently blocking the ramping of EVs on the market.

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