EXPLAINING THE TREND OF CONGESTION: METHOD AND RESULTS

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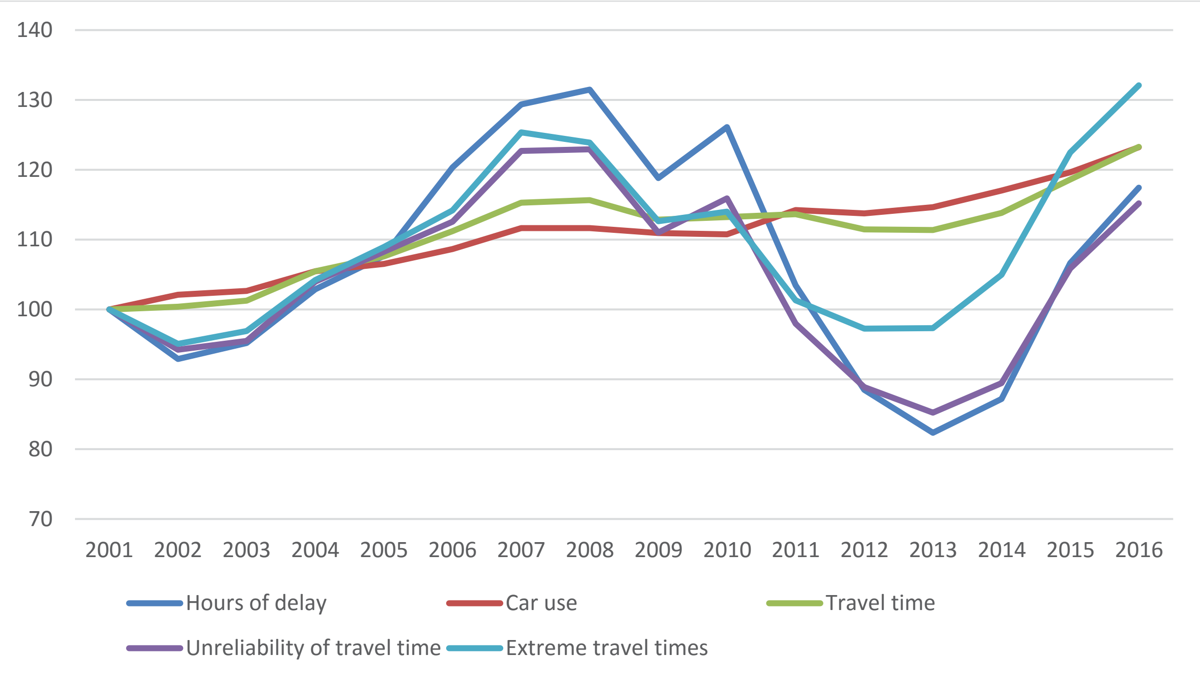
1. INTRODUCTION

An important goal of the Dutch Ministry of Infrastructure and Water Management is to optimise travel time by reducing traffic congestion. In order to understand how to tackle the problem of congestion, insight is needed into how policy measures and other explanatory factors impact the development of traffic congestion. The need to have an explanation for the development of congestion has increased since 2004, because congestion levels fluctuate and do not correlate with the developments in car use (Figure 1). Insights into the impact of policy measures and other factors are also needed for other aspects of accessibility than congestion, such as unreliability of travel time.

Figure 1. Development of hours of delay, car use, travel time, unreliability of travel time and extreme travel times on national roads 2001-2016.



To this end, starting in 2002, the KiM Netherlands Institute for Transport Policy Analysis (or its predecessors) publish annually or biennially an explanatory analysis of trends in congestion on national roads during the past decade. A regression-based method identifies the impacts of policy measures and other factors on hours of delay, car use, travel time, reliability of travel time and

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extreme travel times (henceforward termed 'dependent variables'). This paper describes the method applied and the results for 2000-2016, as well as considerations of the various attempts to further improve the method.

2. RESEARCH QUESTIONS

The central question discussed in this paper is: how to assess empirically the impact of policy measures and other factors on the development of traffic congestion, travel time, reliability of travel time and amount of travel, and to do so independent of the method for forecasting the impacts of policy (using the National Model System, LMS)? The LMS is also based on empirical data, but being a long-term strategic model, it is based on equilibrium assumptions rather than historic time series.

The method developed and described in this paper is based on actual (ex-post) measurements of congestion and influencing factors, instead of using the same instruments as for ex-ante evaluations (transport models such as the National Model System (LMS)). The applied method is therefore independent of the method used for forecasting the impacts of policy measures and other factors. Until now, the regression-based method was used to identify the impacts of adding lanes, adding new roads, traffic management systems (such as dynamic route information systems and ramp metering), reductions of maximum speed, speed reduction enforcements and financial rewards for peak avoidances, respectively. The method was also used for other purposes, including to measure induced demand and explain the trend in freight transport. Until now trends on national roads were analysed, but more data are becoming available to also explain trends in hours of delay and car use on regional and municipal roads. We will discuss the method as currently used, its most recent results and its validation, in respectively sections 4, 5 and 6 of this paper.

In addition, we will examine how the method has evolved over the years and focus in particular on the question of how the method can be further improved. This is discussed in Chapter 7.

3. HOW TO EXPLAIN THE DEVELOPMENT OF CONGESTION: A THEORETICAL APPROACH

Traffic engineers define congestion as the phenomenon that arises when the input volume ("demand for travel") exceeds the output capacity of a facility (Stopher, 2004). In other words, congestion exists when the demand for car travel exceeds the capacity of a road stretch. Economic analysis of congestion generally involves the notion of equilibrium, whereby the profile of demand over a period of time, say a day, is endogenous (Fosgerau, 2009). Congestion is an inherently dynamic phenomenon, since an arrival at some point in time affects only users arriving later, not those arriving earlier (Fosgerau, 2009). Vickrey's (1969) bottleneck model captures many of the essential features of equilibrium demand for a congested facility. The congested facility is described as using a bottleneck congestion technology, whereby queueing users are served at a fixed service rate. A vertical queue builds up when users arrive at a faster rate, and dissipates when users arrive at a slower rate. There is a continuum of users assumed to incur costs of delay and also scheduling costs, such that deviations from their preferred service times are costly. In order to explain congestion, we thus need to take into account factors representing road capacity and travel demand.

Figure 2 presents our theoretical model for explaining traffic congestion. Below we describe which factors we include to represent traffic capacity and demand.

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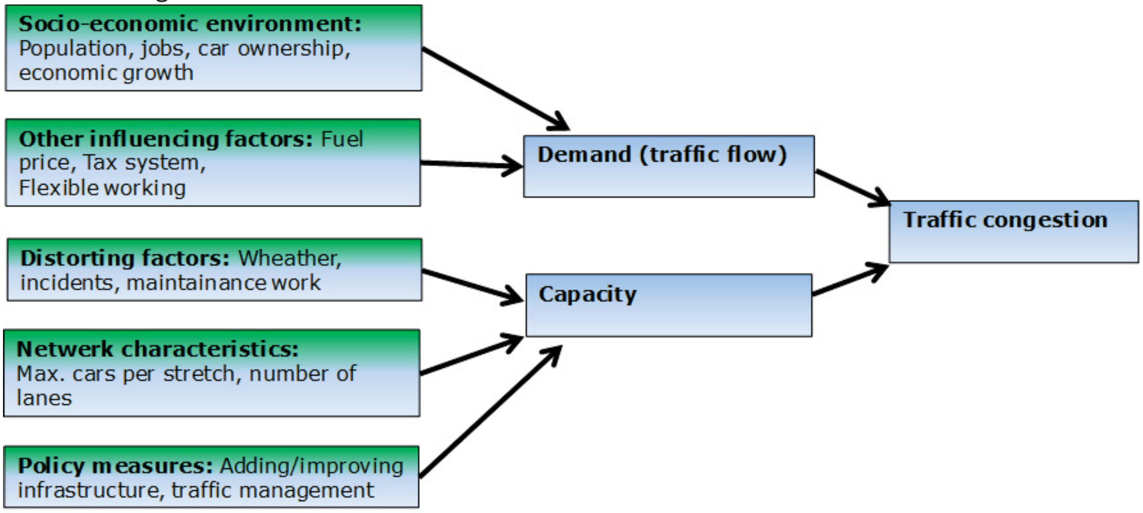
Figure 2. Theoretical model for explaining the main factors and relationships behind the development of traffic congestion on national roads 2000-2016.



Capacity

According to Van Wee et al. (2013), capacity can be defined as the maximum hourly rate at which people or vehicles can reasonably be expected to traverse a point, section or roadway during a given time period under prevailing roadway, traffic and control conditions. Knoop and Hoogendoorn (2018) state that capacity relates directly to the minimum headway drivers are following and the distribution of traffic over the lanes. The Dutch capacity manual describes road capacity in terms of road density, the speed by which cars can pass and the road intensity (Rijkswaterstaat, 2011). Moreover, it includes aspects of highway design, such as the road texture and amount of stretches, lanes and traffic lights ('network characteristics'). Capacity can be structurally affected by policy measures, such as adding an extra lane, placing a traffic light, etc. ('Policy measures'), or temporarily by events such as disasters, (major) accidents or maintenance works (Bell, 1999; Lida, 1999), or weather circumstances ('Distorting factors') (Chun et al., 2006).

Demand

According to the scheduling approach, travellers are likely to plan their trips based on their preferred arrival or departure times. A common assumption is that in order for travellers to choose an optimal schedule for their trip, they trade off travel-time cost against schedule-delay cost, given their appreciation of the possibilities for their travelling. On a more aggregated level, if a region's population is increasing, more people will be wanting to travel, even if capacity remains unchanged, leading to a consequent continued increase in congestion levels (Stopher, 2004). The development in population is therefore included in our approach. Increasing wealth can increase demand (Stopher, 2004; Small and Verhoef, 2007). People tend to increase the distances they travel roughly in proportion to increases in their incomes. It follows then that economic growth can impact demand for highway capacity. To represent the socio-economic situation, we take account of the development in jobs, car ownership and economic growth ('Socio-economic environment'). Moreover, fuel prices are found to influence the demand for car travel (Dargey, 2007), as are possibilities for flexible working (Van der Loop, 2018). For the specific case of the Netherlands, it is also important to take account of the tax

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reform introduced in 2004 pertaining to commuting- and business-related car trips, which included an increase in the amount of money that could be reimbursed for such driving purposes ('Other influencing factors').

4. METHOD

Starting in 2000, recorders in the Dutch road surface permanently measure the traffic volume and speeds of passing vehicles at approximately 3,200 stretches of the trunk road network. For all analyses, we use this data aggregated to 15-minute intervals. Similarly, the Dutch Ministry of Infrastructure and Water Management records accidents, road works (both per stretch and per quarter of an hour) and weather conditions (every hour from around 30 weather stations). Statistics Netherlands (CBS) provides additional data, such as population, job and car ownership rates per municipality per year.

Regression analyses are used to explain the development in traffic congestion, car use, travel time, reliability of travel time and extreme travel times from 2000 to 2016 (see Equation 1 for hours of delay). Box 1 provides a definition for all the dependent variables in our analyses. Independent variables in the analyses are the number of accidents, capacity reduction due to road works, weather conditions, traffic capacity as a constant (maximum number of vehicles per section) and newly introduced policy measures (lanes added, new roads, traffic management, changes in maximum speed and speed enforcement measures).

All data are combined at the 15-minute intervals. For the regression analyses, the dependent and independent variables are further aggregated per month and per road stretch. To explain the hours of delay, travel time, travel time reliability and extreme travel times, we add the traffic volume as an independent variable. To isolate the impacts of influences on the dependent variables that are specific for a certain specific month or year, respectively month and year dummies are added to the regression equation. We use the regression coefficients to calculate the impact that independent factors have on the dependent variables in the regression model.

Box 1. Definitions of dependent variables

- Car use (amount of traffic or traffic flow): the number of vehicle kilometres driven.
- Hours of delay on national roads (highways): the number of hours lost because a speed of 100 km/h could not be reached. This speed approximates the free flow mean speed.
- Travel time: the hours vehicles have used the road.
- Unreliability of travel time: the travel time longer or shorter than the traveller expected prior to the journey (OECD, 2010). We calculate this as the standard deviation (SD) in minutes per month per road stretch per quarter of the hour of all working days in that month, which is considered as the expected travel time. This definition includes all variations in travel time and enables us to identify the impacts of policy measures on reliability.
- Extreme travel time: extremely large amounts of time lost by the traveler due to incidents or large traffic flows. We calculate this as the hours lost if the travel time was higher than three times the SD above the mean travel time and at least 50 percent above the mean travel time (per month per road stretch). In 2016, 7 percent of all hours lost were extreme.

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Based on this regression we create a pre-test and post-test control group design (Cook and Campbell, 1979), which enables us to assess the impact of all policy measures of a certain type by a comparison before and after a policy measure's introduction on the stretches of influence, while the network's other stretches serve as a control group. The stretches of influence of the types of policy measures were identified empirically: extensions of the stretches of influence (e.g. 10-20 km before or after lane extensions) did not add more to the reduction of hours of delay. The stretches of influence that lane extensions had on travel time delay were therefore determined at the road sections of the extension itself and furthermore at stretches 0 to 5 kilometres and 5 to 10 kilometres upstream and downstream, and at crossing roads 0-5 km and 5-10 km. The stretches of influence of dynamic route information systems are 0-5 km before and after the location. Ramp metering: 0-1, 1-2, 2-3 km before and after the stretches with a ramp metering. Changes in maximum speeds: 0-5 km before and on the changed road stretches (if the maximum speed is 80 km/h, the loss-hours between 80 and 100 km/h are not calculated). Financial rewards for avoiding the peak: at the stretches to avoid during peak hours. Road accidents: 0-5 km and 5-10 km before and on stretches affected by accidents (and 0-2.5 km from the accident on the other lane direction) from the moment the accident occurred until the road is clear again. Road works: the percentage of capacity reduction on stretches 0-5 km and 5-10 km before and on stretches directly affected by the capacity reduction during the total period the capacity reduction occurs. Equation 1 presents the regression equation for estimating the impact of all these factors on travel time delay.

$$Y_{ik} = C + \beta_{pk}P_{ik} + \gamma_s S_{ik} + \delta_j Y_j + \phi_i M_i + \eta V_{ik} + \varepsilon_{ik} \quad (1)$$

Y_{ik}	=	hours of delay per month i (12*years in the analysis) and stretch k
C_k	=	constant per stretch k (implicitly, by mean centering)
P_{ik}	=	a set of indicators P that defines whether policy measure p at stretch k is active ("1") or inactive ("0") in month i (indicating the difference before and after implementation of the measure)
S_{ik}	=	a set of indicators to define the situational characteristics per month i at stretches k around locations with accidents, capacity reductions by road works, weather conditions and the reciprocal of road capacity (as a constant)
Y_j	=	a set of variables indicating the impact of calendar year j (years in analysis) in Randstad and other parts of the Netherlands
M_i	=	a set of variables indicating the impact of calendar month i (12)
V_{ik}	=	traffic volume and square of traffic volume per month i (12*years) and stretch k
$\beta, \gamma, \delta, \phi, \eta$	=	partial regression coefficients indicating the impact of a factor on the monthly trend per stretch of the dependent variables
ε_{ik}	=	error term (variation in hours of delay not explained by the preceding factors)

Regression analyses produced coefficients for approximately 1,500 variables (1,400 for the components described above of approximately 350 policy measures), which is too much to present individually in this paper. Of these coefficients, 90% were statistically significant ($\alpha < 0.05$). The fit (*r*

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squared) of hours of delay and the other dependent variables has an order of magnitude of 0.4. This magnitude seems reasonable for data with such large variations.

The coefficients estimated for the policy measures (β_{pk}) reflect the C hours of delay (or the entities of the other dependent factors) that are reduced or increased by the independent factors. In a second step, these impacts are added up for the total network and each expressed as percentages relative to the base year (2000) in order to present the relative impact on congestion and on the other dependent variables.

To estimate the impact of socioeconomic factors on the dependent variables, we use a separate regression at the level of road stretches per year that 'overlaps' and 'extends' the regression on the monthly basis. This consists of two parallel parts: one explaining car use (vehicle kilometres), and the other the hours of delay per vehicle kilometre. This regression has a multiplicative form (Equation 2), whereas the monthly model has an additive form. The yearly changes in population, number of jobs per inhabitant and car ownership per inhabitant per municipality are related to car use and hours of delay per vehicle kilometre at stretches within a distance of 30 kilometres. Several weights of distances (d) of these 'gravity' models have been tested: d-0.25 (municipalities situated further away have a large weight), d-0.50 and d-0.75 (municipalities within 20 kms dominate). The chosen model appeared to have the best explaining values. Because the road capacity was increased with approximately 10% more lanes, the impact of these lanes was added to the hours of delay.

$$\ln Y_{jk} = \ln c_j + \beta_i \ln\left(\sum_{m=1} \left(E_{ijm}/D_{km}^{-0,75}\right)\right) + \varepsilon_{jk} \qquad (2)$$

Y_{jk}	=	(mean centered) car use and hours of delay per vehicle kilometre (+ impact of more lanes) per year *j* and stretch *k*
c_k	=	constant per stretch *k* (implicitly, by mean centering)
E_{ijm}	=	external factor i (E_i is population and number of jobs and cars per inhabitant) per stretch *k* within 30 km from the municipality per year *j*
β_i	=	elasticity of external factor *i* on car use and in vehicle hours of delay per vehicle kilometre
ε_{jk}	=	error term

The GDP per region (COROP) did not explain hours of delay as well as the three variables previously mentioned. The gross value added (GVA) of business services in some years appears to augment the impact of the three variables (although these three variables give a fairly good explanation of the increase in yearly demand, this improves the explanation further especially in years when hours of delay substantially increased).

5. RESULTS

Figure 3 presents the explanation of the development of hours of delay, car use, unreliability of travel time and extreme travel times from 2005 to 2016 on national roads.

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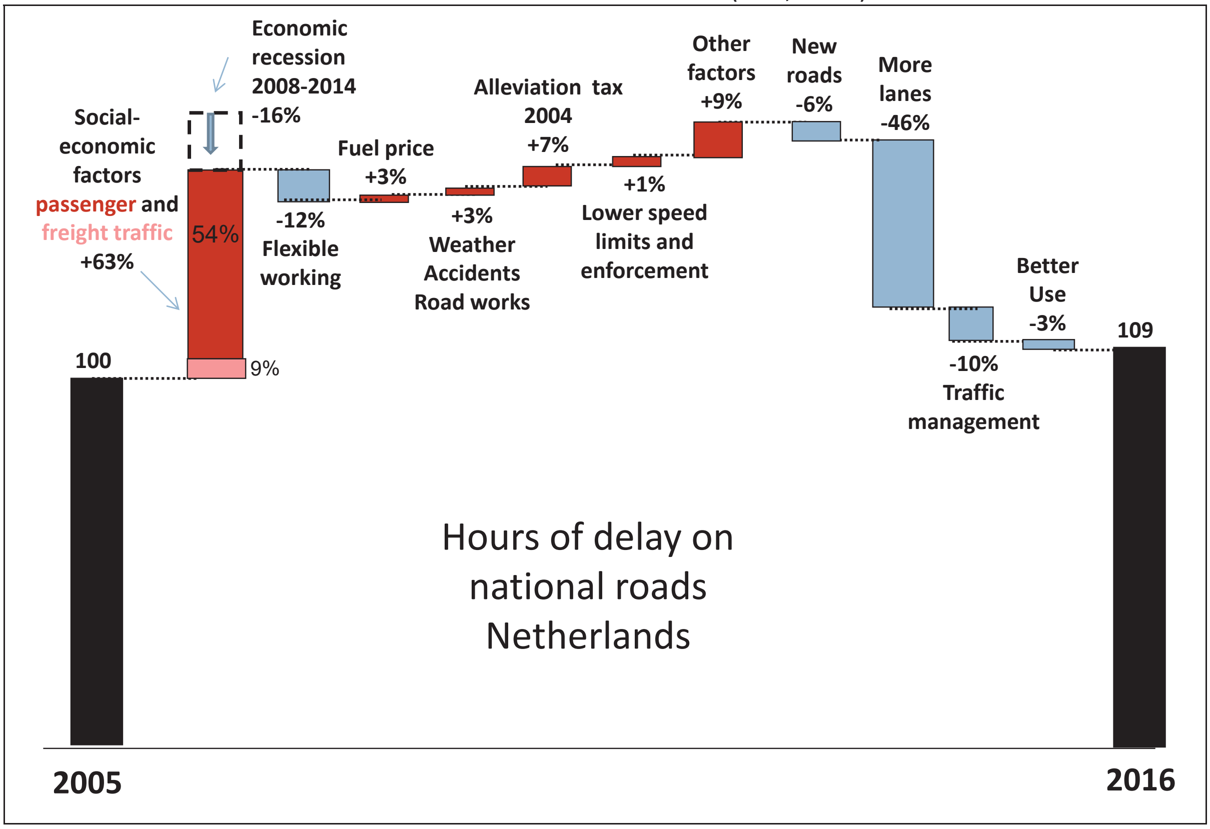
In short, the figures reveal that for all dependents socio-economic factors play the most important role in explaining the development over the period 2005 to 2016. Additional lanes also have a considerable impact. The other included factors have a smaller impact.

Figure 3. Explanations of hours of delay, amount of traffic, unreliability of travel time and extreme travel times on national roads in the Netherlands 2005-2016 (KiM, 2017).



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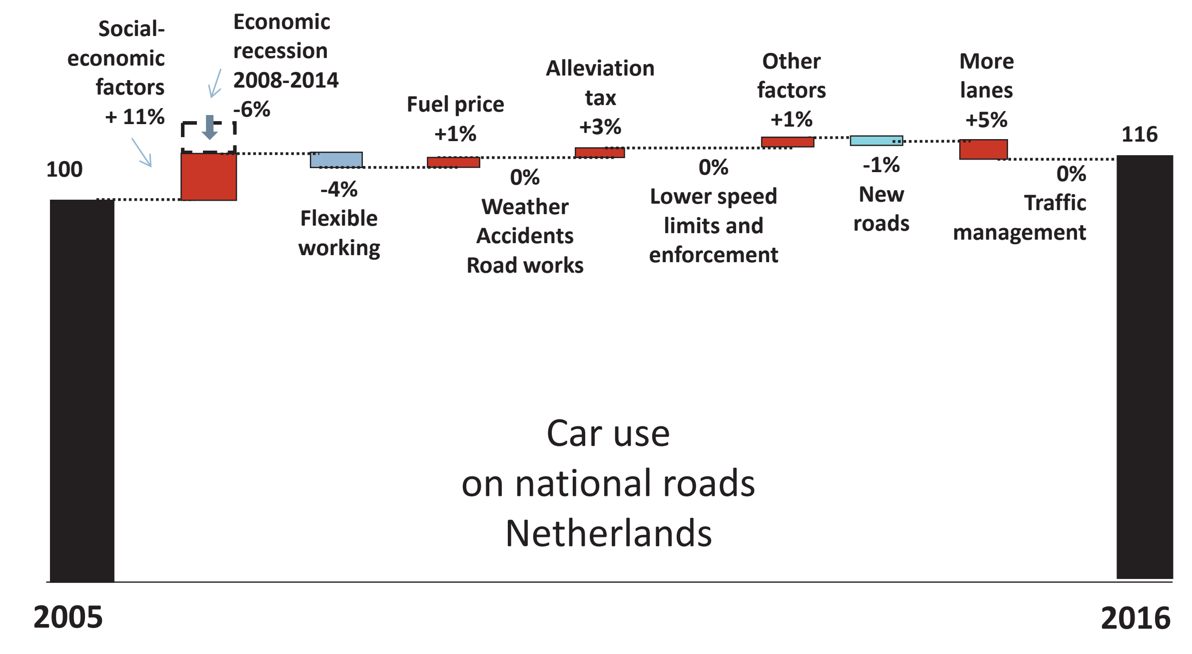

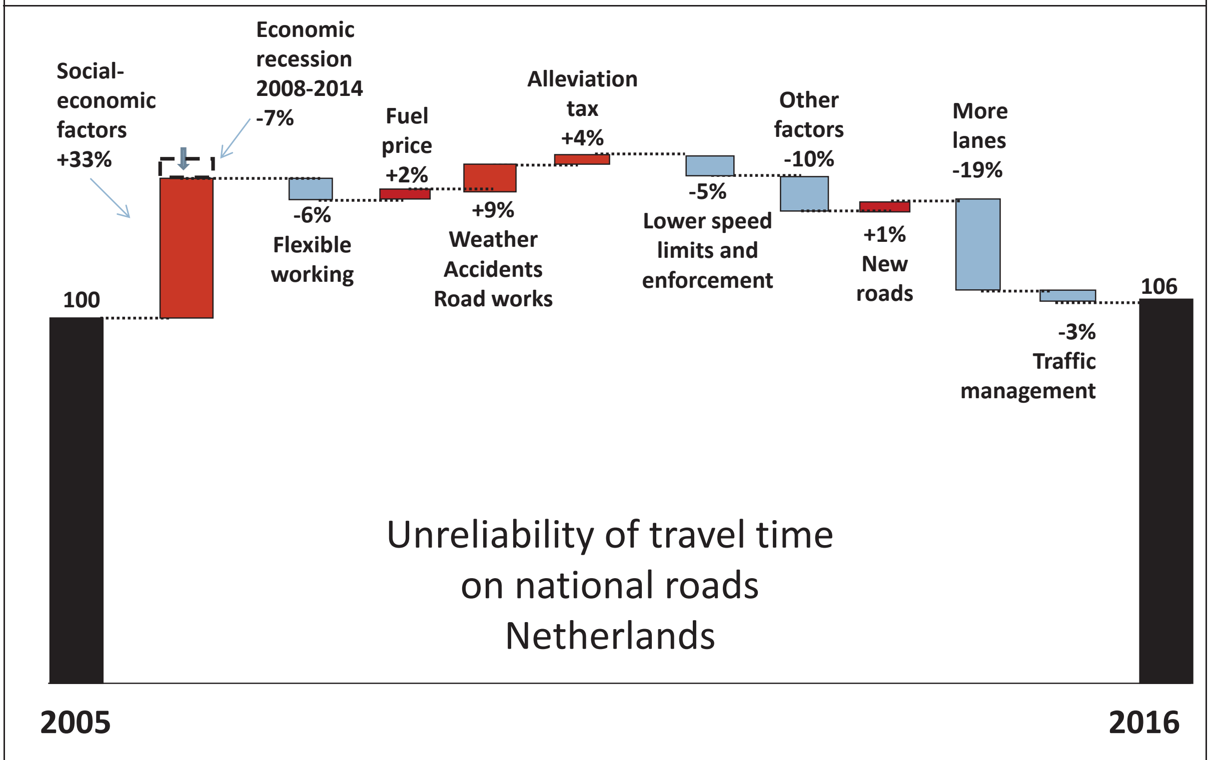

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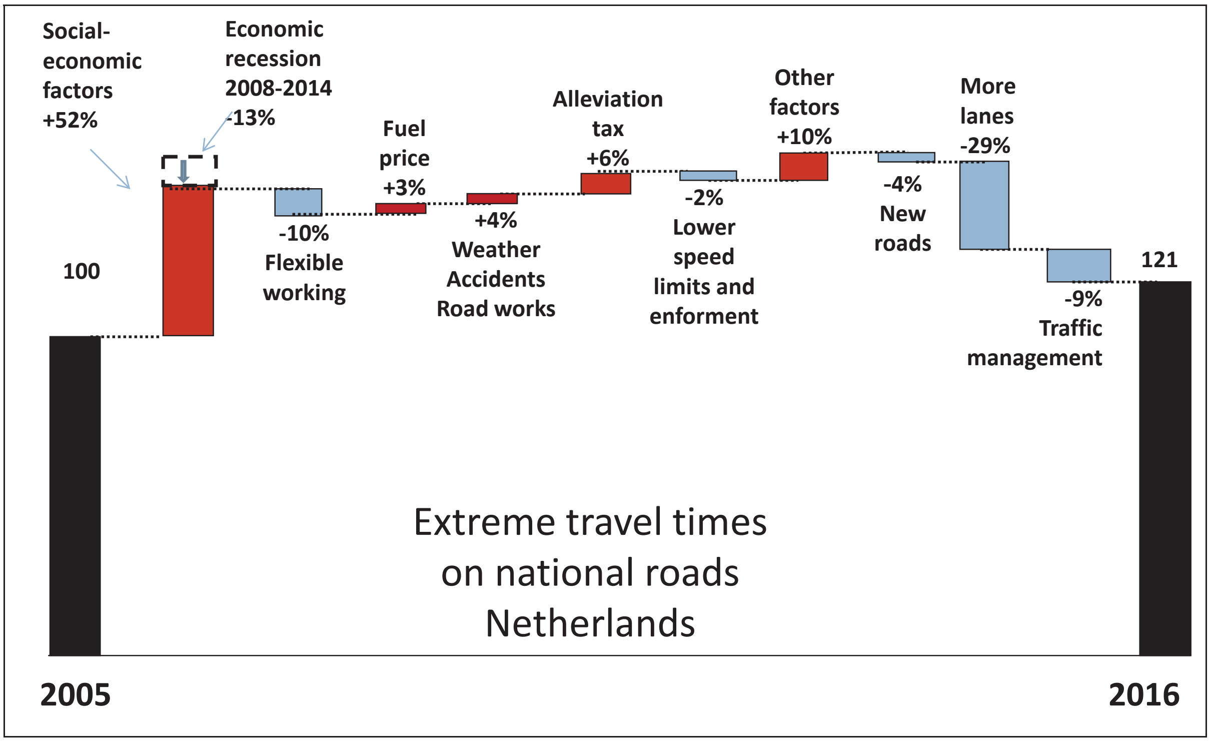

The impact of the yearly changes in socio-economic factors – i.e. population, jobs and car ownership per municipality on hours of delay (equation 2) –- are approximately equal to the joint impact of the changes in car use on hours of delay and of the calendar year factors (equation 1). This suggests that both represent the impacts of changes in demand, influenced by socioeconomic factors.

According to traffic theory and common sense, it could be expected that the development of the hours of delay depends primarily on the development of the amount of traffic (demand) and the road capacity (supply). Nevertheless, the relationship found between the amount of traffic and the hours of delay with the regression analysis as specified in equation 1 appears to be rather limited. The reason for this result seems to be that the relationship between the amount of traffic and hours of delay at the level of a road stretch is not linear, as assumed with equation 1, but nonmonotone (Figure 4). To capture the impact of changes in demand that are not represented by the variable traffic volume, the the calendar years variables were included in equation 1. It appeared that the impacts of traffic volume and calendar year are strongly correlated (0.9). It is therefore concluded that the calender year variables represent all impacts that are specific for a certain year, mostly representing changes in traffic volume. We will examine this further in section 6.

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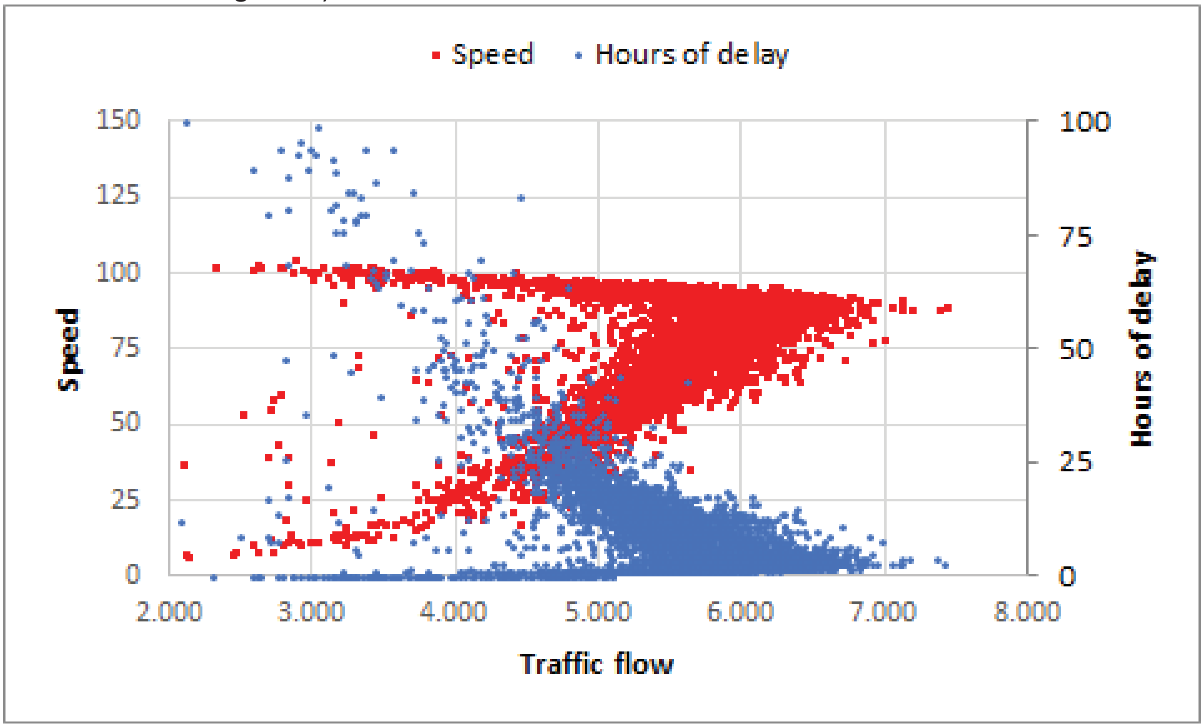
Figure 4. Relationship of traffic flow to hours of delay and speed at a stretch (on A13 with large traffic flow and congestion) of national roads in the Netherlands in 2016.



Apart from long-term explanations, explanations covering shorter term periods also appeared to be possible. This includes changes in hours of delay in the last year (e.g. 2015-2016) or during some years (e.g. 2014-2016 because congestion increased from 2014). In most cases it appeared to be possible to attribute increases or decreases in hours of delay to the factors in equation 1.

A distinction between longer and shorter term effects could also be made for lane extensions. For adding permanent lanes and peak hour lanes (i.e. lanes opened only in cases of heavy traffic), and for using shoulder lanes for through traffic during dense traffic, we found that short-term effects on travel time losses were higher than long-term effects. Additional coefficients were estimated for the first two years that a lane has been added. Figure 5 shows that the average effect of adding permanent lanes is estimated to be 26% higher in the first year compared to the long-term effect. This percentage is even higher for peak hour lanes and the use of shoulder lanes during peak hours: respectively 75% and 35%.

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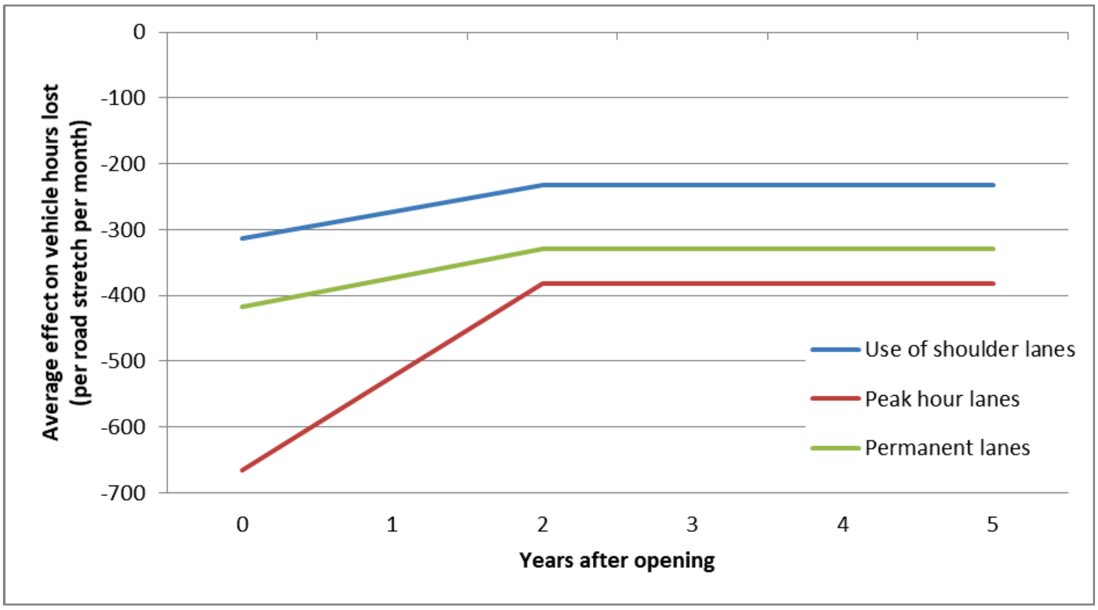
Figure 5. Short- and long-term effects of adding lanes on hours of delay on national roads in the Netherlands 2000-2016.



To allow for comparisons with other studies, the mean impacts of policy measures found are presented in Table 1. Apart from lane extensions, it appeared that the regression method could be used to assess the impacts of “smaller” and “specific” measures, such as dynamic route information systems, ramp metering, and financial rewards for peak avoidances. The impact of dynamic route information systems appeared to be larger than previously published (MuConsult, 2002, 2011). Until now the impact of changes in fuel prices could not be assessed using the current method and data. For this purpose, national yearly changes in fuel prices were available. Moreover, the impact of new provisions in route-planning and congestion-related information could not be estimated because no data were available about the use of these provisions.

Table 1. Impacts of policy measures assessed by monthly regression analysis in 2016 and other publications

	Area (stretches) of influence	Mean impact based on Monthly Regression Analysis (hours of delay per year)	Publication
Adding lanes	20 km to 50 km	Permanent lanes -37% Rush hour lanes -25% Shoulder lanes -14%	
Dynamic route information systems	16 km (5 before, 1 on, 10 after)	-18%	
Ramp metering	4km (3 before + 1 on)	-6%* -7%	* MuConsult, 2002 and 2011
Financial reward for peak avoidance	Stretches to avoid during peak hours	-9%** in peak hours on stretches to avoid during peak hours, in *active* period	** Van der Loop, e.a. 2018.

6. VALIDATION

The method and results have been validated in various ways, as summarized below:

- Check the impact of policy measures and the method with experts such as traffic engineers and other researchers.
- Compare the results with the outcomes of the National Model System (LMS).
- Integrating equation 1 and 2 (simplification)

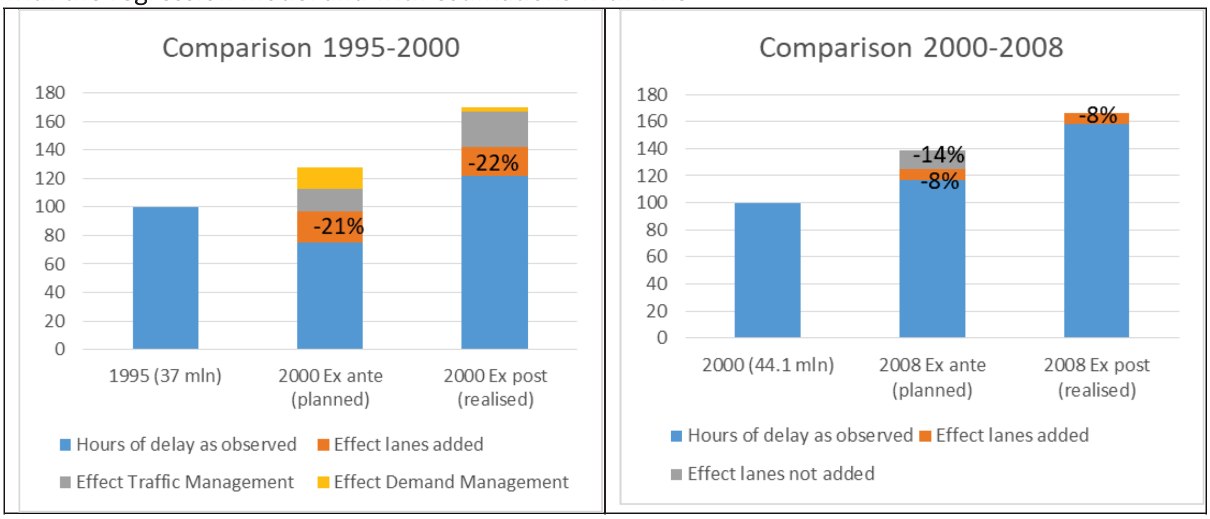
6.1 Check policy impacts with policy experts and other studies

The impacts of the types of policy measures were checked initially and regularly with the current insights of policy experts both nationally and internationally. The impacts estimated using the regression method generally appeared to match with the insights of experts (within the Ministry and at universities) and with the findings of other empirical studies (for studies on lane extensions, see Van der Loop et al, 2016; for studies on traffic management, see MuConsult, 2002 and 2011; for studies on peak avoidance, see Van der Loop et al, 2018).

6.2 Comparison with LMS

We compared the explanation of the development of hours of delay with the planning (forecast) based on LMS (the National Model System) for two periods: 1995-2000 and 2000-2008 (AVV, 2003; KiM, 2010) (Figure 6). The LMS is a forecasting system for simulating developments in mobility, as based on a spatiotemporal-detailed model of the drivers of mobility. In both periods the realised impact of adding lanes measured with the method of monthly regressions was approximately equal to the planned impacts of the realised policy measures as estimated with LMS (resp. -22% and -8%). From 2000 to 2008 some of the planned lanes were not realised; these lanes were estimated to reduce hours of delay by 14%. From 1995 to 2000 the realised impact of traffic management (dynamic route information systems and ramp metering), as measured with the method of monthly regressions, was larger than the previously estimated planned impacts (resp. -25% and -16%), because more traffic management systems were realised than previously planned.

Figure 6. Comparison of explanations of hours of delay on national roads in the Netherlands, estimated with the regression model and with estimations with LMS



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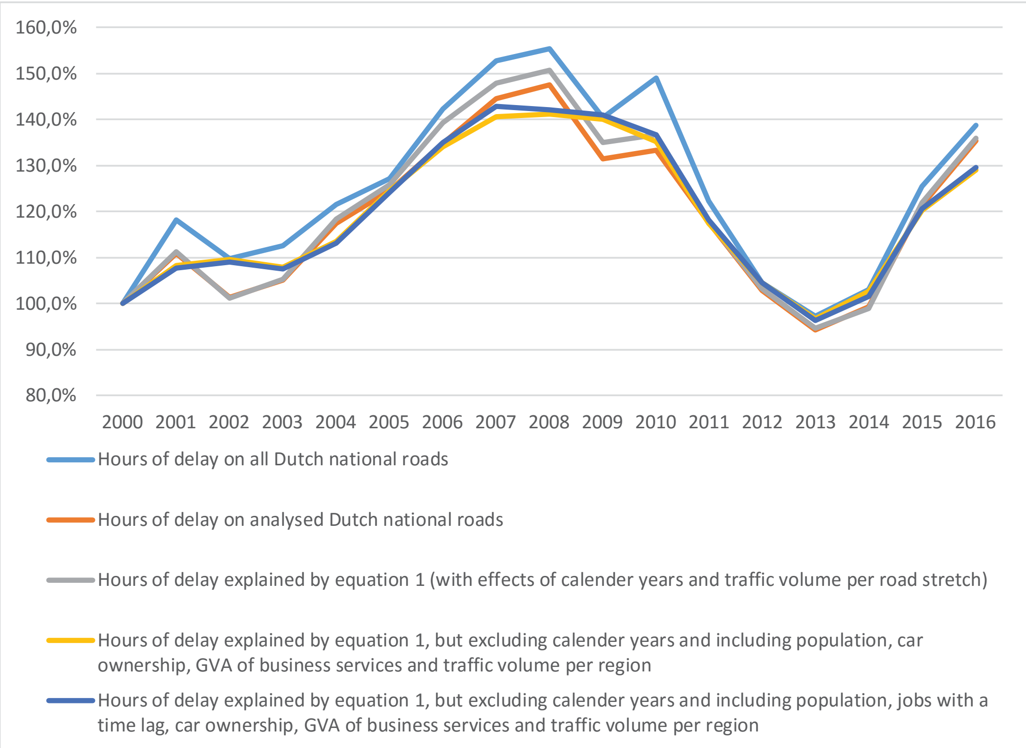
6.3 Integrate equation 1 and 2 (simplification)

As described in section 4, we use two equations to explain the development of hours of delay. To simplify matters, we also developed an alternative model for estimating all impacts in one analysis. In this alternative model, the calendar year effects in equation 1 are replaced by variables representing demand: population, jobs, car ownership per municipality (yearly amount of communities within 30 km per road stretch) and the regional gross value added (GVA) of business services. The traffic volume of eight regions is added to the model, as this provides an additional explanation of the congestion level above the amount of traffic measured at the road stretch.

In this alternative explanation, the changes in jobs appeared to have a negative coefficient. A one-year time lag in the impact of changes in jobs appeared to slightly improve the explanation of increases in hours of delay, especially in years when congestion changed from a decrease to an increase. Jobs appear to have a lagged reaction to economic activities that increase traffic (employers take a certain amount of time to hire new employees; this suggests that new activities already increase before new jobs are created and filled) (Figure 7).

It appears that the model with demand factors explains the development of hours of delay rather well, except in years with low and high peaks. Another disadvantage of the model with demand variables is that the estimation of impacts of policy measures appears to be less accurate than in equation 1, because the regression model assigns unexplained trends to the policy measure coefficients if no calendar year constants are included.

Figure 7. Comparison of development of hours of delay with explanation by the model with factors representing demand.



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7 Further elaboration of the explanation

We describe the following possibilities for elaborating the explanation of the development of hours of delay:

- Including additional explanatory variables
- Two-regime model
- More detailed representation of spatial and temporal relationship between traffic volume and hours of delay
- System of equations
- Another statistical approach

7.1 Including additional explanatory variables

It could be worthwhile to find additional variables for better representing the impact of socio-economic factors in the model. We recently tested some additional variables for the added value they give to the model. We tested the added value of the number of vans per stretch, fuel prices, consumer confidence and the lagged amount of jobs (jobs have a lagged reaction; employers take a certain amount of time to hire new employees). The first three variables were not found to add significantly to the model (without calender year variables). The time lag of the impact of changes in jobs however appeared to improve the explanation of increases in hours of delay, especially in years when congestion increased.

7.2 Two-regime model

To estimate the relationship between traffic volume and hours of delay, a more elaborated model was recently developed using two-regimes. In this model the impact of influencing factors was estimated using the regression model of stretches that per part of the day are congested (mean speed below 70 km/h) or uncongested (speed above 70 km/h). A probit model was used to estimate the probability of each of these regimes occurring and to provide an explanation for occurrence of the two regimes. The results of these three models were added up in a manner comparable with the standard "monthly model". Two other differences with this "monthly model" are: the two-regime model is not per month, but per part of day: morning peak 7:00-9:00, afternoon peak 16:00-18:00 and rest of the day. Also, calendar year impacts are replaced by the impacts of population, jobs, car ownership, and local and regional traffic volume.

The two-regime model did not ultimately explain the development of hours of delay sufficiently (Figure 8). On a national, yearly level, the monthly model without calendar year effects is a better fit for the time series than the two-regime model (correlation with national development is respectively 98.2% and 94.1%). Presumably, the additional degrees of freedom in the two-regime model (distinction between the regimes, distinction between day time periods) do not compensate for the need to model additional aspects of traffic congestion: more differences between road sections and differences between days within a month. One could also say that the monthly model is estimated on data more similar to the national, yearly level, hence it makes sense that this model performs better on that level.

Figure 8. Comparison of development of hours of delay with explanation by the two-regime model and the model with demand factors (the purple line in Figure 7 including jobs with a time lag).

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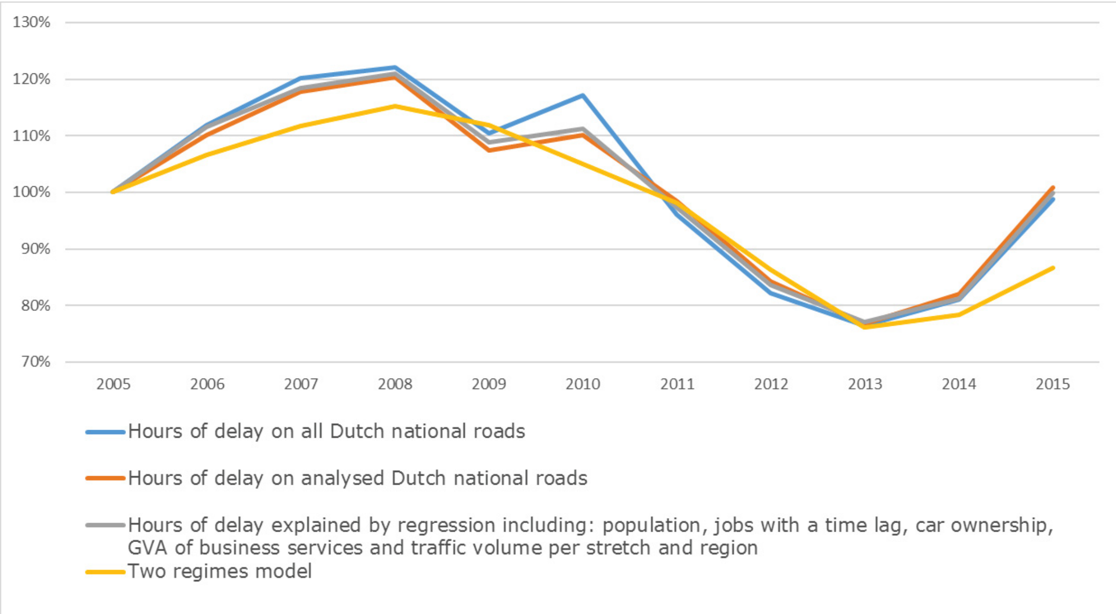

7.3 More detailed representation of spatial and temporal relation of volume and delay
The results of the two-regime model as described above lead us to conclude that a fuller explanation of the relationship between traffic flow and hours of delay would better represent the spatial and temporal relationships between these two factors.

Our regression model accounts for traffic demand and supply for each individual road stretch, resulting in an estimate for the effect of traffic volume (and traffic volume squared) on loss-hours. Each road stretch is considered an independent observation. By applying ‘influence areas’, the model accounts for spatial relationships between road stretches. Moreover, the model implicitly accounts for spatial relationships between road stretches in the sense that consecutive road stretches will have similar levels of traffic volume and values of other explanatory variables (capacity, roadworks, accidents, weather and policy measures).

The vertical queuing theory (which assumes vehicles are stored vertically in a queue) describes the build-up of traffic jams and rebound congestion. Can vertical queuing theory be used to account explicitly for the spatial relationship between road stretches and for the nonmonotone relationship between traffic volume and loss-hours (Figure 4)? In theory this method could be used to account for congestion at road stretch *k* at time *t*, which is not only determined by the input of traffic from stretch *k*-1 and the output to stretch *k*+1, but also by the level of congestion at stretch *k*+1 and k-1 (hence, the cause of congestion is not only a function of characteristics of stretch k at time *t*, but also of stretches downstream and upstream at time *t* or even earlier). To achieve all this, not only must the spatial relationship between road stretches be modelled, but possibly more detailed data are needed (e.g. per minute instead of per 15 minutes), as well as for example analyses on a daily basis instead of monthly aggregated data. This approach seems to demand a more detailed level of data than presently available for long-term explanations. This model is likely to improve further insights, especially for certain specific situations that require detailed analysis, yet the question remains as to whether such a model is applicable for model congestion in all situations (incidental and structural

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congestion, delayed settlement, etc.) and capable of better explaining the total amount of hours of delay than the current model.

7.4 System of equations

Treating travel demand more endogenously is a research direction that has not yet been explored in practice. The methods used and tested thus far use the measured traffic volume as an explanatory factor for congestion, whereas it is actually endogenous because of the speed-flow relationship. The thriving factor of mobility is travel demand: the number of people desiring to make use of a road when there would be no travel time delays. As travel demand cannot be measured directly, it must be estimated.

One approach to including travel demand in the analysis is to estimate a system of equations, in which the explanatory regression analyses are conducted simultaneously in relation to each other. The advantage of this approach is an increased consistency in the analyses of related indicators (e.g. travel times and travel time losses). Travel demand will be an explanatory factor for all the indicators (including traffic volume). The challenge of this approach is how to estimate the interactions between traffic volume and congestion simultaneously. This approach must therefore be developed further before it can be tested.

7.5 Another statistical technique

Another approach to improving the statistical model currently used could be the use of a statistical technique that better describes the nonmonotone relationship between traffic flow and travel delay. Support Vector Machines or Neural Networks might be worthwhile in this respect, as they provide a more data driven rather than theoretical solution to the problem of the relationship between traffic flow and travel delay. Attempts to experiment with machine learning have not yet been undertaken.

8. Conclusions and discussion

In this paper we described the method used by the KiM Netherlands Institute for Transport Policy Analysis to explain the development in travel congestion and related factors. Owing to the availability of extensive data on the stretch level about the amount, speed and delay of travel, it is possible to perform detailed analyses using many explanatory factors. We showed that, if sufficient data are available, at present the current method, with a regression at the road stretches level of approximately 1 kilometre per month with calendar year effects, appears to be the best proven method for estimating the impacts of policy measures and other factors on the longer and shorter term development of congestion, travel flow, travel time, travel time reliability and extreme travel times. This model appears to be robust, as it meets the basic needs of the methodology: it compares a before-and-after situation with and without change; it provides the level of detail needed (per month per stretch); and it controls for unforeseen, specific factors (year coefficients).

Nevertheless, improvements are seemingly still possible and further investigation can improve the insights into the underlying dynamics; for example, added value could be gained from adding explaining factors (lagged change in jobs and perhaps additional still to be tested variables). Other improvements could be possible by further refining the relationships in the model, especially between traffic flow and hours of delay. This could in principle be achieved in three ways: 1) by introducing spatial and temporal relations in the model (e.g. using queuing models), 2) further integrating different equations, or 3) using another statistical technique than linear regression. At present, and as far as we know, no other or complete approaches are known. Our experience shows that gradual improvements from the existing model seem to be more effective than completely new trials for another model or method (e.g. the two-regime model). With this paper we hope to deepen the discussion about how to explain traffic congestion, with the aim to assist transport policy in making our road trips more efficient.

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