4 CEMENT module: validation and verification

4.1 Introduction

The theoretical description of the fuel consumption is implemented in the CEMENT module. Its inclusion enables a numerical evaluation of the energy minimising optimisation theory. This chapter presents the validation and verification of the CEMENT module, and the calibration of its parameters. Validation is determining that a simulation computer program performs as intended, e.g. debugging the computer program, while verification is concerned with determining whether the conceptual simulation model (as opposed to the computer program) is an accurate representation of the system under study. (Descriptions adapted from [Kleijnen, 1993]).

The chapter also elaborates on the uncertainty of the model outcome regarding the system's optimal state. The evaluation of calibration, verification and error estimation starts with the consideration of the impact of each model parameter separately. According to Beck [Beck, 1987], model uncertainties originate in three categories. The first category of uncertainties – in model input and parameter values – shows similarity with stochastic or statistical errors. The chapter starts in section 4.2 with this kind of uncertainty. The aggregation and possible interaction of the separate statistical errors is treated in section 4.2.9, after which the focus shifts in section 4.3 to the second category of uncertainty, the uncertainty about the model structure or so-called systematic errors. The third category concerns the uncertainty about the future.

Section 4.3.4 gives an outlook on the uncertainty that exists in future developments of the traffic intensity. The CEMENT module is not suited to assess the system's uncertainty about the future fully, since the assessment requires a different theoretical approach. Chapter six, which deals with transition paths, will comment on the latter category of uncertainties.

![Figure 4.1 A schematic representation of the CEMENT module inputs and outputs. The direction of the arrows distinguishes into inputs and outputs of the CEMENT module.](image)

A schematic description of the CEMENT module is presented in figure 4.1. The model assumes that the average velocity is determined by the ratio of traffic intensity and road segment capacity, or the intensity/capacity (i/c) ratio. The fixed intensity variable is extended into a distribution set in the beginning of section 4.2 for a ‘distributed approach’ of the CONCRETE model. The latter section looks at the difference between the fixed-value theory and the distributed approach. Section 4.3 attempts to verify the dependence of the velocity on the i/c-ratio.

The primary input variable is the traffic intensity $y$ and the main output is the fuel consumption of the vehicles $F$. The fuel consumption characteristics determine the

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60 The terminology regarding validation and verification is not standard; see also [Law et al., 1991].

61 In [Beck, 1987] a fourth category of problems related to model uncertainty is defined; those problems concern the errors that arise in model calibration and validation. This chapter treats these uncertainties as being incorporated in the first two categories mentioned.
optimal capacity \( x_{opt} \) together with external parameters like the discount rate \( \rho \) and the construction energy intensity \( \alpha \). The (internal) input variables to compute the fuel consumption are \( x \) (road capacity), \( v_{max} \) (speed limit) and \( \ell \) (road segment length). The road architecture also influences the parameters \( f_{max} \) (i/c-ratio at \( v_{max} \)) and \( v_{opt} \) (velocity with highest i/c-ratio). The latter values are fairly constant for motorways in the Netherlands, but they need not be valid for foreign motorways. Other internal parameters are \( x_0 \) (default capacity) and \( c \) (vehicle length). In the computation of fuel consumption, the theoretical description of the vehicular fuel consumption \( g(v) \) is subjected to uncertainty due to the large variations in the car fleet and little empirical data on fuel consumption in different real-life traffic conditions. Finally, the road wear rate \( \delta \) influences the optimal capacity.

Section 4.2 assesses the model uncertainty, while validating the CEMENT module as well, by varying the input parameters \( c, v_{opt}, v_{max}, f_{max}, g(v) \) and \( \delta \) for a road segment of \( \ell=1 \) km and \( x_0=2000 \) vkm/h. Besides the fuel consumption, the CEMENT module also produces the average velocity \( v \) of the traffic flow and the number of vehicles that cannot be accommodated due to insufficient capacity \( (y_{unaccommodated} \geq 0) \). The latter outputs are used in the verification in section 4.3. The entire CEMENT module validation of this chapter does not take variations of \( \alpha \) and \( \rho \) into account. Specifically the energy intensity of construction \( \alpha \) depend greatly on the type of construction, and the spread of variations in \( \alpha \) would cloud the general validation results of the CEMENT module. It is assumed, therefore, that \( \alpha=10000 \) MJ·h/vkm and \( \rho=80 \) yr\(^{-1} \) throughout this chapter.

4.2 CEMENT module validation and sensitivity analysis

4.2.1 Time fluctuations in traffic intensity

4.2.1.1 Setting distribution set size

Section 3.5.5 indicates the optimal capacity to be greater in the case of hourly varying traffic intensities than in the case of a constant traffic volume; see also figure 3.19 therein. This section ascertains the robustness of that assumption by supplying the CEMENT module with several intensity distribution functions. Figure 4.2 shows the theoretical curves indicating the marginal energy benefit of capacity improvement. The intensity distribution functions impact the curves of the marginal energy benefits of capacity improvement \( \gamma \). The intersection with the dashed line that indicates the marginal energy costs of capacity improvement, generally shift towards the right (towards higher capacities). The range of optimal capacities computed lies between 0\% and +40\% of the optimal capacity for the mono-valued intensity case.
Figure 4.2 The impact of fluctuations in intensity on the fuel consumption and marginal energy benefits as function of the capacity for a road with the optimal velocity set at 80 km/h.

The lines of “fixed” input data in figure 4.2 assume a constant intensity at all time; the lines of “distributed 24” data assume 24 distinct intensity categories representing the daily fluctuations in traffic intensity; the “distributed 2016”-lines use data that split a year into 2016 different time periods: for each month (12), each day in the week (7) and each hour of the day (24). It results in 12·7·24 = 2016 time periods. The choices for these set sizes are not arbitrary, but are governed by publicly available data in [MinV&W / AVV, 2003]. The darkest thick line is similar to the thin line of the earlier in this section referenced figure 3.19. However, the grey line uses the intensity figures from the motorway A6 specified into each hour of the day. The intersection with the dashed line that indicates the marginal energy costs of capacity improvement $\alpha$ shifts from 1938 vkm/h to 2686 vkm/h. It constitutes a significant rise in optimal capacity of almost 40%. The marginal energy benefits and fuel consumption indicated by “distributed 2016” are computed using the most detailed intensity figures publicly available. The latter lines deviate only slightly (3.4%) from the lines that use the hourly averages.

The effects of increased time resolution in the distribution frequency of traffic intensity on the optimal capacity are evaluated by supplying the CEMENT module with five theoretical intensity distribution functions as shown in figure 4.3. The conclusion that increased time resolution results in optimal capacities that are about 40% higher than the optimal capacity for a fixed-supply case, is also reached theoretically in figure 4.4, where the size of the distribution sets is not governed by available data. It is concluded, as illustrated by figure 4.2 that the time resolution, by which the traffic intensity is distributed over 24 classes, is adequately accurate. It

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62 The intensity distribution functions were deduced from measurements on motorway A6 near Muiden [MinV&W / AVV, 2003].
produces a systematic error that is small compared to the input errors on which the chapter will continue to report after this section.

Figure 4.3 Five intensity distributions functions, in which the time is divided into 100 classes with a distinct intensity. The “One intensity class” label refers to the distribution in which the intensity is strictly constant in time. The “2 intensity classes” refers to the case in which 50 classes (or 50% of the time) the intensity is half of that of the other 50 classes.

Figure 4.4 Marginal energy benefit curves for several intensity distribution functions (see figure 4.3).

4.2.1.2 Setting distribution set shape
The intensity fluctuations on highways show low night-time traffic, one or two rush-hour peaks and several types of day-time intensity fluctuations. For a large, arbitrary
set of highway segments, the average hourly intensities are sorted in figure 4.5. The bars indicate the standard deviation of the intensity values inside the ‘average set’ and are therefore an indication of the reliability of the approximation of the intensity distribution for a specific road by assuming an average intensity distribution. Ignoring the low intensity values, it shows that especially the highest intensities, or rush-hour traffic, show large fluctuations.

The average intensity distribution function, or load-duration curve, is shown in figure 4.5 by the solid line. The load-duration curve of a congested road, highway A10 is taken as example, is flatter at higher intensities. The traffic seems, at least relatively, to be reallocated over the day. The relatively lower intensities during rush-hour can mean both that the total traffic on the road is less due to congestion and that people are changing their times of departure (not altering the total amount of traffic). A third possibility is that people are changing their routes. The load-duration curve of highway A4 near Delft is presented. It is the end of an unfinished highway (“Midden-Delfland”) and the traffic intensity is therefore significantly less than the road is constructed for. However, it seems to function as overflow for other roads during congestion hours. Therefore, its relative peak intensity is significantly higher than that of an average road.

Figure 4.5 Sorted traffic intensity distribution functions, for three cases: the average intensity distribution of a large, arbitrary set of Netherlands’ highway segments, of a intensely used motorway segment of the A10 near Amsterdam, and of an unfinished motorway near Delft (A4) that shows a sharp peak in intensity, probably due to deflected traffic from congested roads.

Figure 4.5 shows several load-duration curves of the traffic intensity. Conform that figure, it is possible to draw schematised load-duration curves without significant error. The three schematised curves of figure 4.7 are applied in the CEMENT module and can be used to represent the margin of error that occurs due to changing traffic intensity fluctuations.
Figure 4.6 Marginal energy benefits graphs that correspond to the intensity distribution functions of figure 4.5.

Figure 4.7 Schematised load-duration curves for an average road (default), for a road with a short and heavy intensity peak ('short peak') and long and mild intensity peak ('long peak'). The graphs are to be read as the time (in hours) per day that the traffic intensity is at or below the intensity depicted.

The occurrence of short but heavy peak-hour traffic leads to a higher relative optimal capacity than compared to the situation in which the peak-hour traffic is spread out over a longer period of time. The conclusions follow:
A. Intensity distribution functions can be approximated by a straight line;
B. Deviations from conclusion A. occur mainly at high traffic intensities, thus the traffic intensity characteristics of a road segment are mostly determined by the intensity and duration of the peak-hour traffic;
C. Short, intense peak-hour traffic lead to higher relative optimal capacities than long, sustained mild peak-hour traffic;
D. Following conclusion C., spreading the traffic peak-hours will result in a lesser need for additional capacity, from an energy point of view, see figure 4.6.

4.2.2 *Time fluctuations in possible capacity*

It is concluded the traffic intensity should be treated as a distributed variable. This section considers therefore a distributed possible capacity also. The chosen input probability density for the possible capacity is shown in figure 4.8. The graphs of the shadow prices, thus the energy benefits of capacity improvements, are computed for four scenarios: the traffic intensity as distributed variable and as fixed variable, and the possible capacity as distributed and fixed variable. See figure 4.9 and table 4.1. The time-dependent fluctuations in possible capacity result in higher optimal capacities. However, the fixed-capacity scenario assumes a possible capacity as practical capacity of 2000 vkm/h, while the distributed-capacity scenario has the possible capacity of 1700 vkm/h as most likely capacity. The ratio of the optimal fixed capacity of 2725 vkm/h and the optimal distributed capacity of 3237.7 vkm/h is almost identical to the ratio of 2000 vkm/h and 1700 vkm/h. Therefore, it is concluded that the capacity does not have to be treated as stochastic variable.

![Probability density of the possible capacity that is used in the computations of this section.](image)

*Figure 4.8 Probability density of the possible capacity that is used in the computations of this section. The graph is defined by the practical capacity of 2000 vkm/h, by the possible capacity of 1700 vkm/h and by setting the surface underlying the probability density graph to 1.*

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63 See section 3.1 or the terminology section for the definition of possible capacity.
Figure 4.9 Marginal energy benefits of capacity improvements with possible distributed additions for capacity and traffic intensity to the CEMENT module.

Table 4.1 The optimal capacity for the scenarios of figure 4.9.

<table>
<thead>
<tr>
<th>Optimal capacity</th>
<th>Intensity fixed (y01)</th>
<th>Intensity distributed (y24)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity fixed (x01)</td>
<td>1936.8 vkm/h</td>
<td>2725.0 vkm/h</td>
</tr>
<tr>
<td>Capacity distributed (x24)</td>
<td>2301.2 vkm/h</td>
<td>3237.7 vkm/h</td>
</tr>
</tbody>
</table>

4.2.3 Optimal velocity

The CEMENT module assumes that there is a velocity $v_{opt}$ at which the capacity of the road segment is optimal. The parameter $v_{opt}$ influences the $v(x)$ characteristics. Figure 4.10 shows the impact of the choice for $v_{opt}$ on the relation between the traffic flow velocity and the capacity of the road segment.
Figure 4.10 The influence of optimal velocity $v_{opt}$ on the traffic flow velocity $v(x)$ for two values of $v_{opt}$. The optimal velocity is at the point of inflection \(^{64}\) of the graphs.

Figure 4.10 shows that for lower values of $v_{opt}$, the graph shifts to bottom/right: at lower optimal velocities (the dotted line instead of the solid line in the figure), the same velocity is achieved at lower i/c-ratios, in other words at the same i/c-ratios, a lower velocity will occur. The impact of variations in the optimal velocity on the optimal road capacity is illustrated in figure 4.11 that shows the impacts under several conditions. The negative slopes on both curves in figure 4.11 are due to the systems property to move approximately towards the velocity with the lowest vehicular energy use $g(v)$. For low $v_{opt}$ the capacity $x$ needs to be raised in order to maintain a similar velocity. This is in line with the remark that at lower values of $v_{opt}$, the same velocity is achieved at lower i/c-ratios. Furthermore, at high $v_{opt}$ the system becomes insensitive for variations in optimal velocity if a restrictive speed limit is applied. The traffic flow velocity is then no longer determined by the relation $v(x)$, but by the speed limit set. However, the choice of $v_{opt}$ does not influence the fuel consumption $F$ at the optimal i/c-ratio (at the final optimal capacity $x_{opt}$)\(^{65}\).

The optimal velocity is estimated at $(80\pm20) \text{ km/h}$. In conclusion, the dependence of optimal capacity on optimal velocity is characterised by equation (4.1)\(^{66}\):

$$x_{opt} = a - \frac{b}{1 + e^{-(v_{opt}-d)}} \quad (4.1)$$

The example “24 hour” of figure 4.11 fit to parameter values of $a=3837; b=3189; c=0.02541; d=105.4$.\(^{67}\) The optimal capacity of the road is $(1.36\pm0.19)$ times the

\(^{64}\) $\frac{dv}{dx} = 0$ at $v = v_{opt}$.

\(^{65}\) The remark is valid for cases with constant intensity, and for cases with daily varying intensities provided that speed limits are in effect.

\(^{66}\) The power term originates in the description of equation (3.15).

\(^{67}\) The $R^2$ value, on a scale of 0 to 1, has in this fit a value of 0.9994.
average traffic intensity on that road. The total fuel consumption of the traffic flow is not, however, dependent on the optimal velocity. The energy benefits are not affected by the velocity at which the highest number of vehicles is accommodated, as long as the maximum number of vehicles accommodated does not change.

![Figure 4.11 The optimal capacity \( x_{opt} \) as function of \( v_{opt} \) for four situations: the general CEMENT module (‘day average’) without distributed traffic intensity, and the distributed CEMENT module (‘24 hour’) with a traffic intensity distribution in 24 categories; both situations are furthermore varied with or without speed limit of 100 km/h.](image)

**4.2.4 Fall in capacity at high velocities**

The parameter \( f_{\text{max}} \) gives the ratio of relative road capacity and the optimal road capacity at \( v_{\text{max}} \) (default value: \( v_{\text{max}}=120 \text{ km/h} \)). The adjustment in the parameter value for \( f_{\text{max}} \) influences the characteristics of the relation between velocity and intensity for the free flow traffic (\( v>v_{opt} \)). As the optimal capacity corresponds to situations in which the velocity of the vehicles is slightly above the optimal velocity, a change in the parameter value of \( f_{\text{max}} \) has a direct impact on the optimal capacity \( x_{opt} \). A higher value of \( f_{\text{max}} \) implies that the velocity of traffic will decrease in a slower pace in the case of increasing traffic intensity. To achieve the same desired velocity, the gap between intensity and capacity needs to be smaller if \( f_{\text{max}} \) is larger. Therefore, the graph of \( x_{opt} \) against \( f_{\text{max}} \) is a declining one, see figure 4.12.

The graphs in figure 4.12 have a similar distinction at in figure 4.11: output using a constant intensity (“Day average”) and output using hourly fluctuating intensities (“24 hour”). The following remarks follow the figure 4.12:

\[
\frac{\partial x_{opt}}{\partial f_{\text{max}}} < 0 \quad ; \quad \frac{\partial F_{\text{24}}^{x_{opt}}}{\partial f_{\text{max}}} > 0 \quad ; \quad \frac{\partial F_{\text{day}}^{x_{opt}}}{\partial f_{\text{max}}} = 0 .
\]

The fuel consumption at optimal capacity only depends on \( f_{\text{max}} \) if the traffic intensity fluctuates in time. This is due to the fact that the different velocity-intensity characteristics are only relevant if the traffic intensities can vary. The relation
between optimal capacity $x_{opt}$ and relative capacity at 120 km/h $f_{max}$ is given by equation (4.2), with $a=620.0$ and $b=140.9$.68

$$x_{opt}^{24} = a \cdot \ln(b(1-f_{max}))$$  \hspace{1cm} (4.2)

The value of $f_{max}$ is estimated at 0.4±0.1. In conclusion, it results in an optimal capacity of (1.36±0.05) times the average traffic intensity. From an energy point of view, $f_{max}$ should be as low as possible since velocities that are well above the optimal velocity of 80 km/h are highly inefficient in terms of energy use per transport performance.

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4.2.5 Functional length of a vehicle in a traffic jam

The average functional length of a car in a traffic jam, thus the minimum space that an average vehicle possibly can occupy, is set at $c=7.5$ m. The changing of this parameter only affects the characteristics of traffic in forced flow. As the optimal capacity corresponds to free flow traffic, the parameter $c$ should have little influence on this optimal capacity. The relation between $x_{opt}$ and $c$ is almost linear, and an uncertainty in $x_{opt}$ following the estimation of $c=(7.5±2.5)$ m is only $x_{opt}=(1.36±0.01)y$.

4.2.6 Speed limit

Enforcing a speed limit has an immediate effect of preventing speed excesses. The CEMENT module anticipates velocities well above 120 km/h at quiet hours, if no speed limit is set on the road considered. The larger the capacity of the road, the greater the effect described. Thus, in the region of speed limit of 100 to 120 km/h a distinct negative correlation is to be found between the speed limit and the optimal capacity. At speed limits below the optimal velocity, e.g. around 50 km/h, too large

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68 $R^2=0.9986$. See also the first equation in (3.17).
road capacities cannot have any negative impact on fuel consumption rates at quiet hours, and only too small road capacities will lead to adverse impacts on fuel consumption due to traffic jams. Therefore, a positive correlation between speed limit and optimal capacity exists at low values for $v_{\text{max}}$, see figure 4.13.

![Figure 4.13 Sensitivity assessment on $v_{\text{max}}$: impact of $v_{\text{max}}$ on the optimal capacity $x_{\text{opt}}$ and on the fuel consumption of the traffic $F(x_{\text{opt}})$.

In conclusion, the optimal fuel consumption is reached at speed limits between 70 and 90 km/h. Important to note is that this optimum is only a result of velocity reduction in situations of low traffic intensity. It is not a result of changes in traffic flow characteristics. Although large velocity fluctuations inside the traffic flow adversely affecting actual capacity, do occur in reality, the CEMENT module does not consider that particular effect. Variations in the speed limit of $v_{\text{max}}=(120\pm10)$ km/h lead to values for the optimal capacity of $(1.36\pm0.08)$ times the transport demand.

### 4.2.7 Fuel consumption

The fact that the fuel consumption per vehicle depends on the velocity, and the manner in which the dependence is described, introduce a systematic error. The assessment of this uncertainty on the model outcome uses alternative descriptions of the relation $g(v)$. The primary relation, as described in chapter three, is simplified to linear relations between the data points. The underlying data is identical [Veurman et al., 2002], see figure 4.14.
Figure 4.14 Comparison of relations between the energy use of velocity based on data published in [Veerman et al., 2002] and relations described in [Hickman, 1999]. “Original” indicates the functional description introduced in chapter three, while “Linear” implies the linear relation between data points.

Other function descriptions are taken from [Hickman, 1999], in particular the description related to 1.4ℓ-2.0ℓ gasoline engines, one with pre-regulated fuel (before 1971) and one with EURO-I standard (after 1991). The COST emission data of [Hickman, 1999] have been converted into energy terms using the conversion ratio of 0.0692 kg CO₂/MJ. Figure 4.14 shows the fuel consumption-velocity graphs for the alternatives to the original function. For the impact of those modifications to the vehicular fuel consumption function \( g(v) \) on the optimal capacity, the results in table 4.2 show significant variations in the optimal capacity results. These variations are due to the functional differences shown in figure 4.14, notably the vehicular fuel consumption is lower for the “Pre-regulated” and “EURO-I” graphs in the relevant velocity range. It should therefore be noted that the empirical data of [Veerman et al., 2002] is a result of measurements in average trip velocities in which the low velocities are a result of congestion, while the empirical data in [Hickman, 1999] shows a relation for specific fuel-vehicle combinations between emissions and concurrent velocity.

Table 4.2 Impact of fuel consumption function per vehicle on optimal road capacity (in vkm/h), cf. figure 4.14

<table>
<thead>
<tr>
<th>Alternative</th>
<th>( g(v) = \ldots )</th>
<th>24 hour</th>
<th>Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original/Chapter three</td>
<td>-0.730(1-9.29e^{0.9201v}-1.86·10^{-5}v)</td>
<td>2729</td>
<td>1938</td>
</tr>
<tr>
<td>Linear</td>
<td>Linear approximation of “Original”</td>
<td>2938</td>
<td>2275</td>
</tr>
<tr>
<td>Pre-regulated</td>
<td>1005+4.15v-263Ln(v)</td>
<td>2094</td>
<td>1462</td>
</tr>
<tr>
<td>EURO-I</td>
<td>231-3.62v+0.0263·v²+2526/v</td>
<td>2473</td>
<td>1761</td>
</tr>
</tbody>
</table>

Figure 4.15 depicts the results of table 4.2 (“24 hour”) against the fuel consumption level at the optimal velocity \( g(v_{opt}) \). A fairly linear relation exists that can be used to deduce the final uncertainty due to these variations in the systems function.
The estimation of the uncertainty of the fuel consumption at optimal velocity is $g(v_{opt})=(3.0\pm0.5) \text{ MJ/vkm}$. This results in an uncertainty in $x_{opt}$ of $x_{opt}=(1.36\pm0.25) \text{ y}$.

4.2.8 Road wear

Section 3.3.3.6 discussed the definitions of construction and maintenance activities. Closely related to these terms is the deterioration rate or road wear rate $\delta$. This section values the uncertainty that is associated with the manner of implementing the road wear phenomena in the CEMENT module.

The following formulas are taken from a publication of the World Bank [Paterson, 1987]. The road wear of the road surface can be measured in the International Roughness Index (IRI). The World Bank publication gives a specific definition of IRI. Roughness itself can be defined as “the deviations of a surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamics loads and drainage.” An empirical formula to predict the roughness $R$ is:

$$ R(t) = \left( R_0 + 725 \cdot (1 + S)^{-5.0} \cdot L_i(t) \right) \cdot e^{0.015t} $$

The roughness $R(t)$ in m/km IRI, at age $t$ in years since construction depends on two major parameters ($R_0$ is typically between 1 and 3 for new roads): $S$ and $L_i(t)$. $L_i(t)$ is the cumulative traffic loading at time $t$, in million ESA (assuming that the load damage increases with power $i$). Mostly it is predicted that $i=4$. ESA is the number of equivalent 80 kN single axle load. $S$ is the so-called modified structural number of pavement strength. It can be calculated using the formula (see also table 4.3):

$$ S = 0.04 \sum_i a_i h_i + 3.51 \cdot \ln(B) - 0.85 \cdot \ln^2(B) - 1.43 $$

$a_i$: material and layer strength coefficients;
$h_i$: layer thickness in mm ($\Sigma h \leq 700$ mm);
$B$: in situ California Bearing Ratio of subgrade in %.
Table 4.3 Empirical values for $a_i$ and CBR to be used in equation (4.4).

<table>
<thead>
<tr>
<th>Pavement layer</th>
<th>Pavement type</th>
<th>Strength coefficient $a_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface course</td>
<td>Asphalt concrete</td>
<td>0.30-0.45</td>
</tr>
<tr>
<td>Base course</td>
<td>Granular materials</td>
<td>0.0-0.14</td>
</tr>
<tr>
<td></td>
<td>Cemented materials</td>
<td>$0.075 + 0.039 \cdot \text{UCS} - 0.00088 \cdot \text{UCS}^2$</td>
</tr>
<tr>
<td>Subbase and subgrade layers</td>
<td>Granular materials</td>
<td>$0.01 + 0.065 \cdot \ln(B)$</td>
</tr>
<tr>
<td></td>
<td>Cemented materials (UCS $&gt; 0.7$ MPa)</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Typical values for $S$ are between 2 and 6. Let, for argument sake, $S=2.4$; $R_0=1.5$. Equation (4.3) would then lead to (with $t$ in years): $R(t) \approx (1.5 + 1.60 \cdot L_4(t)) \cdot e^{0.0153t}$.

The cumulative traffic loading $L_4$ can be computed as: $L_n = \sum_{a} N_a \cdot \left(\frac{a}{80}\right)^n$ with $N_a$ the number of passing axle loads $a$. For $n$ the commonly used dimension is ESA. Also, a correlation needs to be established between $v$ and $R$. Paterson [Paterson, 1987] gives a graphical representation of that correlation. The velocity is a slowly decreasing function of $R$, see figure 4.16.

![Figure 4.16](image)

**Figure 4.16** The relation between $R$ and $v$, according to Paterson [Paterson, 1987]. The function shown in grey is given by: $v(R) = 166.5 / (1 + 1.62 - R(t))$.

The assumption that the capacity of a road decreases proportionally to the velocity results in an estimation of the autonomous decline in the capacity possible: $x(t)/x_0 = v(t)/v(0)$. It follows that:

$$x(t) = \frac{166.5}{1 + 0.162(R_0 + 1.6 \cdot L_4 \cdot t)} e^{0.0153t} \cdot \frac{1}{v(R_0)} x_0$$

(4.5)

If the transport demand $y$ is constant in time, then $L_4(t)$ is constant in time. Now, using the state equation (3.7) and setting $p=0$ and $m=0$, it is possible to determine the autonomous road wear rate $\delta$, since $\dot{x}(t) = -\delta \cdot x(t) \Rightarrow \delta = -\frac{1}{x(t)} \frac{dx(t)}{dt}$. In figure 4.17 this is numerically determined for $R_0=1.5$ m/km and $L_4 = 1$ ESA. It shows that $\delta$ is not constant in time, but – for traffic densities common in the Netherlands – mostly ranges between 0 and 0.3.

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69 UCS: unconfined compressive strength in MPa after 14 days.
The maintenance standards in the Netherlands state that roads with IRI<2.6 do not require maintenance. Roads where 2.6 ≥ IRI < 3.5 need maintenance planning, since roads with IRI ≥ 3.5 require immediate maintenance. In the Netherlands, 0.2% of the state roads have IRI ≥ 3.5, while 98.7% have IRI < 2.6 [MinV&W / AVV, 1999].

As maintenance is conducted every 6 to 8 years, then it follows, if maintenance m is defined such that \( m(t) \approx \delta \), that \( 0.13 \text{ yr}^{-1} < \delta < 0.17 \text{ yr}^{-1} \) for normal Netherlands’ highway conditions. The conclusion is that on average: \( \delta = 0.15 \text{ yr}^{-1} \).

![Figure 4.17 The road wear rate \( \delta \) declines as a function of time. Regular maintenance in the Netherlands is conducted every 6 to 8 years [Alberts, 2002].](image)

The road wear rate is not only influenced by the elapsed time since construction (figure 4.17), but also on initial road quality and road use (figure 4.18). Table 4.4 summarises the effect of different maintenance rates on the optimal capacity.

**Table 4.4 Impact of maintenance rate on optimal capacity.**

<table>
<thead>
<tr>
<th>Maintenance rate ( m ) (yr(^{-1}))</th>
<th>( x_{opt} ) (Day) in vkm/h</th>
<th>( x_{opt} ) (24hour) in vkm/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.125 (once every 8 years)</td>
<td>1945.9</td>
<td>2759.1</td>
</tr>
<tr>
<td>0.13</td>
<td>1944.3</td>
<td>2753.0</td>
</tr>
<tr>
<td>0.15</td>
<td>1938.0</td>
<td>2729.2</td>
</tr>
<tr>
<td>0.17</td>
<td>1931.7</td>
<td>2708.0</td>
</tr>
<tr>
<td>0.20 (once every 5 years)</td>
<td>1922.2</td>
<td>2677.2</td>
</tr>
</tbody>
</table>

Finally, if one assumes that average maintenance rates vary between once every 5 years and once every 8 years, the resulting variance in the optimal capacity is: \( x_{opt} = (1.36 \pm 0.02) \text{yr} \).

---

70 The planning objective is that the roads do not wear down onto IRI=3.5.
Figure 4.18 The road wear rate after 2 years for several cumulative axle loads \( L_4 \) and values of roughness \( R_0 \).

4.2.9 Conclusion

The impact of all six model parameters on the optimal capacity has been determined. The fluctuations of road intensity \( y \) in time should be modelled as detailed as possible. An approximation of the distribution curve into 24 categories causes a systematic error resulting in an underestimation of optimal capacity of 3% at default construction energy intensities of \( \alpha = 10\,000 \text{ MJ-h/km} \). All the other parameters have been processed as possible input errors. Table 4.5 gives a summary.

Table 4.5 Summary of uncertainties caused by input parameter error for \( \alpha = 10\,000 \text{ MJ-h/km} \).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value range (default value)</th>
<th>Relative error: ( \Delta x_{\text{opt}} / y )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v_{\text{opt}} )</td>
<td>60 … 100 (80) km/h</td>
<td>0.19</td>
</tr>
<tr>
<td>( f_{\text{max}} )</td>
<td>0.3 … 0.5 (0.4)</td>
<td>0.05</td>
</tr>
<tr>
<td>( c )</td>
<td>5.0 … 10.0 (7.5) m</td>
<td>0.01</td>
</tr>
<tr>
<td>( v_{\text{max}} )</td>
<td>110 … 130 (120) km/h</td>
<td>0.08</td>
</tr>
<tr>
<td>( g(v) ) through ( g(v_{\text{opt}}) )</td>
<td>2.5 … 3.5 (3.0)MJ/km</td>
<td>0.25</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.125 … 0.2 (0.15) yr(^{-1} )</td>
<td>0.02</td>
</tr>
</tbody>
</table>

The total error that is introduced by the minimalist construction of the CEMENT module adds up to 0.33 times the traffic intensity. Section 4.2.1.1 concluded that a load-duration curve in 24 categories results in a systematic underestimation of 3%. Compensating for the 3% underestimation, the total capacity of a road with an average traffic intensity of 2000 vkm/h therefore is estimated at \( x_{\text{opt}} = (2.8 \pm 0.7) \cdot 10^3 \) vkm/h.

As a crosscheck, a Monte Carlo simulation is performed [Metropolis et al., 1953]\(^71\). In a Monte Carlo simulation, the model outcome is computed repeatedly. In every model run, the values of the input parameters are slightly varied. If the sample size of model

\(^{71}\) A Monte Carlo simulation is a probabilistic model involving an element of chance.
runs is large enough, the Monte Carlo simulation provides an indication of the change that a certain deviation from the mean model outcome can be observed. Figure 4.19 shows the result of a Monte Carlo simulation with the parameters of table 4.5 varied conform a standard distribution, using the in the table indicated values as $-\sigma...+\sigma (\mu)$, with $\sigma$ the standard deviation and $\mu$ the average value.

Figure 4.19 The result of the Monte Carlo simulation with 55287 computer runs. The distribution of the model runs seems to vary slightly from a standard distribution with a median value at 2675 vkm/h and a most likely value of 2708 vkm/h.

The average and standard distribution as depicted in figure 4.19 give for a road with an average traffic intensity of 2000 vkm/h an optimal capacity of (2.8±0.5) vkm/h, including the 3% compensation for the underestimation due to the traffic intensity fluctuations. The uncertainty is lower in the Monte-Carlo simulation than in the parameter assessment. As the parameter assessment implied an assumption of mutually independent parameters, the uncertainties of the parameters have a limiting effect instead of a neutral or enhancing effect on the model uncertainty.

4.2.10 Discussion

The literature gives several descriptions for the relation between the velocity and the capacity and transport demand. Already in 1935, Greenshields gave a description of the relation between capacity of a road and velocity of the traffic [Greenshields, 1935]. He supposes a relation between velocity (km/h) and density (veh/km) of the form: $v/v_{\text{max}}=1-d/d_{\text{max}}$, with $v$ the velocity and $d$ the density and the subscript $\text{max}$ indicating the maximum value for the parameters. The possible flux is therefore given by:

$$\Phi = d_{\text{max}} \cdot v \left(1 - \frac{v}{v_{\text{max}}} \right),$$

implying a parabolic shape. A formula of this kind is not valid for all velocities, as it is evident that the flux would be negative with velocities higher than allowed. For low velocities, the difference that mounts up to 25% between the
method of Greenshields and the method used in the CEMENT module is shown in the graph of figure 4.20.

![Graph of figure 4.20](image)

**Figure 4.20** Difference in cross-sectional capacity as function of the velocity, for low velocities, between the theory of this chapter and the description of Greenshields.

Another form is the frequently applied BPR function\(^\text{72}\) [Bureau of Public Roads, 1964]. It gives the travel time \(t\) on a road link as function of travel time in free flow mode \(t_l\), the capacity \(x\) and transport demand \(y\), and two parameters \(\alpha\) and \(\beta\):\(^\text{73}\)

\[
 t^{\text{BPR}} = t_l \left(1 + \alpha \left(\frac{x}{y}\right)^\beta\right)
\]  

(4.6)

A variation on the BPR function is developed by Spiess [H.Spiess, 1990]. Formula (4.7) shows that volume-delay function:

\[
 t^{\text{Spiess}} = t_l \left[2 + \sqrt{\alpha^2 \left(1 - \frac{x}{y}\right)^2 + \beta^2 - \alpha \left(1 - \frac{x}{y}\right) - \beta}\right]
\]  

(4.7)

where \(\beta = \frac{2\alpha - 1}{2\alpha - 2}\), \(\alpha > 1\).

Figure 4.21 shows the difference that the various functions have on the travel time on a specific link. The BPR-function depicted has parameter values of \(\alpha=0.5\) and \(\beta=2\); the delay function of Spiess has as parameter value \(\alpha=1.5\).

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\(^{72}\) BPR stands for Bureau of Public Roads.

\(^{73}\) The BPR suggested \(\alpha=0.15\) and \(\beta=4\) (see[Bureau of Public Roads, 1964], chapter V). Furthermore, the BPR defined the capacity \(x\) as the practical capacity, while this thesis uses capacity \(x\) as the capacity under ideal circumstances.
Figure 4.21 The relative delay, computed with the CEMENT module and the functions presented in [Bureau of Public Roads, 1964] and [H.Spiess, 1990].

Figure 4.22 shows the effects of different flow-velocity diagrams on the energy benefits of capacity improvement $\gamma$ and the consequential effects on the optimal capacity.

Figure 4.22 Effect of flow-velocity functions on the optimal capacity. In general, the lower and thus less efficient velocities of the BPR function, compared to the function of this thesis, leads to lower optimal capacity values.
4.3 **CEMENT module verification**

4.3.1 **Introduction**

The CEMENT module described so far is mostly static, thus the verification has to mention the real life dynamics of traffic. The impact of load duration curves, or the frequency distribution of traffic intensity occurrences on optimal capacity levels, is presented in section 4.2.1.2. The CEMENT module of the chapter three and four is coupled to a chain optimisation model comprising several CEMENT modules. By doing so, the coupled modules are able to simulate the formation of traffic jams on highway trajectories consisting of several segments. Section 4.3.4 examines the feedback effect of inducement of traffic from other transport modes and the kindred feedback effect of generated traffic, or the effect that less people will travel as the travel time lengthens.

4.3.2 **Parameter assessment: optimal velocity and practical capacity**

The theoretical curve of velocity against intensity can be adjusted to exclude high i/c-ratios. The curve also depends on an assumption of the optimal velocity – the velocity with the highest possible traffic flux. A comparison with empirical data on intensity and velocity sets a value for this velocity, see figure 4.23.

![Figure 4.23 Comparison of theoretical graph with empirical data on velocity and intensity on motorway A50 between Nijmegen and Arnhem [Hogema et al., 2003].](image)

The empirical data in figure 4.23, presented by the open dots, indicate two diverging velocity trends for high supplies of traffic. The straight dotted line shows, first, that the traffic keeps flowing at high velocities almost until an i/c-ratio of 1. The more disciplined the individual drivers behave, the longer it is possible to maintain the high velocities that theoretically can exceed the i/c-ratio of 1. Second, the dots that lie significantly below this line result from congested traffic. From these points, it is

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74 Appendix 4.5 validates the linkage by comparing traffic jam formations as expected by the model with empirical traffic jam data.
75 Figure 4.23 shows the traffic per lane. Therefore, an intensity of 2000 vkm/h corresponds to an i/c-ratio of 1.
deduced that the optimal velocity lies at \( v_{opt} = 80 \text{ km/h} \) with a maximum flux of \( \Phi = 1700 \text{ vkm/h per kilometre lane} \).

### 4.3.3 Verification results

The fuel consumption does not restrictively depend on the amount of traffic and the average velocity of the vehicles. Obviously, the fuel consumption of traffic is non-linearly dependent on the traffic intensity, since the relation between the intensity and the velocity is non-linear. Furthermore, the traffic intensity shows daily recurring fluctuations. Measurements on the daily recurring fluctuations lead to a more significant verification of the relation between traffic intensity and velocity than the ‘snapshot’ approach of figure 4.23. The case of the motorway A28 (Utrecht-Amersfoort) shows the impact of the fluctuations in intensity on the optimal capacity level. The schematic overview in figure 4.24 shows the location of the eight junctions and the two intersections on the 35.3 kilometre trajectory. This motorway trajectory has thus nine distinct segments.

For this case study, two types of road usage data collected by AVV are used: the traffic intensity on each of the nine segments for each hour of the day [MinV&W / AVV, 2003], and average travel times on the entire trajectory [MinV&W / AVV, 2002]. The average number of vehicles passing the segment per hour of day shows the daily fluctuations in traffic intensity. Figure 4.25 shows that the measurements were available for only four of the nine segments. The adjacent segment hourly traffic intensities are interpolated using the total intensities on the remaining segments. The average velocities on the trajectory, ranging from the Nijkerk junction to the Rijnsweerd intersection, are shown in figure 4.26.

The hourly traffic intensities for the trajectory are therefore the averages of the intensities per segment – weighted over the length of each segment. It results in an overview of the average hourly intensities for the motorway stretch, on an average *weekday*. The latter intensities are next compared to the average velocities as the figure 4.27 shows. The segments are considered
Appendix 4.5 describes how a segment’s inability to handle traffic intensities affects other segments.

The velocity input data consists of four charts: the average velocities of the trips Nijkerk-Utrecht for the years 2000 and 2001 and the return trips Utrecht-Nijkerk for the same years. The velocities correlate to the intensities according to the theory from section 3.3.3, remember also figure 3.8 on page 82.

Figure 4.26 The average velocity (km/h) as function of the time of departure. The grey surface indicates the range of velocities measured (70%).

Figure 4.27: the velocity (km/h) as function of the time, and the average intensity (veh/h) as function of the time.
Figure 4.28 shows the theoretical graph of velocity against i/c-ratio and compares it to intensity and velocity measurements as hourly averages, averaged again over the length of the road section considered. The graph is plotted according to the theory, with adjustment of two parameters: the practical capacity of the road and the highest velocity. Starting with the latter parameter, one should take the physical characteristics of the road into consideration to assess the outcome properly. The road of 30 kilometres has for 20 kilometres a speed limit of 120 km/h, while for the remaining 10 kilometres the speed is restricted to 100 km/h. Furthermore, 15% of the vehicles consist of freight transport vehicles. As the freight transport moves with a velocity of 80 km/h, the average, undisturbed, highest allowed velocity is therefore:

$$v_{max} = \frac{\ell_{total}}{\sum_i \ell_i \cdot v_i + \sum_i f_{cargo} \cdot \ell_i \cdot \ell_{total}}$$

$$= 0.85 \left( \frac{20}{30} \cdot 120 + \frac{10}{30} \cdot 100 \right) + 0.15 \cdot 80 = 108 \text{ km/h},$$

\(v\) velocity; \(f\) fraction of passenger and cargo transport; \(\ell\) length; \(i\) subscript denoting road section \(i\).

The actual velocities achieved in undisturbed traffic are fitted to 105 km/h, which is slightly below the theoretical value. For the higher intensities, roughly those above 2500 veh/h (i/c-ratio more than 0.6), a slightly decreasing average velocity can be observed. The extremely low velocities of heavy traffic jams are mostly averaged out, since traffic jams rarely last longer than one hour. It is hard to specify a distinct traffic intensity beyond which the velocity will drop; furthermore, the theoretical maximum flux of 2000 veh/h per lane is not reached. Indeed, this corresponds to 4000 veh/h per direction for this case since the motorway A28 has two lanes in each direction. The data suggests a level of 3200 veh/h is not exceeded; this ratio (here: 3200 vs. 4000 veh/h) is typically largely influenced by the specific road architecture and driving behaviour. Figure 4.28 shows that at intensities beyond 70 percent of the capacity, average velocities can drop significantly. It results in an increasingly large spread in

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**Figure 4.28 Velocity as function of the intensity/capacity-ratio.** An i/c-ratio of 1 corresponds to 4000 veh/h. Measurements concern the A28 Amersfoort-Utrecht (vv) in the years 2000 and 2001 ([MinV&W / AVV, 2002;MinV&W / AVV, 2003]). The vertical error bars bound the measurement data by the 15 and 85 percentiles. The theory assumes \(v_{opt}=60 \text{ km/h}\).
average velocities at high i/c-ratio’s. Furthermore, it should be noticed that i/c-ratio’s greater than 0.8 do not occur, although the road trajectory concerned is heavily congested. The congestion of the road trajectory is illustrated by its ranking at places 20 and 31 in 2000, and 29 and 35 in 2001, on the traffic jam hot list of the Netherlands [MinV&W / AVV, 1997].

4.3.4 Future uncertainty: estimating transport demand

4.3.4.1 Introduction

The energy function that relates to the future fuel consumption of the vehicles \( F(x(t),y(t)) \) is determined by a complicated relation. Suppose an exogenous function \( y(t) \) exists that forecasts the transport demand. See figure 4.29 for an example. The traffic flux \( \Phi \) is, on average, given by: \( \Phi(t) = y(t)/\ell \). In the example of figure 4.29, in which the length of the road considered \( \ell = 54.3 \) km, the average flux for 2010 is given by:

\[
\frac{A_{12}y_{2010}}{54.3} = \frac{6.64 \times 10^6}{54.3} = 120 \cdot 10^3 \text{ veh/day} = 5065 \text{ veh/h}
\]

Note that this formula does not include rush-hour peak traffic. Unless otherwise specified, the thesis considers the transport demand constant in time: \( y(t) = y \) (besides any stable reoccurring traffic intensity patterns). Answering the question to which extent the transport infrastructure should grow, the value of \( y(t) = y_{max} \) is used in the equations.

![Figure 4.29 The transport performance on the Netherlands’ motorway A12, The Hague-Utrecht, including an extrapolation until 2020. The baseline of \( t \) in years is \( t=0 \) for the year 1986. The extrapolation curve is given by \( y(t) = y_{max}/(1 + e^{0.16 t + 0.258}) \), with \( y_{max} = 2.48 \times 10^9 \text{ vkm/yr} \). The curve is fitted using numerical least squares methods, but the form of the outcome is subjective to the chosen fit curve.](image)

4.3.4.2 Generated or induced traffic

An important issue in transportation science is the phenomenon of generated traffic. Generated traffic is the additional vehicle travel that results from road improvement.
Generated traffic consists in diverted traffic (trips shifted in time, route and destination, and induced vehicle travel (shifts from other modes, longer trips and new vehicle trips" [Litman, 2001]. Particularly estimations of the induced traffic are hard to quantify.

Some of these problems are addressed in section 4.3.4. Other traffic inducing effects can only be evaluated after the network optimising CONCRETE model has been established in chapter five. The focus thus far on only a single trajectory makes the research reported in the section 4.2 insensitive to changes in route or destination choice.

4.3.4.3 Diverted traffic

The effects of the duration and intensity of peak traffic intensity, as defined by the load-duration curves in figure 4.7, have been analysed. Figure 4.30 shows the results of different load-duration curves by the fuel-consumption graphs and energy-benefit graphs respectively. By comparing the effects of the characteristics of the congestion period on the optimisation outcome, the influence of traffic inducing effects (diversion in time) on the results is evaluated.

Figure 4.30 The effects of load-duration curves on the fuel consumption and energy benefits. The traffic intensity is distributed conform the curves of figure 4.7. The road capacity is distributed conform the curve of figure 4.8 in section 4.3.4.2.

Figure 4.30 illustrates that the optimal capacity of a road with a long rush-hour is smaller than the optimal capacity of a road with a short rush-hour, if the generated traffic only consists of a change in travel time. A broad intensity peak (long rush-hour) proves more energy efficient than a short rush-hour.

For capacity improvements with low energy requirements (i.e. standard road widening), one can build to smoothen the traffic jams, since the graphs of figure 4.30 differ substantially at $\gamma=10\,000\,\text{MJ}\cdot\text{h}/\text{vkm}$. However, if sufficient cars will shift their
travel time in the case of potential jams – thus if lack of capacity leads primarily to a broader rush-hour peak instead of traffic jams – this line of reasoning is flawed.

4.3.4.4 Induced traffic (mono-modal)

It is supposed that the travel time, which is needed to move from origin to destination, influences the actual traffic intensity. Therefore, the theoretical transport demand does not equal the actual traffic intensity. The average velocity en route linearly determines the travel time. The relation between travel time and traffic intensity is similar to the relation between velocity and traffic intensity. The linearity conforms to the so-called law of Brever\textsuperscript{76} [Hupkes, 1977]. As reminder, the system is defined by the relations:

\[
\dot{x} = u - \Delta t
\]

\[
J = \int_{0}^{\infty} e^{-\alpha t} (F(x,y) + \alpha u) dt
\]

To the traffic intensity, a function \( f \) for an induced traffic relation is added:

\[
y = y_0 + f(v(x,y))
\]

In this relation, the function \( f(v(x,y)) \) is the component of the traffic intensity that is dependent on the travel time. The variable \( y_0 \) is the autonomous traffic that does not suffer immediate repercussions on changed travel times. This function \( f \) is supposed to be a linear relation, which leads to:

\[
y = y_0 + \frac{Y - y_0}{v_{max}} \cdot v(x,y)
\]

The relation, in which \( v_{max} \) is the speed limit and \( Y \) is the total transport demand, including all latent transport (see figure 4.31), is evaluated numerically in the CEMENT module.

![Figure 4.31 Actual traffic as function of the velocity, for the case of \( y_0=0.5 \); \( Y=1 \) and \( v_{max}=120 \text{ km/h} \).](image)

\textsuperscript{76} Wet van behoud van reistijden en verplaatsingen. \textit{(Conservation law of travel times and trips)}
The impact of the latter relation between traffic intensity and velocity on the fuel consumption is shown in figure 4.32. The resulting marginal energy benefits of capacity improvement are shown in figure 4.33.

Figure 4.32 Impact of level of autonomous transport $y_0$ on the fuel consumption as function of capacity. The percentages in the legend indicate the amount of traffic that is insensitive for changes in travel time, i.e. the value of $y_0$ in equation (4.9).

Figure 4.33 Impact of level of autonomous transport $y_0$ on the energy benefits as function of capacity. The percentages in the legend are the values for $y_0$.

The dotted horizontal line at 10 000 MJ·h/vkm represents the costs of capacity improvements (see section 3.5.5). The intersections of the curves with this line,
therefore, show at which capacity the costs equal the benefits. Thus, the intersections show the values of optimal capacity for various levels of autonomous transport. Figure 4.34 shows the optimal capacity as function of the autonomous transport level, both for the case of mono-valued traffic intensity and stochastic traffic intensity.

![Figure 4.34 The optimal capacity as function of the percentage of autonomous transport.](image)

The curves in figure 4.34 can be approximated by the formula:

\[ x_{opt} = a_1 + a_2 \sqrt{\frac{y_0}{y_1}} - a_3 \]  

(4.10)

The curve that corresponds with the fixed traffic intensity has as values fitted: \( a_1 = 478.8 \) vkm/h; \( a_2 = 1788 \) vkm/h and \( a_3 = 0.3573 \).

The curve that corresponds with the distributed traffic intensity has as values fitted: \( a_1 = 249.8 \) vkm/h; \( a_2 = 3153 \) vkm/h and \( a_3 = 0.3952 \).

Therefore, if the autonomous transport is less than 35% (the value of \( a_3 \)) of the total transport, infrastructure expansion can never reduce the total energy use of transport.

4.3.4.5 Induced traffic (multi-modal)

Induced traffic that occurs within one transport mode is addressed in section 4.3.4.4. It concerns the balance between latent (and thus not occurring) traffic and actual (occurring) traffic. In the multi-modal setting of this section, induced traffic refers to the modal shift phenomenon. It concerns the balance between traffic occurring on the road researched and traffic occurring with other transport modes.

Let the other transport mode be a train connection with energy requirements of 2.0 MJ/pkm (upper bound value, see [Gijсен et al., 2001]). The train travels effectively with \( v_{rail} = 100 \) km/h and the average velocity of the undisturbed vehicles is \( v_{road} \) as calculated by the CEMENT module. The total delay time for the public transport mode is \( t_0 = 30 \) minutes for a trip of \( s = 100 \) kilometres due to waiting and the transport duration from door to station and visa-versa (25 minutes in [Roos et al., 1997]).
The total travel time $t_{\text{road}}$ for a trip by car is:

$$t_{\text{road}} = \frac{s}{v_{\text{road}}}$$  \hspace{1cm} (4.11)

The total travel time $t_{\text{rail}}$ for a trip by train is:

$$t_{\text{rail}} = t_0 + \frac{s}{v_{\text{train}}}$$  \hspace{1cm} (4.12)

The working assumption is that travellers will shift from the road transport mode to the rail transport mode if the travel time by train is smaller than that by car:

$$t_{\text{road}} > t_{\text{rail}}$$

$$\frac{s}{v_{\text{road}}} > t_0 + \frac{s}{v_{\text{train}}}$$

The passengers will shift at:

$$v_{\text{road}} < \frac{s \cdot v_{\text{train}}}{t_0 \cdot v_{\text{train}} + s}$$  \hspace{1cm} (4.13)

The values set in the beginning of this section determine a velocity $v_{\text{rail}}$ of 66.6 km/h. The intensity of the modal shift is approximated by two variables: the characteristics of the shift as defined by equation (4.13) and the part of the traffic that is sensitive for the other transport mode (cf. variable $y_0$ in figure 4.31). Figure 4.35 and figure 4.36 show different sets of variables that are used in the computations of this section.

Figure 4.35 Actual road traffic as function of total road traffic with 20\% of the road travellers to be potentially attracted to rail traffic, for 4 conditions of shift velocity.

Figure 4.36 Actual road traffic as function of total road traffic with 40\% of the road travellers to be potentially attracted to rail traffic, for 4 conditions of shift velocity.

Figure 4.37 shows the results for $y_0=0.8$ and figure 4.38 for $y_0=0.6$. 

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Figure 4.37 Marginal energy benefit of capacity improvement in the case of $y_0=0.8$, cf. figure 4.35.

Figure 4.37 and figure 4.38 show that the optimal capacity for the cases with inducement to other transport modes is lower than the optimal capacity for the case without inducement. Furthermore, a shorter waiting time, i.e. lower value of $t_0$ in equation (4.12), results in a greater attractiveness of the non-road transport mode. The greater attractiveness of the alternative mode leads to higher velocities until which the transport is attracted and to a lower required capacity of the road. Additionally, the total fuel consumption is also lower if the other transport mode is more attractive, since the energy requirements of 2.0 MJ/pkm for rail is at every velocity less than the fuel consumption of the road traffic.

Figure 4.38 Energy benefit of capacity improvement in the case of $y_0=0.6$, cf. figure 4.36.
4.3.4.6 Transport demand estimated

Section 4.3.4.3 concludes that the form (duration and intensity) of the peak intensities, if a better distribution of traffic over the day proves impossible, determine the improvement strategies for highways, under the condition that the improvements do not require large civil engineering projects like tunnels. The results of section 4.3.4.4, which are illustrated by figure 4.32 to figure 4.34, are:

A. The optimal capacity decreases more than linearly with induced traffic;
B. The impact of induced traffic on optimal capacity, as in argument A, is stronger as the traffic is more unevenly distributed over the day;
C. Both argument A and argument B are stronger as the costs of capacity improvements increase.

The results of the runs of the CEMENT module in section 4.3.4.5 conclude that a modal shift from road transport to another more energy efficient transport mode results in lower total fuel consumption and a smaller road capacity required. However, it is important that the overhead transport time (delay time) is as small as possible. If the delay time is too long (see figure 4.38, “inducement until 30 km/h”), no effect occurs of a change in modal split on the optimal road capacity.

4.4 Conclusion

The uncertainty in parameter inputs results in an uncertainty of the CEMENT module outcome in the order of 20% to 25%. However, the use of other velocity-flow characteristics can result in model outcomes that lie beyond this range (>25%). The formulas presented in chapter three can – at least qualitatively – reproduce observed velocity-flow characteristics. The velocity-flow characteristics show that a maximum velocity can be observed. This fairly constant velocity is seen throughout the lower range of intensities. At intensities exceeding 60% of the capacity (i/c-ratio more than 0.6) the range of velocities increases while the average velocity decreases. Intensities larger than 80% of the theoretical maximum are not likely to occur. This phenomenon is not directly included in the mathematical framework and has only a limited impact on the systems outcome and a marginal impact on the systems behaviour, since the phenomenon is implicitly included in the definition of capacity. There seems to be a – albeit diffuse – correlation between the intensity and the velocity on an hourly basis. This correlation is stronger on a smaller time interval. Fairly significant is the fact that the optimal capacity is 30% higher if daily traffic intensity fluctuations are taken into account; however, the data does not need to be more specific than the average hourly fluctuations on weekdays. The 30% rise implies that, given the relatively low energy expenditures for capacity improvement, it will be increasingly beneficial to improve the capacity to combat the adverse energy effects of increasingly small traffic jams. Thus, whenever the costs are small, it might be beneficial to take infrastructural measures to avoid just a few traffic jams.

Induced traffic implies that the optimal capacity is less than based on the assumption of a constant, uninfluenced traffic intensity. The benefits of capacity improvement at low capacities are less due to the induced traffic and the surface underneath the lines $\gamma(x)$ can be used as indication for the total benefits. If one refers to the relative costs of construction efforts as the total costs relative to the total benefits, it therefore shows that the relative costs of the construction efforts in the case of induced traffic exceed those in the case of fixed traffic intensity. A remarkable phenomenon in the curves relating to induced travel phenomena is the apparent conclusion that there might no
longer be an optimal capacity (remember that the zero-capacity option is excluded as valid end-state in the theory). In cases that induced traffic is ignored, the daily fluctuations (diverted traffic) ensure that capacity should improve more than in the case of constant traffic intensities only.

This chapter shows the differences between short, severe intensity peaks, and long, mild intensity peaks. Long intensity peaks are preferable to short peaks. To establish the optimal capacity, it is important to assess the magnitude of the existence of induced traffic. If this magnitude is underestimated and unchecked, too much capacity will be added to the road. If the possibility exists to lure travellers to less energy intensive transport modes, one should aim for such a modal shift provided that the waiting times are short enough to have any effect at all.

Appendix 4.5 shows that the CEMENT module is suited to simulate traffic jams on a road trajectory. In that case, CEMENT modules are linked together, each of them representing a different road segment. The unaccommodated traffic on a congested road segment should be added to the preceding road segment, to simulate traffic jam formation adequately. Otherwise, the CEMENT modules can also be linked into a network as chapter five describes.
4.5 Appendix to chapter four

4.5.1 Traffic jams simulation

4.5.1.1 Introduction

Chapter four uses a model that represents one road segment. This appendix verifies the method to chains the various segment models into a network model. The dependency between sub models is schematically shown in figure 4.39. It is assumed that the traffic that cannot be accommodated on a road segment will raise the traffic intensity in a subsequent road segment. In principle, the difference between both model elements is either a difference in time or a difference in space.

![Figure 4.39 The dependence between the sub models of road segments. Congestion in road segment 1 leads to an increased traffic intensity in road segment 2. The entire model comprised of the sub models of road segment 1 and road segment 2, results in a total vehicular fuel consumption $F_{\text{tot}}$ and $\nu_{\text{average}}$.](image)

The appendix starts with the simulation of network congestion. As the optimisation outcome of the single road model depends on the capacity at which formation of traffic jams occurs frequently, the network model has to be able to simulate this formation of jams as well.

4.5.1.2 Prediction of average velocity on a trajectory

The function of the core element of the optimisation model is to predict the fuel consumption of road traffic. This calculation uses the predicted average velocity as auxiliary variable. The average velocity can also be used as an indicator for congestion formation. As the

![Figure 4.40 Overview of the road trajectory of this exercise and (some of) its road segments.](image)
average velocities have been measured for 30-km long motorway trajectories [MinV&W / AVV, 2002], this section simulates the traffic on motorways over a distance of 30 km. To start, this is attempted for a section of 30 kilometres between Leiden and Rotterdam on the motorways A4 and A13, see figure 4.40. The road trajectory Leiden-Rotterdam is differentiated into ten road segments. In the optimisation model, each road segment is represented by particular sub model. The sub models are identical in architecture, but different in the input variables of traffic intensity, road capacity and speed limit. In the first attempt, these sub models are independent ($\text{vnaccommodated}=0$). The program uses the predicted velocity of each road segment to produce the average velocity on the 30 km road trajectory. Figure 4.41 repeats this for each of the 24 hours in an average weekday.

![Figure 4.41 The average velocity on the road section between Leiden and Rotterdam in 2001 [MinV&W / AVV, 2002]. The thick grey line is the average velocity; the black lines show the 15, 50 (median) and 85 percentiles. The grey bars show the velocity as output of the optimisation model.](image)

The fluctuations in traffic throughout the day are in practice larger than the optimisation model predicts. One may argue that the traffic jams form and end more abruptly than the model assumes. Partly, this is a known limitation of the model, as the model incorporates the road capacity in a crude manner. The capacity of a two-lane road is assumed at 3400 vkm/h, and that of a three-lane road at 4250 vkm/h\(^77\). In reality, specific road characteristics - curves and narrow or heavily used junctions - limit the capacity further. However, one can also debate the independence of the road segments if no internal parameter adjustments of the model suffice\(^78\).

4.5.1.3 Interdependence of traffic intensity on road segments in time or space

Interdependences are created by including the propagation of traffic jams. One can assume that the traffic that cannot be accommodated due to congestion at one moment

\(^77\) A kilometre of single lane has a previously established capacity of 1700 vkm/h and that of a double lane therefore 2x1700 vkm/h. The efficiency of adding more lanes is less. [MinV&W / AVV, 2003] A three-lane road has therefore less than 3x1700 vkm/h capacity, and is here set at 2.5x1700=4250 vkm/h.

\(^78\) Varying the model parameters $f_{\text{max}}$ ($v/c$-ratio at speed limit), $v_\text{opt}$ (optimal velocity), $x_0$ (road capacity of a single lane) does not change the velocity characteristics as function of time of day.
$(t = 0)$, will be added to the autonomous traffic intensity at the next moment $(t = 1)$. Figure 4.42 illustrates the principle of $y' = y'_{\text{autonomous}} + y'_{\text{unaccommodated}}$

Figure 4.42 Schematic representation of the propagation of traffic jams in time.

Another approach is to assume that the traffic jam propagates in space, and more specifically in the reverse direction of the traffic flow, see figure 4.43.

Figure 4.43 Schematic representation of the propagation of traffic jams in place.

These two options are evaluated in the optimisation model and the results are shown in figure 4.44. Results of propagation in space, shown by the dotted line, deviate slightly from the original calculation. The propagation in time does not suffice. As it is clear to see in figure 4.44, the traffic keeps building up during the day, resulting in a still declining average velocity on the roads that are in fact not congested during the evening hours. At the end of the day, not all traffic has been accommodated and should thus be shifted towards the next day. This outcome is not realistic, since it does not converge in time to a stable intensity pattern.
Figure 4.44 The average velocity on the A4/A13 motorway between Leiden and Rotterdam in 2001.

Figure 4.45 The average velocity on the A4/A13 trajectory. Figure 4.41 shows the same graph without dependencies, this graph includes the model outcome including interdependencies.

A comparison between figure 4.41 and figure 4.45 shows that the fluctuations in figure 4.45 are somewhat larger. It also shows that the fluctuations in the latter figure represent the measured grey line better. An auxiliary output is created in figure 4.46 to show the size of the non-accommodated traffic in time and place.
The two most persistent traffic jam locations on this route are “Overschie Zuid-Kp.Kleinpolderplein” (no. 9 of top50) and “Delft Zuid-Berkel en Rodenrijs” (no. 18 of top50). One would therefore assume high values of $\gamma_{\text{unaccommodated}}$ on the preceding road segments “Berkel en Rodenrijs-Overschie Zuid”, which do not appear, and “Delft-Delft Zuid”, which does show.

4.5.1.4 Conclusion and discussion

The exercise of figure 4.45 is repeated for a different road trajectory: the motorway A2 from Beesd to Maarssen. This trajectory contains the numbers 1, 16 and 36 of the traffic jam top50 of 2001; suffice it to say that this trajectory is highly congested. The outcome presented in figure 4.47 shows a serious, but intended, limitation of the model.
morning. However, the computed average velocity remains high at more than 90 km/h. The explanation of this phenomenon is as follows. The real velocity on (parts of) this road trajectory drops below the optimal velocity for a long period. Therefore, the measured intensity is less than the capacity of the road. The computer program uses only the measured intensity and the capacity as input variables. It sees that the intensity is less than the capacity and therefore assumes that the road trajectory is not congested, resulting in velocities higher than the optimal velocity of 80 km/h.

The results of section 4.5.1.3 prove to be somewhat misleading. Presumably, by having set the road capacity in the optimisation model to slightly lower values than the actual capacity of the road, the optimisation model simulates traffic jams on segments with high measured intensities that are in reality just not congested. Meanwhile, the model simulates free flow traffic on segments with lower intensities that in reality are congested. The aggregated travel time, or average velocities over the trajectory as shown by figure 4.45, can therefore still exhibit the same behaviour as the measurement, but the locations of the congested and non-congested traffic occurrences are interchanged.

In conclusion, the coupled CEMENT modules can simulate the dynamics of traffic jam formation; however, the coupled modules cannot reproduce the actual traffic jams using intensity data only. The CEMENT module can predict future traffic jams, but cannot identify existing jams. Possible adaptations are to include the latent traffic in the traffic intensity, or to ‘manually’ set the CEMENT module to assume congestion.

The CEMENT module is suited to simulate traffic jams on a road trajectory. In that case, CEMENT modules are linked together, each of them representing a different road segment. The unaccommodated traffic on a congested road segment should be added to the preceding road segment, to simulate traffic jam formation adequately.