Investigating Effect of Holidays on Daily Traffic Counts

Time Series Approach

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Different modeling philosophies are explored to explain and to forecast daily traffic counts. The main objectives of this study are the analysis of the impact of holidays on daily traffic and the forecasting of future traffic counts. Data from single inductive-loop detectors, collected in 2003, 2004, and 2005, were used for the analysis. The different models investigated showed that the variation in daily traffic counts could be explained by weekly cycles. The Box–Tiao modeling approach was applied to quantify the effect of holidays on daily traffic. The results showed that traffic counts were significantly lower for holiday periods. When the different modeling techniques were compared with a large forecast horizon, Box–Tiao modeling clearly outperformed the other modeling strategies. Simultaneous modeling of both the underlying reasons of travel and the revealed traffic patterns certainly is a challenge for further research.

In today's society, mobility is one of the driving forces of human development. The motives for travel are not confined to work or educational purposes but reach across a spectrum of diverse goals. Mobility is more than a cornerstone for economic growth; it is a social need that offers people the opportunity for self-fulfillment and relaxation (*1*).

Governments recognize the significance of mobility as evidenced by the mobility plans that are formulated by government agencies at different policy levels—for example, at the European level, the European Commission's White Paper "European Transport Policy for 2010: Time to Decide" (*2*), and at the Belgian regional level, "Mobiliteitsplan Vlaanderen" [Mobility Plan Flanders (*3*)]—and by the transportation research that is directly or indirectly funded by governments.

In order to formulate an efficient policy, governments require reliable predictions of travel behavior, traffic performance, and traffic safety. A better understanding of the events that influence travel behavior and traffic performance will lead to better forecasts and consequently policy measures that are based on more accurate data. Such improved information would allow policy makers to provide more precise travel information and adapt dynamic traffic management systems so that an important goal, more acceptable and reliable travel times (*1*), could be achieved.

Events such as special holidays (e.g., Christmas, New Year's Day), school holidays (e.g., in July and August), sociodemographic changes, and weather can have an influence on mobility in different ways, as is illustrated by Figure 1 (*4*). First, they can affect the travel market, in which the demand for activities and the supply of activity opportunities in space and time result in travel patterns. Second, these events can have an influence on the transport market, in which the demanded travel patterns and the supply of transport options come together in a transport pattern that assigns passenger and goods trips to vehicles and transport services. Finally, these events can have an effect on the traffic market, in which the required transport patterns are confronted with the actual supply of infrastructure and the associated management systems, resulting in actual use of the infrastructure as revealed by traffic patterns.

As the list of examples (Figure 1) shows, people may perform activities during holidays other than what they do on ordinary days. During holidays, people go to the beach, for example, whereas on normal days, people go to work. Another example indicated in Figure 1 involves the closing of amusement parks during the winter. People wishing to visit such a park during the winter will do something else instead, for instance, go ice skating. These are merely two examples of how holidays and seasonal effects influence the activities that people pursue and, in turn, how these activities have an impact on the travel market. A third example shows how mode choice can be influenced by the type of day, which can have an impact on the transport market, and the fourth example demonstrates how the environment can have an impact on the traffic market. The list of examples given in Figure 1 is not restrictive but is meant to exemplify how the three markets and hence mobility can be influenced by various events.

The main objectives of this study are the identification of the effects of holidays on daily traffic and the prediction of future traffic volumes. A Box–Tiao model is used to quantify these effects. The combination of a regression model with autoregressive moving average (ARMA) errors raises the opportunity to build a model with desirable statistical properties and thus to minimize the risk of erroneous model interpretation (*5*).

DATA

The impact of holidays on daily traffic will be analyzed by studying the effect on daily highway traffic counts. First, the dependent variable (daily traffic count) is further explored. Then the different covariates, called interventions in Box–Tiao terminology, are described.

Daily Traffic

The aggregated daily traffic counts originate from data by minute of two single inductive-loop detectors located on the E314 Highway in the direction of Brussels in Gasthuisberg (Leuven, Belgium), collected

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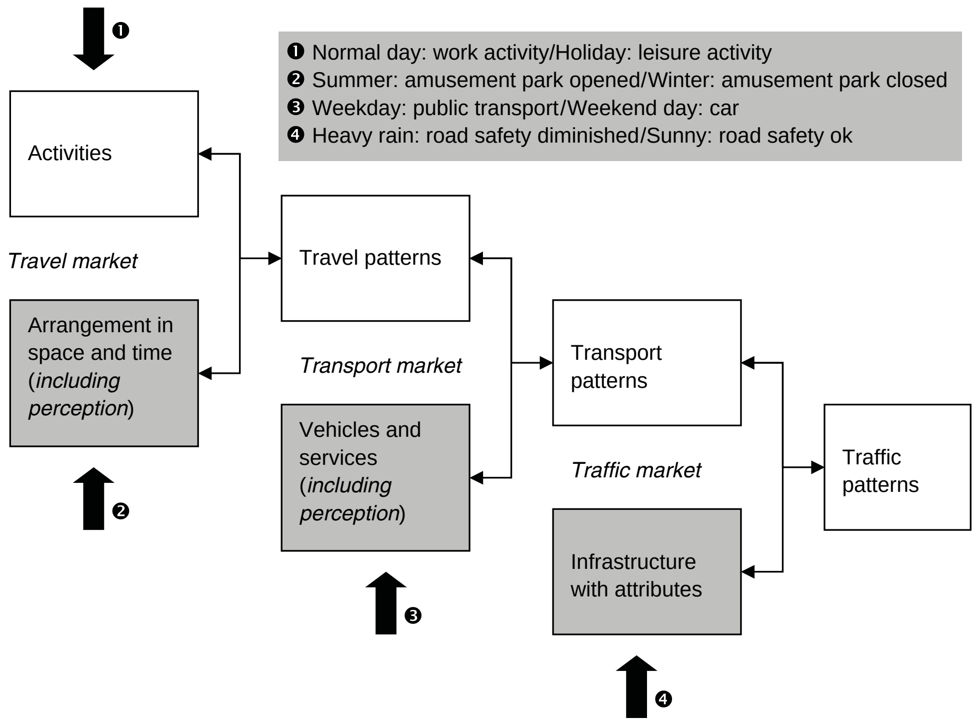

FIGURE 1 Three-market model and examples of influences on mobility.

in 2003, 2004, and 2005 by the Vlaams Verkeercentrum (Flemish Traffic Control Center). Figure 2 pinpoints the traffic count location under study. The highway that is analyzed is one of the entryways to Brussels and thus heavily used by commuters.

Every minute, the loop detectors output four variables: the number of cars driven by, the number of trucks, the occupancy of the detector, and the time mean speed of all vehicles (*6*). The number of cars and trucks is added for both detectors, yielding a total traffic count for each minute. These data by minute can only be aggregated on a daily basis when there are no missing data for that day. When some or all of the minute data are missing, a defensible imputation strategy must be applied.

About half of all days that were analyzed contained no missing data, as is shown in Table 1. Obviously, for these days no imputation strategy needed to be applied. This, however, means that for the other half, there were some (in 41.78% of the days) or a lot (in 7.84% of the days) of the minute-count data missing. When at least 2 h of data, or at least 120 of the 1,440 data points, was available, an imputation strategy was applied that is similar to the reference-days method proposed by Bellemans (*7*). When there were fewer than 120 data points available in a day, a more general imputation strategy was applied.

Imputation Strategy 1

Bellemans (*7*) assumed in his work the existence of an a priori known reference day that is representative of the day for which missing values have to be estimated. The imputed value is then calculated by scaling the reference measurement so that it corresponds to the traffic dynamics of the day under study. In Bellemans's study, the scaling factor was the fraction of the measurement and the reference measurement in the previous minute.

The imputation strategy applied in this study uses the idea of reference days and a scaling factor. The new measurements $x_{new}(t)$ are calculated in the following way:

$$x_{new}(t) = \delta x_{ref}(t)$$

where $x_{ref}(t)$ is the reference measurement and δ is the scaling factor. To determine the reference measurement, 21 reference days (7 days for each of 3 holiday statuses) were used. For each reference day, the reference measurements were defined as the average of the modus, median, and mean of the available days that corresponded to the reference day. The average of these three measures of central tendency was taken because each of them has its own unique attributes (central location, robustness, highest selection probability) and favoring one could obscure model interpretation. The scaling factor δ is calculated as follows:

$$\delta = \frac{\sum_{t=1}^{1,440} d_t}{\sum_{t=1}^{1,440} m_t}$$

where

$$d_t = \begin{cases} \dfrac{x(t)}{x_{ref}(t)} \Leftrightarrow x(t) \text{ not missing} \\ 0 \Leftrightarrow x(t) \text{ missing} \end{cases}$$

$$m_t = \begin{cases} 1 \Leftrightarrow x(t) \text{ not missing} \\ 0 \Leftrightarrow x(t) \text{ missing} \end{cases}$$

In these equations, $x(t)$ is the measurement at minute t and $x_{ref}(t)$ is the reference measurement at minute t.

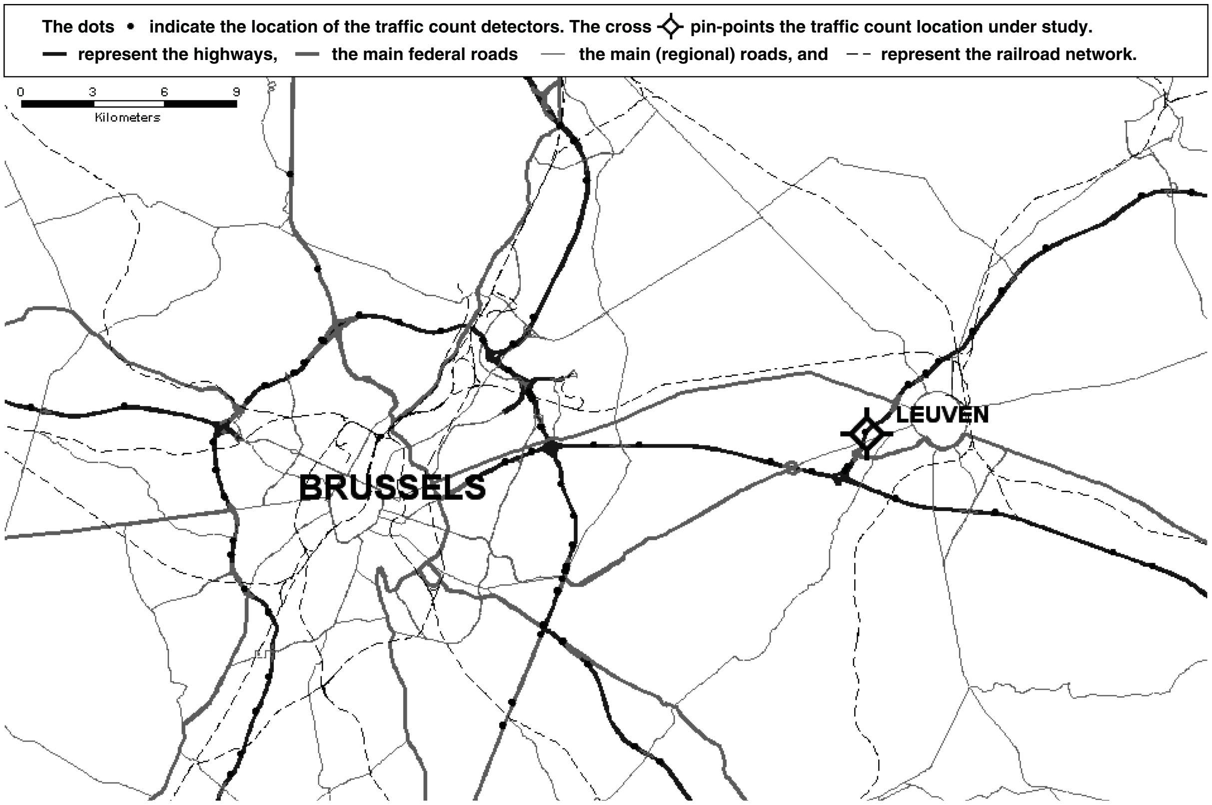

FIGURE 2 Geographical representation of traffic count location under study.

Imputation Strategy 2

For the imputation strategy just described, a scaling factor was required to match the reference measurement to the day under study. When all, or almost all, of the data points are missing, the scaling factor could not be calculated. In this case, the missing values are replaced by the reference measurements, which is equivalent to setting the scaling factor equal to 1.

Evaluation of Implemented Imputation Strategies

Circumspection is essential when imputation strategies are applied, since imputation processes encompass the risk of distorting the distributions of the data and thus biasing the results. The magnitude of the risk must be indicated and potential patterns of the missing data need to be analyzed.

When the risk of data distortion is addressed, a thorough look at the minute data places the risk in the correct context. Of the 1,578,240 min (1,096 days multiplied by 1,440 min a day) that were aggregated on a daily basis, 140,860 min (8.93%) were missing. Communication errors (e.g., due to system failures) account for 135,654 min (8.60%) of missing data. The remaining 5,206 min (0.33%) were due to other reasons such as physical errors of the loop detectors, disturbances in the electronic systems of the substations, and inaccurate measurements.

When the imputation strategies are evaluated on the daily level, a first observation is that 81.56% (50.36% + 31.20%) of the days contains at least 95.83% (more then 1,380 of the 1,440 data points) of the data points that day. Thus, the imputation strategy has nearly no effect on these days. For the days (4.65% + 0.27%) that contained nearly no information (fewer than 120 of the 1,440 data points available), just a measure of central tendency was used as the imputed value, taking into account the day type (which day of the week and whether it was a holiday). For 10.58% (4.38% + 6.20%) of the days between 50% and 95.83% of the data points were available, so the scaling factor used for the imputation strategy was still based upon a reliable amount of data. Only for 2.92% of the days, less than 50% but at least 8.33% of the data points were available. It might be judged that the imputation strategy could result here in significantly distorted values. Different imputation strategies could be applied to this part of the data to assess the effect of the chosen strategy. However, as it is only a very small part of the entire data set, it was judged not to have a significant impact on the remainder of the study.

TABLE 1 Missing-Data Analysis and Corresponding Imputation Strategy

Quality Assessment	Number of Days	% of All Days	Imputation Strategy
No minutes missing	552	50.36	No strategy
1–60 min missing	342	31.20	Strategy 1
61–240 min missing	48	4.38	Strategy 1
241–720 min missing	68	6.20	Strategy 1
721–1,320 min missing	32	2.92	Strategy 1
1,321–1,439 min missing	3	0.27	Strategy 2
Entire day missing	51	4.65	Strategy 2
Total	1,096	100.00	

It is important to stress that the imputation strategies applied use a measure of central tendency that takes into account the day of the week and the holiday status. Thus, the significance of these variables (day of week, holiday status) is not affected by the choice of the measure of central tendency. It is fair to recapitulate and infer that the implemented imputation strategies had no significant distorting effect on the results or conclusions.

Plot of Data

Figure 3 shows the aggregated daily traffic count data, taking into account the imputation strategies that were implemented. A similar pattern is visible over the 3 years. A drop in the number of passing vehicles at the beginning and end of each year is noted, and during summer holidays, the intensity of daily traffic clearly is lower than during the other months.

Holiday Effect

A dummy variable was created in order to model the effect of holidays. Normal days were coded zero, and holidays were coded 1. The following holidays were considered: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Monday, vacation for the construction industry (3 weeks starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints' Day and All Souls' Day), and finally Remembrance Day. It should be noted that for all these holidays, the adjacent weekends were considered to be a holiday too. For holidays occurring on a Tuesday or on a Thursday, the Monday and weekend before and the Friday and weekend after, respectively, were also defined as a holiday, because people often have a day off on those days, and thus have a leave of several days, which might be used to go on a long weekend or on a short holiday.

Day-of-Week Effects

Six dummy variables were created in order to model the day-of-week effect. It should be noted that in general $k-1$ dummy variables have be to created if one wants to analyze the effect of a categorical variable with k classes (*8*). As there are seven days in a week, the first six days (Monday until Saturday) were each represented by one of the dummies, equal to 1 for the days they represent and zero elsewhere. The reference day was Sunday, so for all traffic counts that were collected on a Sunday, the corresponding six dummies were coded zero.

METHODOLOGY

In this study, two main philosophies were explored in order to model the daily traffic counts. The first philosophy is based on the fact that consecutive traffic counts are correlated and that therefore present and future values can be explained by past values. Two types of models that use this philosophy are investigated in this study, namely, exponential smoothing and ARMA modeling. The second philosophy

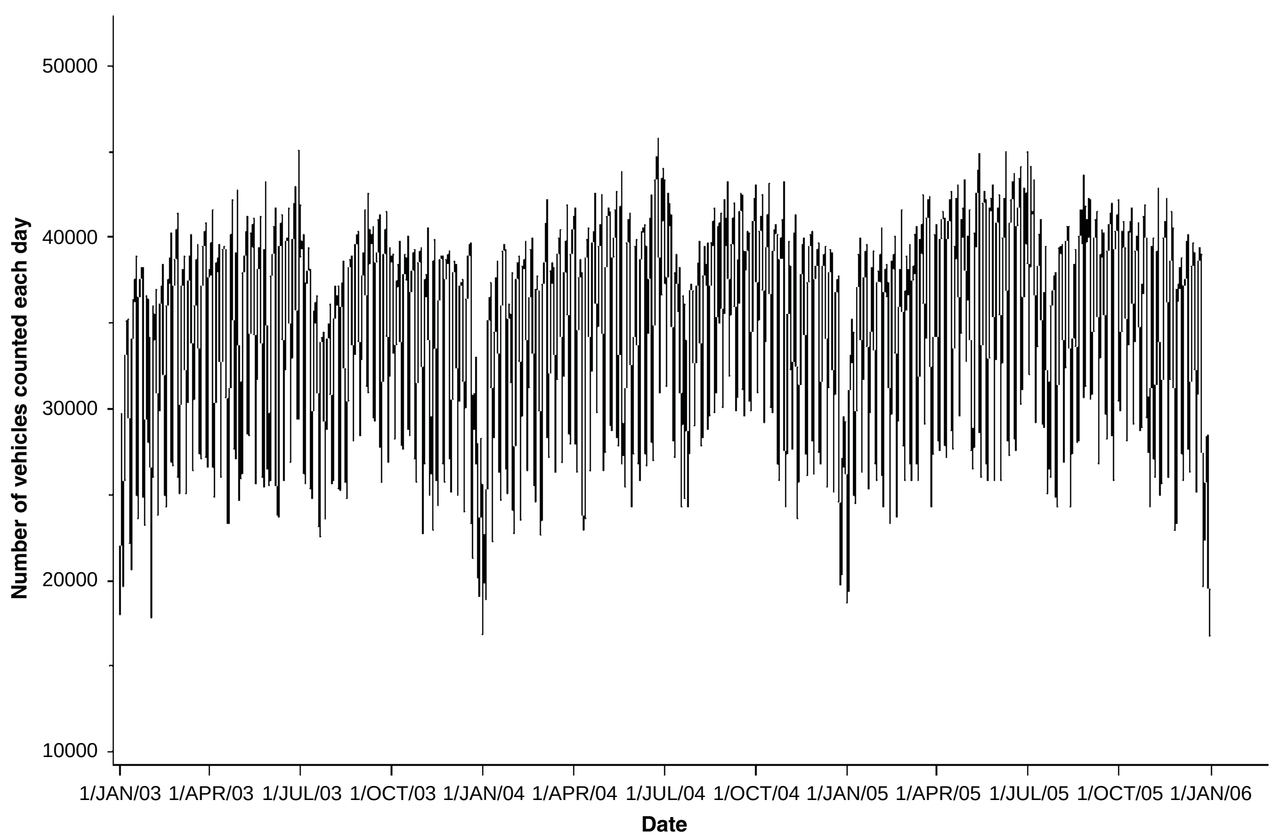

FIGURE 3 Evolution in time of daily traffic counts.

is the regression philosophy, which postulates that the dependent variable, in this study the daily traffic counts, could be explained by other variables. Since different assumptions have to be met before the linear regression model yields interpretable parameter estimates, the Box–Tiao model is also investigated. The latter is capable of taking into account dependencies between error terms. For an introduction on time series analysis, the reader is referred to the text by Yaffee and McGee (*9*). Neter et al. (*8*) give a comprehensive overview of regression models.

Exponential Smoothing

Simple Exponential Smoothing

Simple exponential smoothing is a way of forecasting future observations by producing a time trend forecast, in which the parameters are allowed to change gradually over time and in which recent observations are given more weight than observations further in the past (*9*). The technique assumes that the data fluctuate around a reasonably stable mean. The formula for simple exponential smoothing is $S_t = \alpha Y_t + (1 - \alpha)S_{t-1}$, where each new smoothed value S_t is computed as the weighted average of the current observation Y_t and the previous smoothed observation S_{t-1}. The magnitude of the smoothing constant, α, ranges between zero and 1. If the constant equals 1, the previous observations are ignored entirely. If the constant equals zero, the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value; thus, as a consequence, all smoothed values will be equal to the initial smoothed value S_0.

Multiplicative Holt–Winters Exponential Smoothing

To accommodate the simple exponential smoothing model to account for regular seasonal fluctuations, the Holt–Winters method combines a time trend with multiplicative seasonal factors (*10*). The general formula for the multiplicative Holt–Winters model is

$$\hat{Y}_{t+h} = (\mu_t + b_t h) S_{t-p+h}$$

where

$\hat{Y}_{t+h}$ = estimated value for time series at time $t + h$,
h = number of periods into forecast horizon,
μ_t = permanent component at time t,
b_t = trend component at time t,
S_{t-p+h} = multiplicative seasonal component at time $t - p + h$, and
p = periodicity of seasonality (number of periods in one cycle of seasons).

Each of the three parameters (μ_t, b_t, S_t) is updated with its own exponential smoothing equation (*9*). The permanent component is updated by the following equation:

$$\mu_t = \alpha\left(\frac{Y_t}{S_{t-p}}\right) + (1 - \alpha)(\mu_{t-1} + b_{t-1})$$

Dividing the series Y_t by its seasonal component at its periodic lag removes the seasonality from the data. Therefore, only the trend component and the prior value of the permanent component enter into the updating process for μ_t. The updating equation for the trend component is given by $b_t = \gamma(\mu_t - \mu_{t-1}) + (1 - \gamma)b_{t-1}$. Thus, the trend component is simply the smoothed difference between two successive estimates of the deseasonalized level. The last parameter, the multiplicative seasonal component, is updated by the following smoothing equation:

$$S_t = \delta\left(\frac{Y_t}{\mu_t}\right) + (1 - \delta)S_{t-p}$$

Thus, the seasonal component is updated by a portion of the ratio of the series value over the average plus a smoothed portion of the seasonality at its periodic lag.

ARMA Modeling

Like exponential smoothing, the ARMA modeling approach tries to explain current and future values of a variable as a weighted average of its own past values. In most cases, the model consists of a combination of an autoregressive (AR) part and a moving average (MA) part.

When Y_t is modeled as an AR process, AR(p), Y_t can be expressed in terms of its own past values. Suppose that Y_t is modeled as an AR process of order 2, AR(2); then $Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + e_t$, where

ϕ_1, ϕ_2 = weights for AR terms,
c = constant, and
e_t = new random term.

With a backshift operator B_i on Y_t, defined as $B^i(Y_t) = Y_{t-i}$, this process can be written as $Y_t = c + \phi_1 BY_t + \phi_2 B^2 Y_t + e_t$ or $(1 - \phi_1 B - \phi_2 B^2)Y_t = c + e_t$.

When the series Y_t is modeled as an MA process, MA(q), Y_t can be expressed in terms of current and past errors, also called shocks. Suppose that Y_t is modeled as an MA process of order 2, MA(2); then $Y_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$, where θ_1, θ_2 are the weights for the MA terms. With the backshift operator, previously defined, this process can be written as $Y_t = c + (1 - \theta_1 B - \theta_2 B^2)e_t$.

When a series Y_t is modeled as a combination of an AR process of order p, AR(p), and an MA process of order q, MA(q), the combined process is called an ARMA(p,q) process. The model is then given by

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)Y_t = c + (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)e_t$$

The ARMA model is valid only when the series satisfies the requirement of weak stationarity. A time series is weakly stationary when the mean value function is constant and does not depend on time and the variance around the mean remains constant over time (*11*). If the variance of the series does not remain constant over time, a transformation, such as taking the logarithm or the square root of the series, often proves to be a good remedial measure to achieve constancy (*8*). To achieve stationarity in terms of the mean, it sometimes is required to difference the original series. Successive changes in the series are then modeled instead of the original series. When differencing is applied, the ARMA model is called an ARIMA model, where *I* indicates that the series is differenced.

Regression Modeling

Instead of modeling a series Y_t as a combination of its past values, the regression approach tries to explain the series Y_t with other covariates. Formally, the multiple linear regression model can be represented as follows:

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \epsilon_t$$

where

Y_t = tth observation of dependent variable;
$X_{1,t}, X_{2,t}, \ldots, X_{k,t}$ = corresponding observations of explanatory variables;
$\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ = parameters of regression model, which are fixed but unknown; and
ϵ_t = unknown random error (*8*).

Estimates for the unknown parameters can be obtained by using classical estimation techniques. If $b_0, b_1, b_2, \ldots, b_k$ are the estimates for $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$, the estimated value for the dependent variable Y_t is given by $\hat{Y}_t = b_0 + b_1X_{1,t} + b_2X_{2,t} + \cdots + b_kX_{k,t}$. When the error terms are independently and identically normally distributed with mean zero and variance σ^2, the estimators for the parameters are the best linear unbiased estimators.

Box–Tiao Modeling

When regression modeling is applied to a time series, the assumption of independence of the error terms is often violated because of autocorrelation (the error terms being correlated among themselves). This violation of one of the underlying assumptions of linear regression increases the risk for erroneous model interpretation, because the true variance of the parameter estimates may be seriously underestimated (*8*).

Box–Tiao modeling can be used to solve this problem of autocorrelation. A Box–Tiao model corrects for autocorrelation by describing the errors terms of the linear regression model by an ARMA(p,q) process. Let $Y_t = \beta_0 + \beta_1X_{1,t} + \beta_2X_{2,t} + \cdots + \beta_kX_{k,t} + N_t$ be the regression model, where $(1 - \phi_1B - \phi_2B^2 - \cdots - \phi_pB^p)N_t = (1 - \theta_1B - \theta_2B^2 - \cdots - \theta_qB^q)\epsilon_t$ and ϵ_t is assumed to be white noise. Then the Box–Tiao model can be represented as follows:

$$Y_t = \beta_0 + \beta_1X_{1,t} + \beta_2X_{2,t} + \cdots + \beta_kX_{k,t} + \frac{\left(1 - \theta_1B - \theta_2B^2 - \cdots - \theta_qB^q\right)}{\left(1 - \phi_1B - \phi_2B^2 - \cdots - \phi_pB^p\right)}\epsilon_t$$

The parameters in this equation are estimated by using maximum likelihood. Studies comparing the least-squares method with the maximum-likelihood method for this kind of model show that maximum-likelihood estimation gives more accurate results (*12*). The likelihood function is maximized by nonlinear least squares using Marquardt's method (*10*). When differencing of the error terms is required to obtain stationarity, all dependent and independent variables should be differenced (*5, 13*).

Model Evaluation

Because different types of models are considered to estimate the daily traffic counts, it is required that an objective criterion be used to determine which model performs better (*14*). The following criteria were used to determine the appropriateness of the models: the Akaike information criterion (AIC), the mean square error (MSE), and the mean absolute percentage error (MAPE). The models were constructed on a training data set containing the first 75% of the observations. The remaining 25% of the observations make up the validation or test data set, which can be used to assess the performance of the models by calculating the MSE and MAPE for the forecasts. The choice of these percentages is arbitrary but common practice in validation studies [see, e.g., the paper by Wets et al. (*15*) or the thesis by Moons (*16*)].

The AIC is defined as AIC = −2 × log likelihood + 2 × number of free parameters. Models with a lower value for this criterion are considered to be the more appropriate ones (*17*). The MSE equals the sum of all squared errors divided by its degrees of freedom, which are calculated by subtracting the number of parameters in the model from the number of observations. The MAPE is defined as the average of the absolute values of the proportion of error at a given point of time.

RESULTS

In this section, the parameter estimates of the models are interpreted, and the different models are compared with each other. Predictions of the daily traffic counts are graphically displayed. A distinction is made between the predictions that are based on the training data (Figure 4), and the predictions that are based on the test data (Figure 5).

Holt–Winters Multiplicative Exponential Smoothing

The best Holt–Winters model, in terms of AIC, was obtained when a cycle of seven seasons (the seven seasons correspond to the seven days of the week), combined with a linear trend, was considered. In this model, nine (seven plus two) parameters had to be estimated: the parameter for the permanent component ($\hat{\mu}_1 = 35{,}154$), the parameter for the linear component ($\hat{b}_1 = -64.56$), and the seven factors of the seasonal component. The estimated seasonal parameters are given by $\hat{S}_1 = 1.122$, $\hat{S}_2 = 1.228$, $\hat{S}_3 = 1.137$, $\hat{S}_4 = 0.781$, $\hat{S}_5 = 0.731$, $\hat{S}_6 = 1.009$, $\hat{S}_7 = 1.091$, where $i = 1, 2, \ldots, 7$ represents the ordering of the seasonal parameters. The average of these seven parameters must be equal to 1 (*9*). These seasonal factors correspond to the different days of the week. As the first observation in the data set was a Wednesday (January 1, 2003), the first seasonal factor also represents a Wednesday. Similarly, the other seasonal factors represent the other days of the week. It should be recalled that the Holt–Winters method uses smoothing equations for updating the parameters. The smoothing parameters for the permanent component and the linear component are given by $\alpha = \gamma = 0.106$ and the smoothing parameter for the seasonal component is given by $\delta = 0.25$.

When the estimates for the seasonal parameters are compared, the difference between the components that correspond to the weekend days and the components that correspond to the weekdays is appealing. The results indicate that on weekend days the daily traffic count will be much lower. This tendency can also be observed in Figure 4.

ARMA Modeling

To obtain stationarity, the ARMA model was developed on differenced data. The autocorrelation function and the partial autocorrelation function of the residuals were investigated to determine which AR and MA factors were required to build the model. If $\nabla_1 Y_t$ denotes the first difference of the data ($Y_t - Y_{t-1}$), then the obtained model could be written as

$$\nabla_1 Y_t = \frac{\left(1 - 0.79134B\right)\left(1 - 0.94883B^4\right)\left(1 - 0.9998B^7\right)}{\left(1 - 0.308B\right)\left(1 - 0.87767B^4\right)\left(1 - B^7\right)}\epsilon_t$$

This model contains three multiplicative AR and three multiplicative MA factors. It should be noted that if the model is worked out, other AR and MA factors also play a role. When the parameter estimates

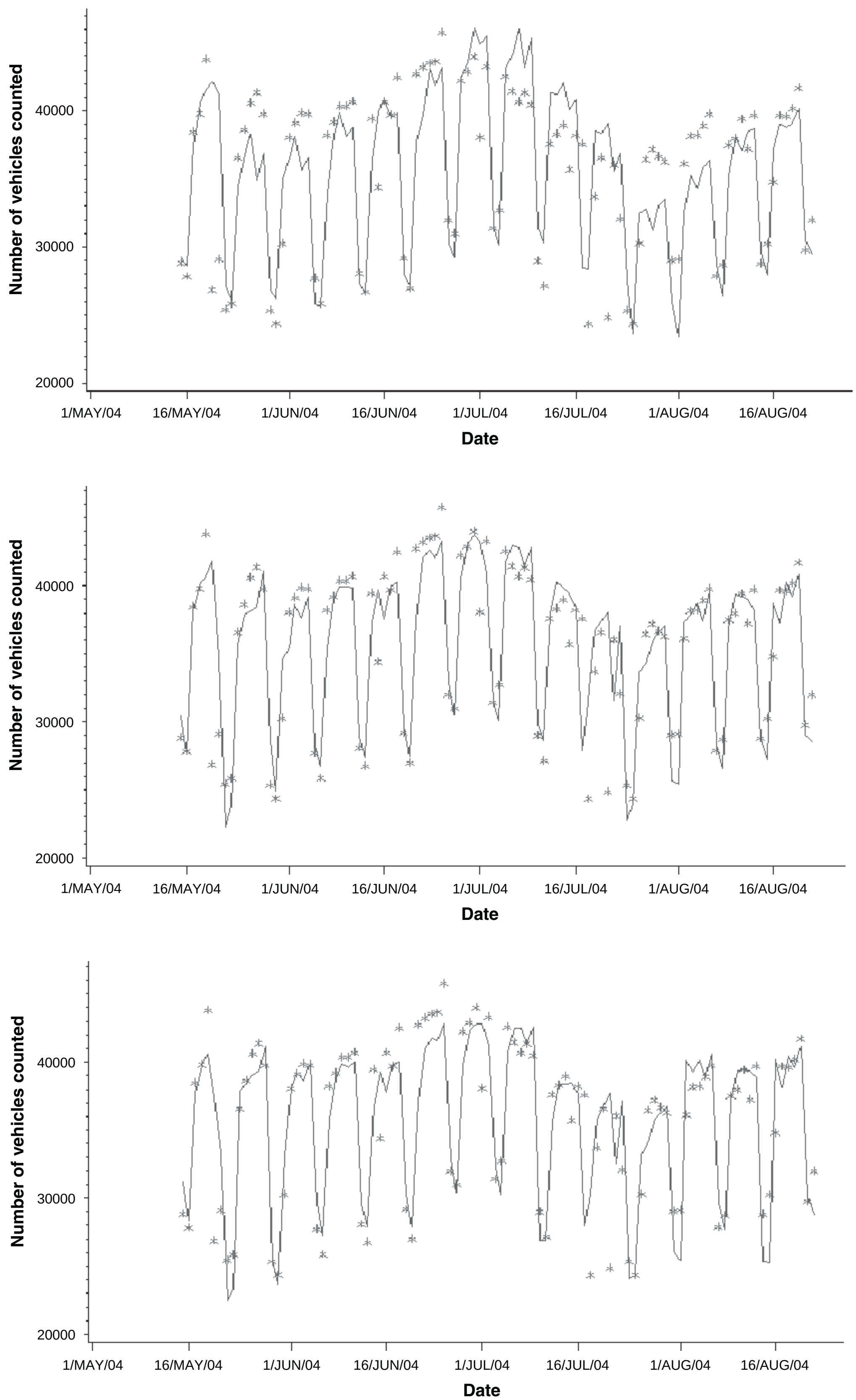

FIGURE 4 Daily traffic counts and their corresponding predicted values (subset of training data set) (stars, *, represent actual data from training data set; solid lines represent predicted values).

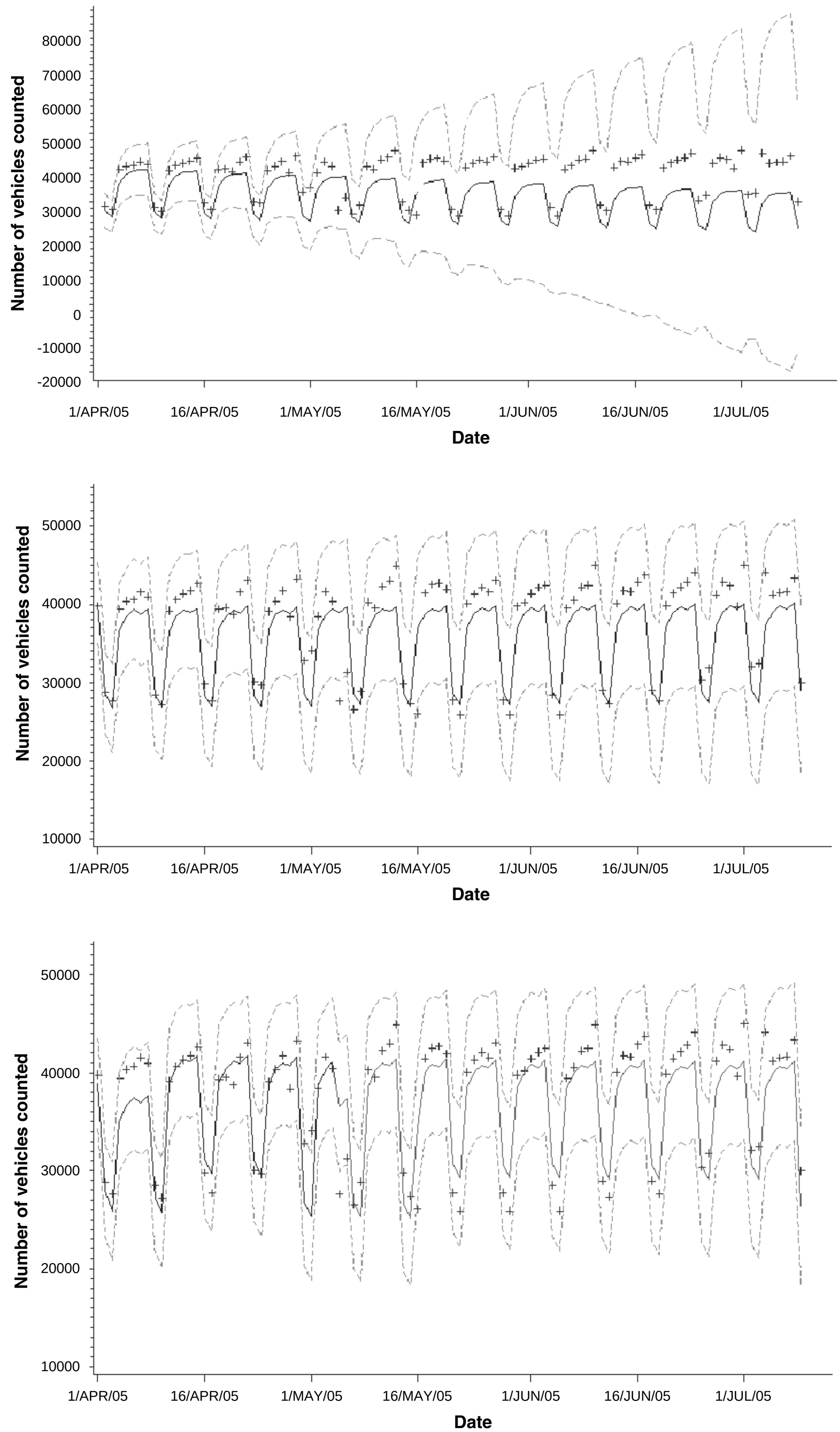

FIGURE 5 Daily traffic counts and their corresponding predicted values and confidence bounds (subset of test data set) (pluses, +, represent actual data from test data set; solid lines represent predicted values; dashed lines represent 95% confidence intervals).

TABLE 2 Parameter Estimates for Box–Tiao Model

Parameter	Estimate	Standard Error	*t*-Value	*p*-Value
Moving average (Lag 1)	0.858	0.026	32.7	< 0.0001
Moving average (Lag 4)	0.937	0.047	20.1	< 0.0001
Auto regressive (Lag 1)	0.272	0.046	5.9	< 0.0001
Auto regressive (Lag 4)	0.893	0.061	14.5	< 0.0001
Holiday	−4,130	303.67	−13.6	< 0.0001
Monday	9,176	264.38	34.7	< 0.0001
Tuesday	10,812	299.24	36.1	< 0.0001
Wednesday	11,546	307.85	37.5	< 0.0001
Thursday	11,295	306.17	36.9	< 0.0001
Friday	12,053	296.99	40.6	< 0.0001
Saturday	1,450	260.18	5.6	< 0.0001

for the ARMA factors are investigated, it can be seen that the estimates for the terms of the seventh order are very close to or equal to 1. This finding is an indication for the weekly cyclic behavior, which was also evidenced by the Holt–Winters model. The high parameter estimates for the ARMA factors of the fourth order might be evidence of some half-week recurring pattern in daily traffic counts. The dependency on the previous day was much smaller, yet significant.

Box–Tiao Modeling

The classical linear regression modeling approach did not yield valid results because of the problem of autocorrelation of the error terms. As indicated in the earlier section on Box–Tiao modeling, this modeling is an approach that can tackle the problem of autocorrelation.

As for the ARMA modeling, for the Box–Tiao modeling it was required to take the first difference of the data to obtain stationarity. For both the ARMA model and the Box–Tiao model the intercept was dropped from the equations. When differencing is done, the intercept is interpreted as a deterministic trend, and that is not always realistic (*13*). The final error terms obtained were accepted to be white noise according to Ljung–Box *Q**-statistics (*18*). The final Box–Tiao model obtained is as follows:

$$\nabla_1 Y_t = \begin{cases} -4130\nabla_1 X_{\text{Holiday},t} \\ +9176\nabla_1 X_{\text{Monday},t} + 10812\nabla_1 X_{\text{Tuesday},t} + 11546\nabla_1 X_{\text{Wednesday},t} \\ +11295\nabla_1 X_{\text{Thursday},t} + 12053\nabla_1 X_{\text{Friday},t} + 1450\nabla_1 X_{\text{Saturday},t} \\ +\dfrac{(1-0.858B)(1-0.937B^4)}{(1-0.272B)(1-0.893B^4)}\epsilon_t \end{cases}$$

The six dummy variables to model the day-of-week effect and the dummy variable of the holiday effect were all significant (*p*-value < 0.0001) as can be seen from Table 2. This finding shows that daily traffic counts are influenced by holidays. Interpretation of the parameter estimates is not straightforward since both the dependent and independent variables were differenced.

The parameter estimate for the holiday effect could be interpreted in the following way. When the holiday starts (the differenced holiday dummy equals 1), the daily traffic count will be 4,130 vehicles lower than the day before. The day after the holiday (the differenced holiday dummy equals minus 1), the daily traffic count will increase again by 4,130 vehicles. It should be noted that for all other days the differenced holiday dummy equals zero.

For interpretation of the parameter estimates for the day-of-week effects, the Wednesdays are taken as an example. On a Wednesday, the differenced dummy of the Wednesday effect equals 1, and the differenced dummy of the Tuesday effect equals −1. All other differenced day-of-week dummies equal zero for a Wednesday. Thus, on a Wednesday, the traffic count will be 734 (11,546 – 10,812) vehicles higher than the day before (obviously the Tuesday before).

Model Comparison

When the different models were compared, the weekly cyclic behavior was exposed by all three models. In the Holt–Winters exponential smoothing model, this cyclicality was revealed by the seasonal component, in the ARMA model by the high estimates for the seventh-order AR and MA factors, and in the Box–Tiao model by the clearly significant day-of-week effect. Differences between different weekdays were also discovered by Weijermars and van Berkum (*19*). In their work, they used cluster analysis techniques that revealed the differences.

To determine whether predicting daily traffic counts with other covariates, such as the holiday effect and the day-of-week effects, adds insight, different criteria that assess the model fit are shown in Table 3.

According to the AIC, the best model is the Holt–Winters model, but when the other criteria are assessed, the Box–Tiao model outperforms the other models, indicating that considering a holiday effect and day-of-week effects with a Box–Tiao model really adds insight into the

TABLE 3 Criteria for Model Comparisons

Criterion	Holt–Winters	ARMA	Box–Tiao
Comparison based on training data set			
AIC(Model)	13,295.7	15,284.8	15,095.2
MSE(Model)	10,469,329	6,708,034	5,573,994
MAPE(Model)	6.788	5.373	4.976
Comparison based on test data set			
MSE(Forecast)	125,737,853	14,638,087	9,375,331
MAPE(Forecast)	27.683	7.685	6.482

cyclicality of daily traffic counts. Liu and Sharma (*20*) also identified a significant holiday effect.

Figure 4 shows that the predictions based on the training data set are comparable for the three modeling strategies. The MSE and MAPE criteria for these predictions indicate that the ARMA and Box–Tiao models perform better; however, the AIC favors the Holt–Winters model.

When the different models are validated by a test data set, it can be seen from Figure 5 that the Box–Tiao model performs best. The ARMA model also performs quite well, but the Holt–Winters model performs well only for a short forecast horizon. The MSE and MAPE criteria demonstrate that the ARMA and Box–Tiao model approaches outperform the Holt–Winters exponential smoothing model, favoring the Box–Tiao model.

CONCLUSIONS AND FURTHER RESEARCH

In this study, different modeling approaches were considered to predict daily traffic counts. The different techniques pointed out the significance of day-of-week effects: weekly cycles seem to determine the variation of daily traffic flows. On weekends the daily traffic flows turn out to be lower than those during the week. The Box–Tiao model approach demonstrated that on holidays daily traffic flows are significantly lower.

When forecasting of daily traffic flows is required, the Box–Tiao model appears to be an approach that performs reasonably well. Smoothing techniques, like the Holt–Winters exponential smoothing model, are to be avoided for predictions with a large forecast horizon.

These findings can be used by policy makers to fine-tune current policy measures. More precise travel information can be provided and dynamic traffic management systems can be improved. In this way, the findings of this study contribute to the achievement of an important goal: more acceptable and reliable travel times.

The analysis of day-of-week and holiday effects in this study was done on the revealed traffic patterns. Generalization of the discussed results is possible when traffic patterns of other parts of the road network are analyzed. In order to get more insight into how holidays affect mobility, further analysis is required. The different modeling techniques described could be applied to data from national travel surveys to determine potential effects on travel behavior. Simultaneous modeling of both the underlying reasons of travel and the revealed traffic patterns certainly is a challenge for further research.

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