Investigating the Variability in Daily Traffic Counts Through Use of ARIMAX and SARIMAX Models

Assessing the Effect of Holidays on Two Site Locations

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In this paper, daily traffic counts are explained and forecast by different modeling philosophies: an approach using autoregressive integrated moving average (ARIMA) models with explanatory variables (i.e., the ARIMAX model) and approaches using a seasonal autoregressive integrated moving average (SARIMA) model as well as a SARIMA model with explanatory variables (i.e., the SARIMAX model). Special emphasis is placed on the investigation of seasonality in daily traffic data and on the identification and comparison of holiday effects at different sites. To get insight into prior cyclic patterns in the daily traffic counts, spectral analysis provides the required framework to highlight periodicities in the data. The analyses use data from single inductive loop detectors, which were collected in 2003, 2004, and 2005. Four traffic count locations are investigated in this study: an upstream and a downstream traffic count site on a highway used extensively by commuters, and an upstream and a downstream traffic count site on a highway typically used for leisure travel. The different modeling techniques show that weekly cycles appear to determine the variation in daily traffic counts. The comparison between seasonal and holiday effects at different site locations reveals that both the ARIMAX and the SARIMAX modeling approaches are valid frameworks for identifying and quantifying possible influencing effects. The techniques yield the insight that holidays have a noticeable impact on highways extensively used by commuters, while having a more ambiguous impact on highways typically used for leisure travel. Future research challenges are the modeling of daily traffic counts on secondary roads and the simultaneous modeling of underlying reasons for travel and revealed traffic patterns.

For governments to implement and guide efficient traffic policies, it is essential that they have reliable predictions of travel behavior, traffic performance, and traffic safety. Policy tools such as advanced traveler information systems (ATISs) and advanced traffic management systems (ATMSs), as well as control strategies such as ramp metering, depend on the quality of forecasts of traffic volumes (*1*). Therefore, a deeper understanding of what affects traffic performance will improve the quality of predictions of traffic volumes, and consequently policy measures will be based on more accurate data.

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Good overviews of the different techniques for investigating the variability in daily traffic counts are provided by Han and Song (*2*) and Van Arem et al. (*3*). An initial category to distinguish is time-series models, which can be further divided into Box and Jenkins techniques, smoothing techniques, Kalman-filtering theory, and spectral analysis. Early applications of Box and Jenkins techniques in the field of traffic forecasting were implemented by Ahmed and Cook (*4*) and Nihan and Holmesland (*5*). More advanced techniques have been applied recently, including autoregressive integrated moving average (ARIMA) models with intervention *x*-variables (ARIMAX) (*6*), seasonal ARIMA models (SARIMA) (*7*), Kohonen-enhanced ARIMA models (*8*), and multivariate approaches such as the multivariate-state space approach (*9*) and the vector autoregressive and dynamic space–time models (*10*). The first application of Kalman-filtering theory within the field of traffic flow forecasting can be attributed to Okatuni and Stephanedes (*11*). Xie et al. (*12*) also used the Kalman filter, but with discrete wavelet decomposition, to forecast traffic volumes.

Neural network models are the second category of techniques that can be identified. Smith and Demetsky (*13*) were among the first to apply a neural network approach to the domain of traffic flow forecasting. Yun et al. (*14*) conducted a performance evaluation of neural networks. Time-delay neural networks (*15*), dynamic neural networks using a resource allocating network (*16*), and Bayesian combined neural networks (*17*), all appear to be valuable examples of neural network modeling.

Other techniques used for predicting traffic volumes include nonparametric models (*18*), cluster-based methods (*19*), principal component analysis (*20*), pattern recognition (*21*), fuzzy set theory (*22*) and support vector machines (*23*).

Cools et al. (*24*) used ARIMA modeling and Box–Tiao modeling (two Box and Jenkins techniques) to demonstrate how events such as holidays (e.g., Christmas Day, Easter Sunday) including school holidays (e.g., spring half-term) can significantly influence daily traffic performance. The authors highlighted how these events influence mobility in different ways. First, these events can affect the demand for activities and the supply of activity opportunities. Second, these events can influence the distributions of passenger and goods trips to vehicles and transport services. Finally, these events can affect infrastructures (e.g., available parking facilities) and their associated management systems.

The aforementioned study was limited because the analyses were for a specific location and the study did not explicitly account for seasonality. To promote the generalization of that study's results, therefore, this paper presents an analysis of upstream and downstream traffic count data taken from two diverse site locations. Furthermore, this paper explicitly focuses on seasonality and recurrences in daily traffic data.

The main objectives of this study are to unravel the variability in daily traffic counts, to identify and compare holiday effects at different site locations, to predict future traffic volumes, and to validate the suggested modeling framework. The cyclicality in the daily traffic data is explored using spectral analysis. To quantify holiday effects and predict future traffic counts, the main statistical model approaches envisaged are ARIMAX and SARIMA with intervention-*x* variables (SARIMAX). The combination of a regression model with ARIMA or SARIMA errors raises the opportunity to build a model with desirable statistical properties and thus minimize the risk of erroneous model interpretation (*25*).

DATA

The variability in daily traffic is investigated by analyzing the influence of cyclic patterns, day-of-week effects, and holidays on daily highway traffic counts. While traditional short-term traffic forecasting predominantly investigates traffic flows using 15- and 30-min intervals, in this paper daily traffic flows are used to investigate cyclicality so as to filter out possible shifts in traffic volumes that are the result of changes in time of day (e.g., caused by accidents). First, the dependent variable (daily traffic count) for all four traffic count locations is explored, and then the different explanatory variables (often referred to as interventions in time-series terminology) are described.

Daily Traffic

The aggregated daily traffic counts originate from minute-by-minute data that comes from single inductive loop detectors, which were collected in 2003, 2004, and 2005 by the Vlaams Verkeerscentrum (Flemish Traffic Control Center). Four traffic count locations are investigated in this study; these locations in Belgium are shown in Figure 1. The first two locations are on the E314, a highway that is one of the main routes into and out of Brussels and is extensively used by commuters. The detectors in Gasthuisberg (near Leuven, Belgium) are used to analyze the upstream traffic counts on the E314; the detectors in Herent (also near Leuven, Belgium) are used to analyze the downstream traffic counts on the E314. The second two traffic count locations are located on the E40, a highway that is one of the main accesses to the Belgian seashore and thus is typified by leisure traffic. Belgium has a moderate maritime climate, which makes holidays on the Belgian seashore an attractive recreational option for residents. Both the upstream and downstream traffic counts are analyzed by data from detectors in Zandvoorde (which is near Ostend, Belgium).

On a minute-by-minute basis, the loop detectors generate four statistics: the number of cars that drive by the detector, the number of trucks that drive by the detector, the occupancy of the detector (i.e., the percentage of time that the detector is "occupied" by vehicles), and the time-mean speed of all vehicles (*26*). Adding up the number of cars and trucks for all lanes in a specific direction (two lanes in each direction at each of the four traffic count locations under analysis) yields a total traffic count for each minute. Although single loop detectors can distinguish between cars and trucks, it was decided to use the aggregate of both car and truck traffic to analyze the affect of holidays, because the algorithm used to distinguish between cars and trucks has demonstrated inferior performance during congested periods.

Holiday Effect

To assess the impact of holidays on traffic counts, the first step was to identify what holidays are celebrated in Belgium. The following holidays or holiday periods were considered: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Monday, vacation of the construction industry (a 3-week period starting on the second Monday in July), Assumption Day, fall break (including All Saints' Day and All Soul's Day), and Remembrance Day. (The Belgian national holiday, which falls on July 21, is included in the vacation of the construction industry period.) To evaluate the impact of these holidays, the weekends adjacent to the individual holidays are considered part of the holiday period. For a holiday that falls on a Tuesday, the preceding Monday and weekend before are also defined as part of the holiday period; similarly, for a holiday that falls on a Thursday, the following Friday and weekend afterwards are defined as part of the holiday period. This choice was made because people often have those intervening days off and thus take leave (i.e., a long weekend or short holiday) that is several days long. To model the impact of these aforementioned holidays, a dummy variable was created; days defined as holidays were coded as one and all other remaining days were coded as zero.

Day Effect

In addition to the holiday effect, this study also addresses the day-of-week effect. Six dummy variables were created to model this effect. In general it is necessary to create $k - 1$ dummy variables to analyze the effect of a categorical variable with k classes (*27*). The choice was made to represent the first six days of the week (Monday until Saturday) by, respectively, one dummy each, equal to one for the day the dummy represents and zero elsewhere. Representing the first six days by six dummy variables entails treating the remaining day, Sunday, as a reference day, which implies that for all traffic counts collected on a Sunday, the corresponding six dummies are coded zero.

METHODOLOGY

This study emphasizes the investigation of cyclicality in the daily traffic data and the identification and comparison of holiday effects at different site locations. To get prior insight in the cyclic patterns in the daily traffic counts, spectral analysis provides the required framework to highlight periodicities in the data.

For forecasting daily traffic counts, two modeling philosophies are explored. The basic principle of the first philosophy is since consecutive traffic counts are correlated, present and future values can be (partially) explained by past values. In this research, SARIMA models are fitted because this kind of model is extremely suitable for handling seasonality in the data.

The second modeling philosophy is regression. The basic premise of this approach is that the dependent variable (in this case, daily traffic counts) can be explained by other variables. Nevertheless, a linear regression model only yields interpretable parameter estimates when different underlying assumptions are satisfied. Since correlation

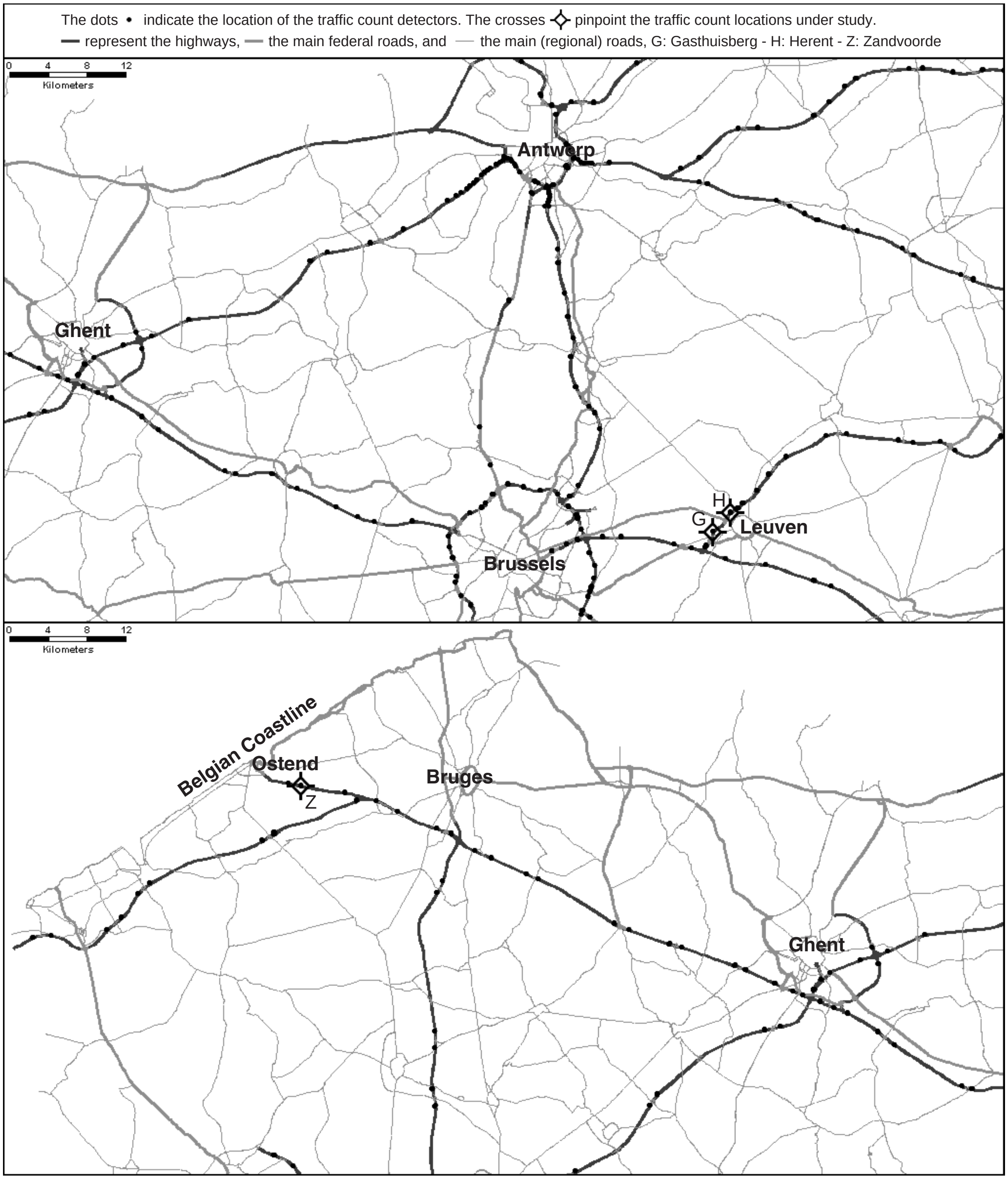

FIGURE 1 Geographical representation of traffic count locations under study.

between error terms is present, two accommodations to the classical linear regression model—the ARIMAX model (also referred to as the Box–Tiao model) and the SARIMAX model—are investigated. The latter models can account for dependencies between error terms.

The following is a brief overview of the underlying mathematical theory of the proposed time-series models. For an introduction on time-series techniques, the reader is referred to Shumway and Stoffer (*28*). Yaffee and McGee (*29*) and Brocklebank and Dickey (*30*) provide a comprehensive overview of how to fit time-series models using statistical analysis system software.

Spectral Analysis

Spectral analysis is a statistical approach to detect regular cyclical patterns or periodicities. In spectral analysis, data are transformed with a fine Fourier transformation and decomposed into waves of different frequencies (*31*). The Fourier transform decomposition of the series x_t is

$$x_t = \frac{a_0}{2} + \sum_{k=1}^{m}\left[a_k \cos\left(w_k t\right) + b_k \sin\left(w_k t\right)\right]$$

where

t = time subscript,
x_t = the data,
m = number of frequencies in Fourier decomposition [$m = n/2$ if n is even; $m = (n-1)/2$ if n is odd],
n = number of observations in series,
a_0 = mean term ($a_0 = 2\bar{x}$),
a_k = cosine coefficients,
b_k = sine coefficients, and
w_k = Fourier frequencies ($w_k = 2\pi k/n$).

Functions of the Fourier coefficients a_k and b_k can be plotted against frequency or wavelength to form periodograms, which are estimates of a theoretical quantity called a spectrum. The amplitude periodograms, also referred to as the periodogram ordinates, can then be smoothed to form spectral density estimates. The weight function used for smoothing, $W(\ )$, is often called the spectral window. The following simple triangular weighting scheme is used to produce a weighted moving average estimate for the spectral density of the series: 1/64π, 2/64π, 3/64π, 4/64π, 3/64π, 2/64π, 1/64π.

SARIMA Modeling

SARIMA modeling is a time-series technique that accommodates ARIMA modeling and accounts for seasonality in the data. This approach tries to predict current and future values of a variable by using a weighted average of its own past values. If the series Y_t is modeled as a SARIMA $(p, d, q) \times (P, D, Q)_s$ process, then the model is given by

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)e_t$$

where

s = length of periodicity (seasonality);

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

= the nonseasonal autoregressive operator of order p;
$\phi_1, \phi_2, \ldots, \phi_p$ = the corresponding nonseasonal autoregressive parameters;

$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps}$

= the seasonal autoregressive operator of order P;
$\Phi_1, \Phi_2, \ldots, \Phi_P$ = the equivalent seasonal autoregressive parameters;

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

= the nonseasonal moving average operator of order q;
$\theta_1, \theta_2, \ldots, \theta_q$ = the associated nonseasonal moving average parameters;

$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs}$

= the seasonal moving average operator of order Q;
$\Theta_1, \Theta_2, \ldots, \Theta_Q$ = the corresponding seasonal moving average parameters;
$(1-B)^d$ = the nonseasonal differencing operator of order d to produce nonseasonal stationarity of the dth differenced data (usually d = 0, 1, or 2); and
$(1-B^s)^D$ = the seasonal differencing operator of order D to produce seasonal stationarity of the Dth differenced data (usually D = 0, 1, or 2).

In the above model equation B^i is used as a backshift operator on Y_t and is defined as $B^i(Y_t) = Y_{t-i}$.

A SARIMA model is valid only when the series satisfies the requirement of weak stationarity. This requirement is fulfilled when the mean value function is constant and does not depend on time, and when the variance around the mean remains constant over time (*28*). A transformation, like taking the logarithm or the square root of the series, often proves to be a good remedial measure to achieve constancy of the variance of the series (*27*). To achieve stationarity with the mean sometimes requires differencing the original series. Successive changes in the series are then modeled instead of the original series. Therefore in its most general form (as represented above), the SARIMA model includes a seasonal and nonseasonal differencing operator.

ARIMAX and SARIMAX Modeling

In contrast with purely 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. Attention is needed when the classical linear regression approach is applied to time series, as the assumption of independence of the error terms is often violated because of autocorrelation (the error terms being correlated among themselves). The transgression of this assumption increases the risk for erroneous model interpretation, because the true variance of the parameter estimates may be seriously underestimated (*27*).

ARIMAX and SARIMAX models provide the required modeling frameworks to rectify the problem of autocorrelation by describing the errors terms of the linear regression model by respectively an ARIMA(p, d, q) and SARIMA$(p, d, q) \times (P, D, Q)_s$ process. Formally the ARIMAX and SARIMAX models can be represented by the following equations:

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \frac{(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)}{(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)} \epsilon_t$$

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \frac{(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)(1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs})}{(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)(1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps})} \epsilon_t$$

the first being the formal representation of the ARIMAX model, the latter of the SARIMAX model, where

Y_t = tth observation of the dependent variable,
$X_{1,t}, X_{2,t}, \ldots, X_{k,t}$ = corresponding observations of the explanatory variables,
$\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ = parameters of the regression part, and
$\phi_1, \phi_2, \ldots, \phi_p, \Phi_1, \Phi_2, \ldots, \Phi_P, \theta_1, \theta_2, \ldots, \theta_q$, and $\Theta_1, \Theta_2, \ldots, \Theta_Q$ = weights for the nonseasonal and seasonal autoregressive terms and moving average terms.

The remaining error terms ϵ_t are assumed to be white noise. For clarity of the formulas, the differencing operators were left out of the equations.

The parameters of the ARIMAX and SARIMAX models are estimated using maximum likelihood. Studies comparing least squares methods with maximum likelihood methods for this family of models show that maximum likelihood estimation gives more accurate results (*30*). The likelihood function is maximized via nonlinear least squares using Marquardt's method (*32*). When differencing of the error terms is required to obtain stationarity, all dependent and independent variables should be differenced (*25*).

Model Evaluation

To compare the different types of models considered and to compare models for upstream and downstream traffic intensity on the one hand, and models for different highways on the other hand, there need to be objective criteria for determining the models' performance (*33*). To determine the appropriateness of the models and to substantiate the validity of the proposed modeling framework, the following criteria were considered: the Akaike information criterion (AIC), the mean square error (MSE) and the mean absolute percentage error (MAPE). Only the latter criterion can be applied for comparing models of different traffic count locations. By constructing the models on a training data set containing the first 75% of the observations, the remaining 25% of the observations make up a validation or test data set. This test data set can then be used to assess the forecasting performance of the models, by calculating the MSE and MAPE for the predictions for this test data. The choice of these percentages is arbitrary, but common practice in validation studies [e.g., Wets et al. (*34*)].

The following three definitions determine the three criteria considered. The AIC is defined as $-2 \times \log \text{likelihood} + 2 \times$ the number of parameters in the model. 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. Models with lower values for these criteria are considered to be the more appropriate ones (*35*).

To evaluate the predictive strength of the proposed models, and more precisely to test whether the differences in MAPE for the different models are significant, the Friedman test and the Wilcoxon signed-rank test (*18*) are used. The predictions (test data) of the different forecasting methods are ranked, and on the basis of these ranked predictions the nonparametric repeated measures tests are performed. The Friedman test evaluates the null hypothesis that three or more related samples are from the same population, and this test is therefore used to assess whether the MAPEs for the different approaches are equal. The Wilcoxon signed-rank test evaluates the null hypothesis that two related samples have the same distribution. This test is adopted to test whether pairwise differences in MAPE are significant or not.

RESULTS

This section presents the results, interprets the parameter estimates of the models, and compares the different models. First, the periodicities in the data are highlighted. Then, the results of the three model approaches are provided, and their performances are carefully assessed. Finally, the models for upstream traffic count data and downstream traffic count data are compared for the two highways, and then differences in variability between the two highways are discussed.

Spectral Analysis

Prior insight in the cyclic patterns present in the daily traffic counts can be obtained by looking at the results of the spectral analysis presented in Figure 2. This figure displays the spectral density estimates against the periods. From this figure, it is clear that for three of the four traffic count locations the spectral density reaches a local maximum in period 3.5 and a global maximum in period 7. This global maximum can be interpreted as a weekly recurring pattern in the traffic data. For the remaining traffic count location (E40, downstream) only a local maximum in period 7 is attained. Note that the other maxima (in periods 2.33 and 3.5) also contribute to an explanation of weekly cyclicality, as repetition of these patterns also yields a weekly pattern. In addition to the weekly periodicity, differences between the two highways can be highlighted: the weekly structure accounts for almost all variability on the E314 (typified by commuting traffic), while weekly patterns only partially explains the variability on the E40 (characterized by leisure traffic).

SARIMA Modeling

To obtain stationarity for all four traffic count locations, it was required to develop the corresponding SARIMA models on differenced data. A thorough investigation of the autocorrelation function and the partial autocorrelation function of the residuals was required, to evaluate which autoregressive and moving average factors were required for the model-building process. The following SARIMA models are obtained by using the AIC as selection criterion:

E314, upstream (Gasthuisberg):

$$\text{SARIMA } (1,1,1)\times(1,0,1)_7$$

E314, downstream (Herent):

$$\text{SARIMA } (2,0,1)\times(0,1,1)_7$$

E40, upstream (Zandvoorde):

$$\text{SARIMA } (1,1,1)\times(1,1,2)_7$$

E40, downstream (Zandvoorde):

$$\text{SARIMA } (0,1,2)\times(1,1,1)_7$$

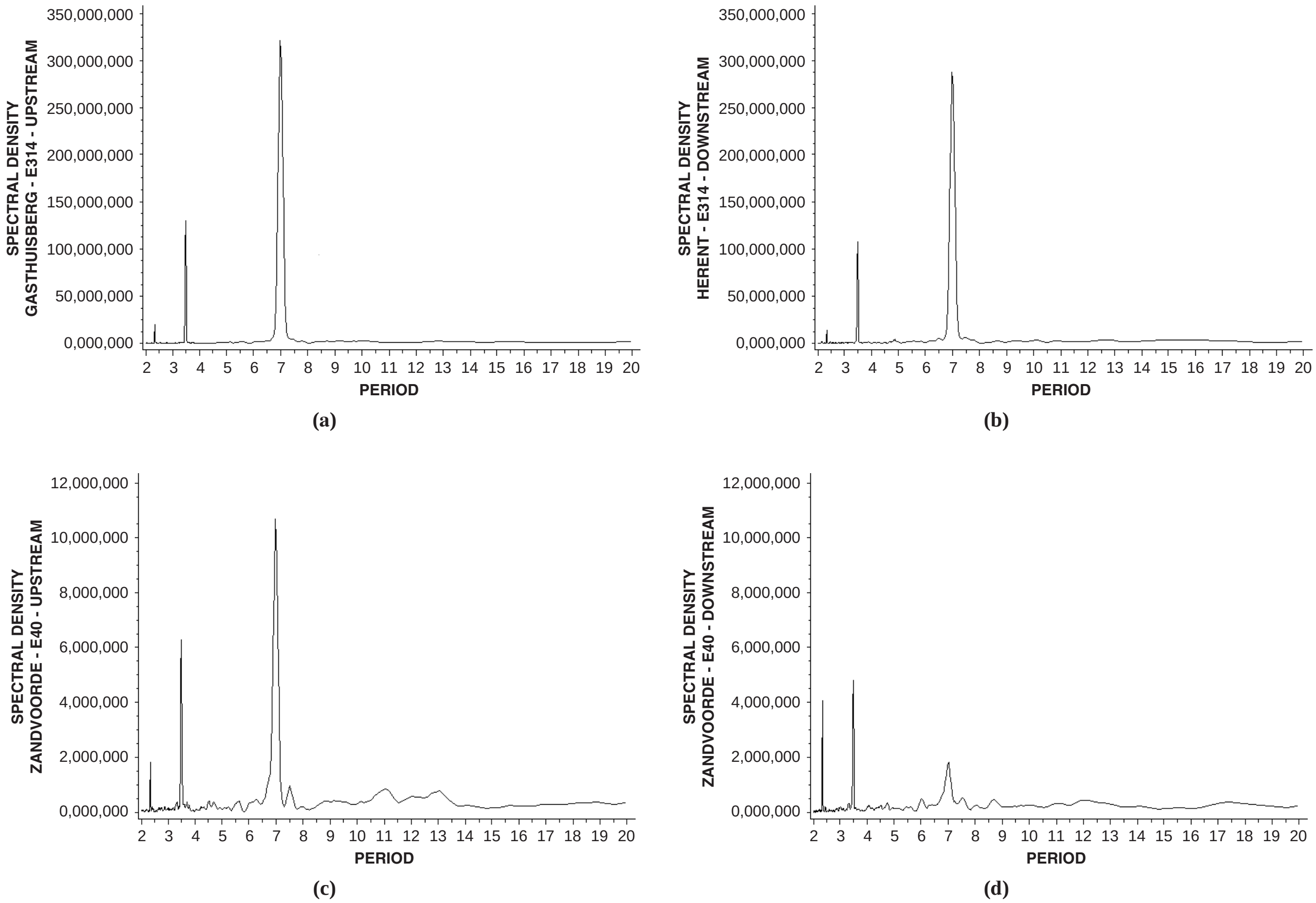

FIGURE 2 Spectral analysis of daily upstream and downstream traffic counts for two highways.

The estimates for these final-obtained SARIMA models for the four traffic count locations can be formally represented by the following equations:

E314, upstream (Gasthuisberg):

$$(1-B)Y_t = \frac{(1-0.812B)(1-0.999B^7)}{(1-0.349B)(1-B^7)}\epsilon_t$$

E314, downstream (Herent):

$$(1-B^7)Y_t = \frac{(1-0.775B)(1-0.994B^7)}{(1-1.256B+0.304B^2)}\epsilon_t$$

E40, upstream (Zandvoorde):

$$(1-B)(1-B^7)Y_t = \frac{(1-0.926B)(1-1.593B^7+0.598B^{14})}{(1-0.485B)(1-0.700B^7)}\epsilon_t$$

E40, downstream (Zandvoorde):

$$(1-B)(1-B^7)Y_t = \frac{(1-0.457B-0.324B^2)(1-0.978B^7)}{(1-0.077B^7)}\epsilon_t$$

These models all contain seasonal and nonseasonal moving average factors, and in addition contain seasonal or nonseasonal (or both) autoregressive factors if required. If these models were to be worked out completely, other autoregressive and moving factors would also play a role. Investigation of the SARIMA models draws immediate attention to the seasonality in the data: a 7-day cyclicality seems to predetermine daily traffic counts. This can be seen from the facts that a seasonal difference operator (taking the 7th-order difference) is included in three of the four models and that the SARIMA factors for the first model (E314, upstream) are very close or equal to one. Moreover, other SARIMA factors play an important role, indicating that traffic counts can be explained by weekly cyclic patterns.

ARIMAX and SARIMAX Modeling

As with the SARIMA modeling approach, it was necessary with the ARIMAX and SARIMAX modeling approaches to develop a model on differenced data to achieve (weak) stationarity, and the intercept was dropped from the equations to attain realistic interpretations. Recall that when differencing is applied, the intercept is interpreted as a deterministic trend, and this interpretation is not always realistic (*36*). The final error terms obtained in the four models are accepted to be white noise according to the Ljung–Box Q*-statistics (*37*). Table 1 shows the parameter estimates for the ARIMAX and SARIMAX models. The standard errors and values of the significance tests are provided as well. The estimates of the (S)ARIMA parameters are not shown because they serve as a remedial measure for autocorrelation

TABLE 1 Parameter Estimates for ARIMAX and SARIMAX Models

	E314 Upstream (Gasthuisberg)				E314 Downstream (Herent)			
Parameter	Estimate	SE	*t*-Value	*p*-Value	Estimate	SE	*t*-Value	*p*-Value
ARIMAX (1, 1, 1)					ARIMAX (1, 1, 1)			
Holiday	−4,197	295	−14.2	<.001	−3,863	351	−11.0	<.001
Monday	9,203	256	36.0	<.001	9,011	308	29.3	<.001
Tuesday	10,832	293	37.0	<.001	10,548	362	29.2	<.001
Wednesday	11,522	303	38.1	<.001	11,022	378	29.2	<.001
Thursday	11,311	301	37.6	<.001	10,863	376	28.9	<.001
Friday	11,983	291	41.2	<.001	11,028	359	30.7	<.001
Saturday	1,390	252	5.5	<.001	1,428	303	4.7	<.001
SARIMAX $(1, 1, 1) \times (1, 0, 1)_7$					SARIMAX $(2, 0, 1) \times (0, 1, 1)_7$			
Holiday	−4,219	290	−14.6	<.001	−3,839	351	−10.9	<.001

	E40 Upstream (Zandvoorde)				E40 Downstream (Zandvoorde)			
Parameter	Estimate	SE	*t*-Value	*p*-Value	Estimate	SE	*t*-Value	*p*-Value
ARIMAX (1, 1, 2) with holiday effect					ARIMAX (3, 1, 1) with holiday effect			
Holiday	−196	164	−1.2	.234	95	143	0.7	.504
Monday	933	126	7.4	<.001	−193	112	−1.7	.086
Tuesday	1,121	158	7.1	<.001	−398	135	−3.0	.003
Wednesday	1,370	164	8.3	<.001	−473	131	−3.6	<.001
Thursday	1,651	163	10.1	<.001	−222	131	−1.7	.089
Friday	3,119	156	20.0	<.001	−107	134	−0.8	.424
Saturday	738	124	6.0	<.001	−2,122	110	−19.3	<.001
ARIMAX (1, 1, 2) no holiday effect					ARIMAX (3, 1, 1) no holiday effect			
Monday	963	124	7.8	<.001	−207	110	−1.9	.059
Tuesday	1,155	155	7.5	<.001	−416	133	−3.1	.002
Wednesday	1,406	162	8.7	<.001	−491	129	−3.8	<.001
Thursday	1,680	162	10.4	<.001	−237	129	−1.8	.066
Friday	3,147	154	20.4	<.001	−121	132	−0.9	.362
Saturday	737	124	6.0	<.001	−2,122	110	−19.3	<.001
SARIMAX $(1, 1, 1) \times (1, 1, 2)_7$					SARIMAX $(0, 1, 2) \times (1, 1, 1)_7$			
Holiday	−178	161	−1.1	.269	50	135	0.4	.711

NOTE: SE = standard error.

and because focus lies on the interpretation of the regression part of the models. No day-of-week effect is included in the SARIMAX models, as seasonal differencing of the day-of-week variables would yield variables having a zero variance, and thus the model estimation would become infeasible. For the traffic count location for upstream traffic on the E314 (Gasthuisberg), it would have been feasible to include day-of-week effect, because no seasonal difference operator was used in this model. Nonetheless, when day-of-week effect is included, the seasonal autoregressive and moving average parameters are not significant, and the model unfolds into the ARIMAX model.

Table 1 demonstrates that day-of-week effects are significant at all four traffic count locations. All six individual day-of-week dummy variables are significant at three of the four locations, while at the remaining traffic count location (E40 downstream) half of the day-of-week dummy variables turn out to be significant. Note that the spectral analysis also pinpointed this contrast between the E40 downstream location and the other three. This phenomenon could be partially explained by the fact that the lowest traffic counts are (generally) observed on Sundays (as compared with other days), but that at this particular location, on Sundays traffic-intensity rates peak due to traffic from people returning home from their leisure trips to the seashore. Furthermore, the analysis reveals that the holiday effects are only significant for the traffic count locations on the E314. For the traffic count locations on the E40, the holiday effects are not significant. Therefore, Table 1 presents the parameter estimates for both the ARIMAX model that includes holiday effects and the ARIMAX model that does not include holiday effects, for the E40 locations. With the SARIMAX models, only the models that include holiday effects are displayed in Table 1, since the models without holiday effects are obviously the SARIMA models described in the previous section.

Model Comparison

When the performance of the different modeling philosophies is assessed, it is clear from Table 2 that all three modeling approaches—

TABLE 2 Criteria for Model Comparisons

	Training Data			Test Data	
	AIC	MSE	MAPE (%)	MSE	MAPE (%)
E314 Gasthuisberg (upstream)					
SARIMA (1, 1, 1) × (1, 0, 1)$_7$	15,275.0	6,654,557	5.37	17,877,684	8.85
ARIMA(X) (1, 1, 1)	15,074.8[a]	5,451,893[a]	4.90[a]	10,380,923[a]	7.12[a]
SARIMA(X) (1, 1, 1) × (1, 0, 1)$_7$	15,116.6	5,515,467	5.06	18,557,140	10.18
E314 Herent (downstream)					
SARIMA (2, 0, 1) × (0, 1, 1)$_7$	15,387.0	8,905,383	6.05	16,779,060	9.13
ARIMA(X) (1, 1, 1)	15,383.8	7,939,285[a]	5.82[a]	14,453,314	8.46
SARIMA(X) (2, 0, 1) × (0, 1, 1)$_7$	15,295.4[a]	7,994,919	5.84	13,501,012[a]	8.24[a]
E40 Zandvoorde (upstream)					
SARIMA (1, 1, 1) × (1, 1, 2)$_7$	13,883.0[a]	1,440,592	6.67	3,883,197	11.92
ARIMA(X) (1, 1, 2) with holiday	13,978.7	1,433,216[a]	6.59[a]	3,246,433[a]	10.11
ARIMA(X) (1, 1, 2) no holiday	13,978.2	1,433,935	6.60	3,296,933	10.07[a]
SARIMA(X) (1, 1, 1) × (1, 1, 2)$_7$	13,883.8	1,440,650	6.67	3,948,399	12.14
E40 Zandvoorde (downstream)					
SARIMA (0, 1, 2) × (1, 1, 1)$_7$	13,661.1[a]	1,101,579	6.06	3,025,826	9.67
ARIMA(X) (3, 1, 1) with holiday	13,775.2	1,090,283	5.91	3,052,143	9.24
ARIMA(X) (3, 1, 1) no holiday	13,753.7	1,089,540[a]	5.89[a]	3,003,765[a]	9.16[a]
SARIMA(X) (0, 1, 2) × (1, 1, 1)$_7$	13,662.9	1,102,956	6.07	3,017,484	9.59

[a]Best model for specific traffic count location, according to evaluation criterion.

SARIMA, ARIMAX, and SARIMAX—perform reasonably well in explaining the variability of daily traffic counts. The three criteria based on the training data (AIC, MSE, and MAPE) favor different modeling approaches, suggesting that the three model approaches tested are valid for use in investigating daily traffic counts. Concerning forecasting of daily traffic counts, at three of the locations the ARIMAX models outperform the SARIMA and SARIMAX models on the basis of the two criteria from the test data (MSE and MAPE); at the fourth location (E314 downstream) only small differences in performance are observed. This suggests that when the focus is put on forecasting, the use of the ARIMAX model approach should be preferred.

In addition, forecasting on the E314 yields more reliable results than forecasting on the E40. For example, with the best models (indicated by [a] on Table 2), MAPEs of 7.12% and 8.24% are observed for, respectively, upstream and downstream traffic for the E314, while MAPEs of only 10.07% and 9.16% were attained for, respectively, upstream and downstream (no holiday) traffic for the E40. This finding matches perfectly with the results from the spectral analysis, namely that the weekly structure accounts for almost all variability on the E314 (typified by commuting traffic), while weekly patterns only partially explain the variability on the E40 (characterized by leisure traffic). The superior forecasting on the E314 is also evident from Figure 3. The predictions of daily traffic counts on the E314 (the two upper plots) are much closer to the actual values than predictions on the E40 (the two lower plots).

When the statistical testing procedures are used to assess the predictive value of the models, the Friedman tests all indicate that significant differences in MAPE exist. For three of the four locations the corresponding p-values are below 0.01. For the models for downstream traffic on the E40, the differences are only borderline significant (p-value equals 0.046). Note that for this location, the MAPEs based on the test data set are much closer to each other as compared with the three other locations. When the differences are tested in pairwise comparison, accounting for multiple testing, significance differences can be found between most of the MAPEs, except for the models predicting downstream traffic on the E40.

These sundry techniques all highlight a weekly cyclic behavior at all four locations. The holiday effect, however, turns out to be significant only for upstream and downstream traffic of the E314. For the traffic count locations on the E40 highway, no significant holiday effects are retrieved. Nevertheless, further elaboration on this insignificance of the holiday effect is worthwhile, since the daily travel time expended on commuting is clearly lower on holidays than on regular days (*38*). Thus, one can conclude that for the E40 traffic count locations, the decrease in the number of vehicles that results from less commuting traffic on holidays is compensated by an increase in the number of vehicles that is the result of leisure traffic, which is shown by the nonsignificant effect of holidays on the sum of all traffic, as considered here. The simultaneous analysis of travel goals and traveling itself (traffic counts) seems therefore an interesting avenue for further research.

A comparison of upstream and downstream traffic counts yields quite diverse results for the locations on the E314 and on the E40 (Table 1). On the E314, upstream and downstream traffic seems to yield comparable findings: significantly lower traffic counts on weekend days and holidays, and maximum levels of traffic intensity on Wednesdays and Fridays. Conversely, the upstream and downstream traffic locations of the E40 result in quite divergent outcomes; upstream traffic seems to top out on Fridays and is least intense on Sundays, while downstream traffic reaches the maximum on Sundays. This discrepancy between upstream and downstream can be (partially) explained by the fact that people make a weekend trip to the seashore, starting their leisure trips on Friday evening and returning home on Sunday.

CONCLUSIONS AND FURTHER RESEARCH

In this study, three modeling approaches, the SARIMA, ARIMAX, and SARIMAX, were considered to predict daily traffic counts. These different modeling techniques, as well as the spectral analysis, point out the significance of the day-of-week effect: weekly cycles seem to determine the variation of daily traffic flows. The comparison of

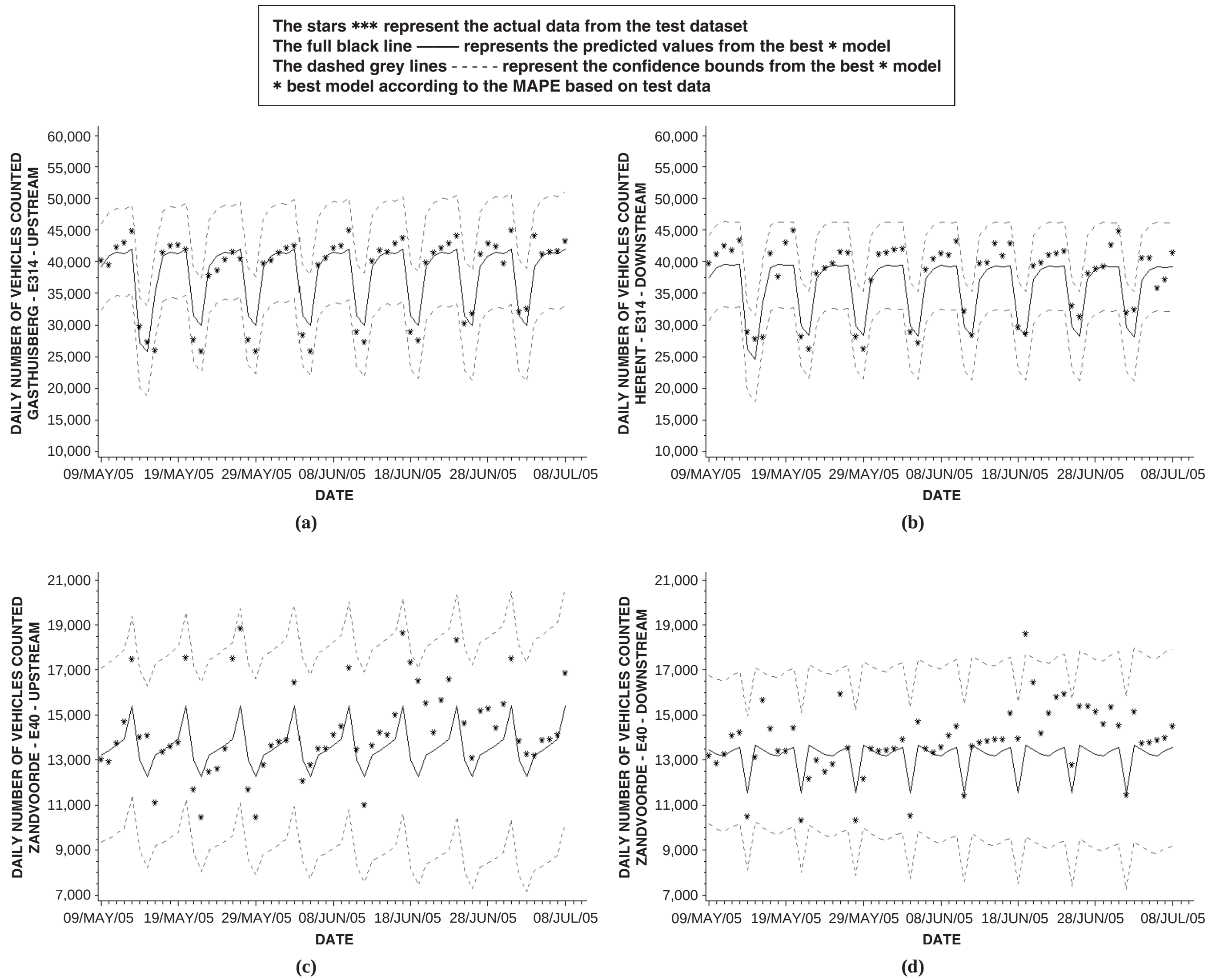

FIGURE 3 Daily traffic counts and their predicted values and confidence bounds.

day-of-week effects or seasonal effects and holiday effects at different site locations reveal that all three modeling approaches perform reasonably well in explaining the variability of daily traffic counts, favoring the ARIMAX model, when the focus is on forecasting daily traffic counts. Results reveal that the ARIMAX and SARIMAX modeling approaches are valid frameworks for identifying and quantifying possible influencing effects. Nonetheless, the explicit incorporation of day-of-week effects into the ARIMAX approach yields additional insight for policy decision makers: that holiday effects play a noticeable role on highways extensively used by commuters and have a more ambiguous effect on highways typically used for leisure travel.

The results discussed in this paper generalize the findings of Cools et al. (*24*) so that policy makers can fine-tune current policy measures based on these results. Thus, the performance of policy tools like ATISs and ATMSs can be improved. One example is online calendars that pinpoint the days when traffic volumes are expected to be high; travelers can use the information provided to reschedule or adapt their planned travel trips. A second example is to focus policy actions such as carpooling initiatives on days when traffic intensity is highest. For instance, as a response to upstream traffic on the E40, there could be a focus on stimulating alternatives to reduce the intensity of Friday traffic. The examples illustrate that the findings of this study contribute to the achievement of an important goal: namely, the policy keystone of "more acceptable and reliable travel times."

Further generalization of the results is possible when traffic patterns from other parts of the road network are analyzed. Modeling of daily traffic counts on secondary roads and simultaneous modeling of different traffic count locations are certainly important pathways for further research. A key challenge will be the simultaneous modeling of underlying reasons of travel and revealed traffic patterns.

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