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Dynamic Prediction of Traffic Flow and Congestion at Freeway Construction Zones

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It is often necessary to establish construction zones on roadways for pavement and bridge repair and rehabilitation activities. A construction zone reduces the number of lanes available for traveling vehicles and therefore forms a bottleneck section for traffic flow. The ability of dynamically predicting traffic flow rates with real-time data is essential for both highway engineers and construction contractors. For highway engineers, the predicted values of traffic flow rates could be utilized to maintain smooth traffic flows at construction zones. It would enable them to apply traffic control measures to prevent traffic congestion at construction zones rather than to deal with traffic problems after traffic congestion already occurred. For contractors, knowing the future traffic conditions around construction zones would be great advantageous in scheduling construction activities and equipment movements. It was found in this study that using the Kalman predictor in combination with the first-order autoregressive time series provided satisfactory dynamic predictions of construction zone traffic flow. A prediction of traffic flow at a construction zone also constitutes a prediction of traffic congestion if the traffic capacity of the construction zone is known. If the predicted traffic flow rate is equal to or greater than the traffic capacity, then traffic congestion is expected in the coming time period and appropriate traffic control actions can be taken to prevent the traffic congestion.

Key Words: Dynamic Prediction, Traffic Flow, Congestion, Work Zone, Time Series, Kalman

Introduction

It is often necessary to establish construction zones on roadways for pavement and bridge repair and rehabilitation activities. A construction zone reduces the number of lanes available for traveling vehicles and therefore forms a bottleneck section for traffic flow. Traffic congestion occurs at a construction zone when traffic flow exceeds the capacity of the construction zone. Consequently, during congestion vehicles go through the construction zone at reduced speeds and with fluctuated traffic flow rates (Jiang, 1999). Vehicles on the roadway, including construction vehicles that haul construction materials to or from the construction zone, endure considerably greater traffic delays at the construction zone under congested traffic conditions than under uncongested conditions. Therefore, the ability of dynamically predicting traffic flow rates with real-time data is essential for both highway engineers and construction contractors. For highway engineers, the predicted values of traffic flow rates could be utilized to maintain smooth traffic flows at construction zones. It would enable them to apply traffic control measures to prevent traffic congestion at construction zones rather than to deal with traffic problems after traffic congestion already occurred. For contractors, knowing the future traffic conditions around construction zones would be great advantageous in scheduling construction activities and equipment movements. As traffic flow is maintained smooth and traffic congestion is prevented, the safety of the motorists and construction workers can be improved.

Several methods of adaptive traffic forecasting have been explored by researchers. Ahmed and Cook (1982) applied the time series methods to provide short-term forecast of traffic occupancies for incident detection. Okutani and Stephanedes (1984) employed the Kalman filtering theory in dynamic prediction of traffic flow. Davis et al. (1990) used pattern recognition algorithms to forecast freeway traffic congestion. Lu (1990) developed a model of adaptive prediction of traffic flow based on the least-mean-square algorithm. As part of the effort to improve traffic control at construction zones, this study applied the time series theory and Kalman filtering theory to adaptively predict traffic flow at the construction zones on Indiana's freeways with real-time data. It was found that using the Kalman predictor in combination with the autoregressive process of time series could provide satisfactory dynamic predictions of construction zone traffic flow. As traffic capacity values of Indiana's freeway construction zones were determined (Jiang, 1999), a prediction of traffic flow also constitutes a prediction of traffic congestion. If the predicted traffic flow rate is equal to or greater than the traffic capacity, traffic congestion is expected in the coming time period and appropriate traffic control actions can be taken to prevent the traffic congestion.

Construction Zone Types and Data Collection

Construction zone is defined in the 1994 Highway Capacity Manual (TRB, 1994) as "an area of highway in which maintenance and construction operations are taking place that impinge on the number of lanes available to moving traffic or affect the operational characteristics of traffic flowing through the area". This study focused on the two types of construction zones used on Indiana's four-lane divided highways, as shown in Figures 1 and 2 and defined as follows (FHWA, 1989):

1. Partial Closure (or single lane closure) - when one lane in one direction is closed, resulting in little or no disruption to traffic in the opposite direction.
2. Crossover (or two-lane two-way traffic operations) - when one roadway is closed and the traffic, which normally uses that roadway, is crossed over the median, and two-way traffic is maintained on the other roadway.

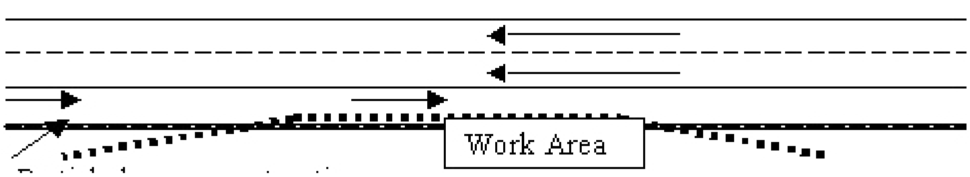

Figure 1. Partial closure construction zone.

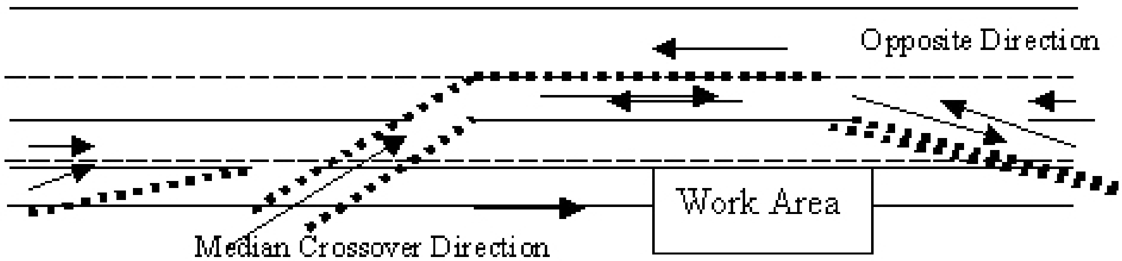

Figure 2. Crossover construction zone.

Traffic data at select construction zones on interstate highway sections was collected between October 1995 and April 1997. Traffic counters with road tubes were used for data collection. Traffic volume, vehicle speed and classification were recorded in order of time series. The vehicle counters were set up to classify the detected vehicles into three groups: 1). passenger cars, 2) heavy trucks and 3) buses. To express traffic flow in passenger cars per hour, the traffic flow rate was converted to hourly volume and the adjustment factors from the 1994 Highway Capacity Manual were used to convert trucks and buses to passenger car equivalents.

Prediction of Traffic Flow Using Time Series

Based on the collected traffic data, the traffic capacity values were determined (Jiang, 1999) for four types of construction zone layouts on Indiana four-lane freeways, i.e., crossover construction zone in the opposite direction, crossover construction zone in the crossover direction, partial closure with right lane closed, and partial closure construction zone with left lane closed. Table 1 presents the four construction zone capacity values obtained with traffic data at construction zones on Indiana four-lane freeways (Jiang, 1999).

Table 1

Traffic Capacities of Construction Zones on Indiana's Four-Lane Freeways

Construction Zone Type	Traffic Capacity
Crossover (Opposite Direction)	1745 Passenger Cars Per Hour
Crossover (Crossover Direction)	1612 Passenger Cars Per Hour
Partial Closure (Right Lane Closed)	1537 Passenger Cars Per Hour
Partial Closure (Left Lane Closed)	1521 Passenger Cars Per Hour

Given the construction zone capacity values, it was desired to develop methods to predict traffic flow and congestion at construction zones so that appropriate traffic control strategies could be applied to avoid traffic congestion and to reduce traffic delay. Traffic flow rate constantly changes with time on any given highway sections. To predict traffic conditions, the relationship between traffic flow and time must be studied. The time series theory (Cryer 1986, Bowerman and O'Connell, 1979) is a frequently used tool to study the traffic and time relationship. One of the time series models is the *autoregressive process* $\{Z(t)\}$. A *p*th-order autoregressive process, AR(p), satisfies the following equation:

$$Z(t) = \phi_1 Z(t-1) + \phi_2 Z(t-2) + \cdots + \phi_p Z(t-p) + \varepsilon_t \qquad (1)$$

where:

$Z(t)$ = value of the process Z at time t;

ϕ_i = unknown parameters; i = 1, 2, 3, ..., p

ε_t = a random variable with zero mean and variance σ_w^2.

This equation requires that the mean of the series has been subtracted out so that *Z(t)* has a zero mean (Cryer, 1986). This time series implies that the current value of the series *Z(t)* is a linear combination of the *p* most recent past values of itself plus an error term ε_t.

To show the use of the time series method in traffic flow prediction, the recorded traffic flow data at a construction zone on Interstate 65 over Indiana's State Road 46 was selected for fitting the first-order autoregressive process model. It was a crossover construction zone for bridge rehabilitation. The traffic flow data was collected inside the construction zone in the crossover direction at 10-minute intervals from 4:00 a.m. to noon on November 2, 1996. Figure 3 shows the observed traffic flow rates in order of time. With the traffic flow data at this construction zone, an AR(1) model was fitted using the Minitab (1996) software. The AR(1) equation for the traffic flow rate is expressed as follows:

$$f(t) = \phi_1 f(t-1) + \varepsilon_t \qquad (2)$$

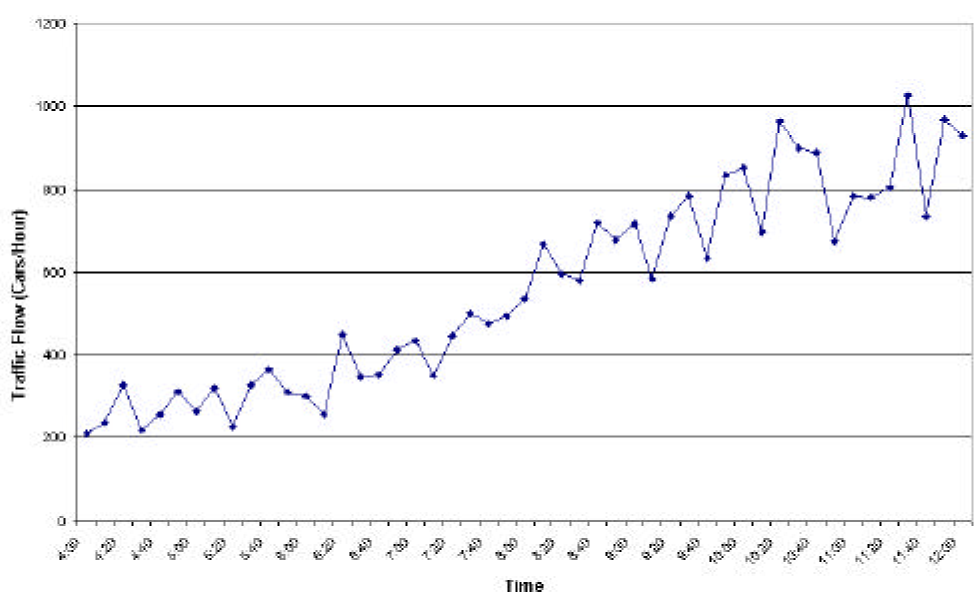

Figure 3. Observed construction zone traffic flow.

In Equation 2, *f(t)* denotes the traffic flow rate at time t. As expressed by the equation, the traffic flow rate at time t, *f(t)*, can be predicted from the traffic flow rate observed at the most recent past time point t-1, *f(t-1)*. It should be noted that the mean of the series of traffic flow rates must be subtracted from *f(t)* as required by the autoregressive model of Equation 1. The actual prediction is then the calculated *f(t)* plus the mean. If *f(t-1)* is given, then *f(t)* can be predicted as:

$$\hat{f}(t \mid t-1) = \bar{\phi}_1 f(t-1) \qquad (3)$$

In this equation, $\bar{\phi}_1$ is the estimate of ϕ_1, and $\hat{f}(t \mid t-1)$ is the predicted value of *f*(*t*) based on the most recent observed traffic flow rate, *f*(*t*-1). Through this equation, predictions of traffic flow rates at the given construction zone were calculated from 4:00 a.m. to noon at 10-minute intervals. For comparison, plotted in Figure 4 are the predicted and observed values of the traffic flow rates.

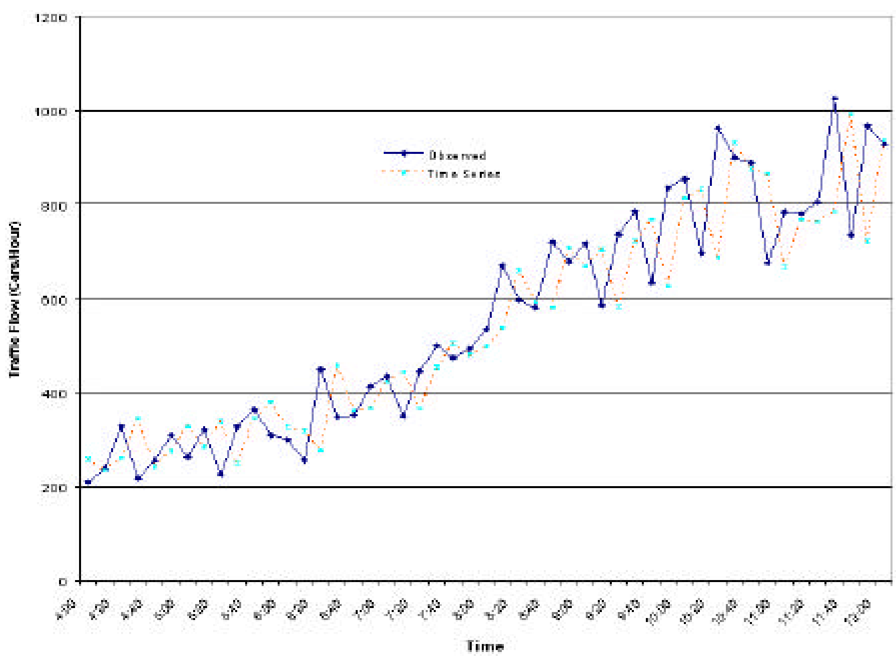

Figure 4. Observed and time series predicted traffic flow rates.

The curves in Figure 4 indicate that the predicted values followed the patterns of the observed traffic flows. The accuracy of the time series predictions is reflected by the values of residuals. In this case, a residual is the difference between the observed traffic flow rate and the traffic flow rate predicted by the time series model, that is, residual = $f(t) - \hat{f}(t \mid t-1)$. The residuals of the time series predictions are listed in Appendix A for all data points during the eight-hour period. To examine the magnitudes of the residuals, the absolute values of the residuals were used to calculate the statistics. As shown in Appendix A, the absolute values of residuals have a mean of 83.9, a standard deviation of 72.9, and a minimum of 1.7, and a maximum of 276.1. Although these values are not extremely unacceptable, they certainly suggest the needs for improvement in the accuracy of the time series predictions.

Prediction of Traffic Flow Using Kalman Predictor in Combination with Time Series

One of the applications of control theory is to use the Kalman predictor (Bozic, 1979) in recursive predictions of random signal processes. For example, the signal model can be a first-order autoregressive process:

$$x(t+1) = a\, x(t) + w_t \qquad (4)$$

The observation (or measurement) is affected by additive random error v_t:

$$y(t) = c\, x(t) + v_t \qquad (5)$$

where:

v_t is a random variable with zero mean and variance σ_v^2.

The Kalman predictor for the above signal model can be expressed as follows:

Predictor equation:

$$\hat{x}(t+1\,|\,t) = a\, \hat{x}(t\,|\,t-1) + k(t)[y(t) - c\hat{x}(t\,|\,t-1)] \qquad (6)$$

Predictor gain:

$$k(t) = \frac{acp(t\,|\,t-1)}{c^2 p(t\,|\,t-1) + \sigma_v^2} \qquad (7)$$

Prediction mean-square error:

$$p(t+1\,|\,t) = \frac{a}{c} k(t)\sigma_v^2 + \sigma_w^2 \qquad (8)$$

Equations 6, 7 and 8 are called one-step Kalman predictor of the signal process expressed by Equations 4 and 5. The Kalman method yields the estimate of *x(t + 1)*, i.e. the signal at time t+1, given the measured data *x(t)* and the previous estimate $\hat{x}(t\,|\,t-1)$ at time t. It can be proved (Bozic, 1979) that this one-step prediction estimate, denoted as $\hat{x}(t+1\,|\,t)$, is an optimum estimate because the Kalman recursive prediction process minimizes the mean-square prediction error $E[x(t+1) - \hat{x}(t+1\,|\,t)]^2$.

Some features of the Kalman predictor, such as recursive, continuously incorporating the most recent real-time data, and optimum prediction, are exactly the desirable functions for an efficient traffic flow prediction model. To use the Kalman predictor in traffic flow prediction, the AR(1) time series model as in Equation 2 can be used as the traffic flow model, that is:

$$f(t+1) = \phi\, f(t) + \varepsilon_t \qquad (9)$$

Equation 9 is the first-order autoregressive process for the traffic flow. In addition, the observation (or measurement) of the traffic flow, m(t), is affected by additive random error v_t:

$$m(t) = \beta f(t) + v_t \qquad (10)$$

Equation 10 is related to the accuracy of the traffic data measurement devices used in data collection. The one step Kalman recursive prediction equations can then be readily obtained from Equations 6 through 8:

Predictor equation:

$$\hat{f}(t+1\,|\,t) = \phi\,\hat{f}(t\,|\,t-1) + k(t)[m(t) - \beta\,\hat{f}(t\,|\,t-1)] \qquad (11)$$

Predictor gain:

$$k(t) = \frac{\phi\,\beta\,p(t\,|\,t-1)}{\beta^2 p(t\,|\,t-1) + \sigma_v^2} \qquad (12)$$

Prediction mean-square error:

$$p(t+1\,|\,t) = \frac{\phi}{\beta}k(t)\sigma_v^2 + \sigma_\varepsilon^2 \qquad (13)$$

With Equations 9 through 13, traffic flow rate at t+1, $f(t+1)$, can be predicted as $\hat{f}(t+1\,|\,t)$ for each observed data at time t, $f(t)$. Since Equation 9 is a time series model of the first order autoregressive process, this Kalman predictor model is a combination of the time series and the Kalman predictor. It was expected that this prediction model would improve the prediction accuracy over the time series model as defined in Equation 2. To verify this, the Kalman predictor model was also applied to the construction zone traffic flow data described in Figure 3. The predicted traffic flow rates from the Kalman predictor along with the corresponding observed values and the values from the time series method are plotted in Figure 5.

As shown in the figure, most of the predicted values from the Kalman model are closer to the observed values than the predicted values from the time series model. This indicates that the Kalman method indeed improved the prediction accuracy over the time series method. The differences in the prediction accuracy of the two methods can be more clearly described by plotting their corresponding residual values into the same graph, as shown in Figure 6. The residual graph distinctly shows that the most residuals of the Kalman predictions are considerably smaller than those of the time series predictions. Therefore, the improvement of the Kalman predictor over the time series method in traffic flow prediction is apparent and significant.

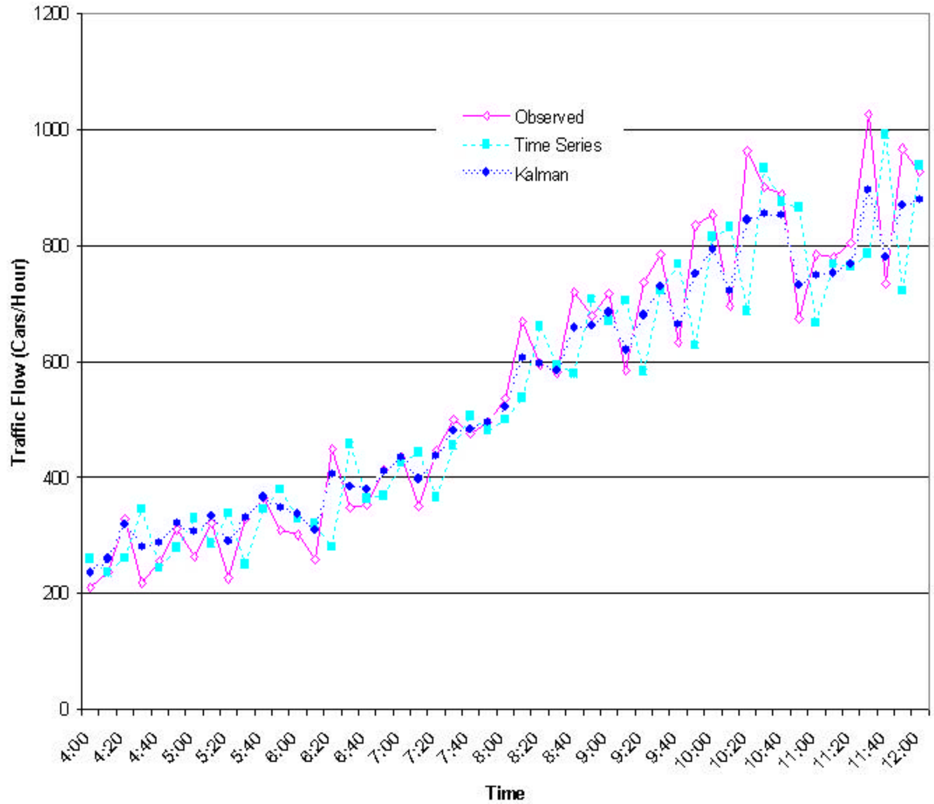

Figure 5. Observed and Kalman and time series predicted traffic flow rates.

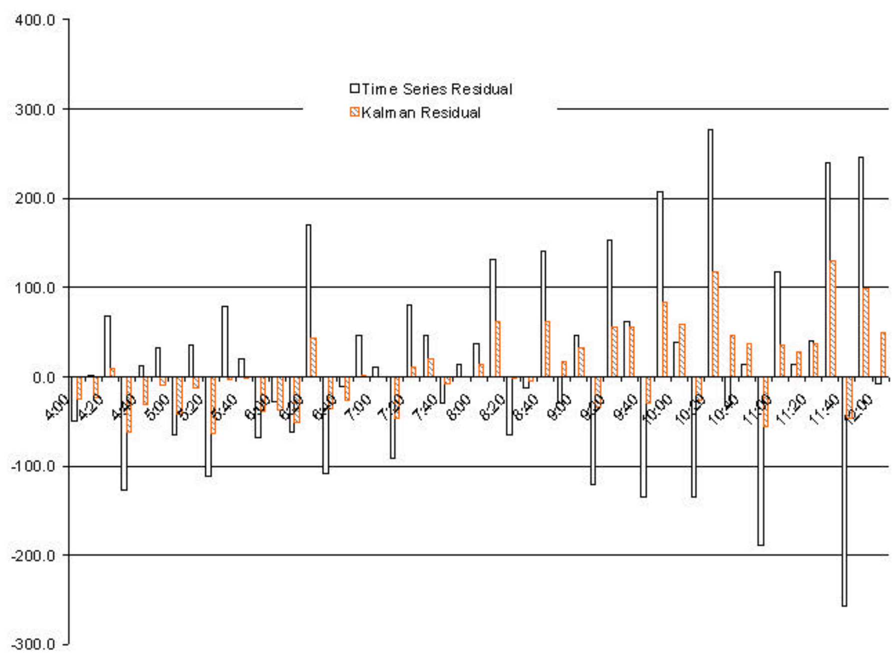

Figure 6. Residuals of Kalman predictor and time series predictions.

For a quantitative comparison, the values of the observed and predicted traffic flow rates are presented in Appendix B with the corresponding residual values. In addition, the differences between the absolute values of the time series and Kalman residuals are also included in the table. Because there are positive and negative residuals, the use of the absolute values of the residuals is to compare the magnitudes of the residuals from the two prediction methods. The magnitude of a residual is the difference between the observed value and the predicted value. Therefore, a more accurate prediction yields a smaller magnitude of residual. If the absolute value of time series residual (TR) minus the absolute of Kalman residual (KR) is positive, i.e., abs(TR)-abs(KR) > 0, then the magnitude of time series residual is greater than the Kalman residual, indicating the time series prediction is less accurate than the Kalman prediction.

As shown in the last column of Appendix B, there are 40 positive values and 9 negative values of abs (TR)-abs (KR). This indicates that 40 out of the 49 Kalman predictions are more accurate than the time series predictions. The statistics of the absolute values of residual were also calculated for the predictions from the two methods. As shown in Appendix B, the Kalman predictions have smaller values of mean, standard deviation, minimum and maximum of the absolute residuals than the time series predictions. Compared to the time series predictions, the Kalman predictions reduced the mean of the absolute residual values by (83.9-37.1)/83.9=55.8% and the standard deviation by (72.9-29.0)/72.9=60.2%. These large reductions in the values of the mean and standard deviation represent a significant improvement in the traffic flow predictions.

To statistically compare the predictions of the two methods, a paired t-test was performed. Since a t-test requires the data follow a normal distribution, the Anderson-Darling normality test (Minitab, 1996) was used to check if the absolute values of the residuals follow a normal distribution. The normality test resulted in a p-value of 0.000 for the absolute values of the time series residuals and a p-value of 0.015 for the absolute values of the Kalman residuals, indicating neither of the data sets follows a normal distribution at a level of $\alpha = 0.05$. Then the data sets were transformed by square root of the absolute values of the residuals, i.e., $r'_{1i} = \sqrt{abs(TR)}$ and $r'_{2i} = \sqrt{abs(KR)}$. The Anderson-Darling normality test on the transferred data yielded a p-value of 0.135 for r_{1i} and a p-value of 0.175 for r_{2i}. Therefore, both of the transformed data sets are normally distributed at a level of α = 0.05 and the paired t-test can be applied to compare them. The paired t-test was used to test if the difference between the mean of r_{1i} (μ_2) and the mean of r'_{2i} (? $_2$) is zero or greater than zero. The hypotheses to be tested are as follows:

H_0: $\mu_1 - \mu_2 > 0$

H_a: $\mu_1 - \mu_2 > 0$

If the Type I error is controlled at α = 0.05, then the p-value of the paired t-test can be compared to the α value according to the decision rule:

If p-value $\geq \alpha$, conclude H_0.
If p-value $< \alpha$, conclude H_a.

The p-value of the paired t-test is 0.000, which is less than ? ? 0.05. Therefore, H_a is concluded, i.e., the mean difference is greater than zero or μ_1 is significantly greater than μ_2. This implies that the Kalman predictor in combination with the time series method provides much better predictions of traffic flow rates than the time series method.

Prediction of Traffic Congestion

Once the traffic capacity of a construction zone is known, the dynamic prediction of traffic flow rates discussed above constitutes a dynamic prediction of traffic congestion at the construction zone. As previously indicated, the traffic data used in the above example was collected at a crossover construction zone in the crossover direction. From Table 1, it can be found that the traffic capacity of this type of construction zone in Indiana is 1612 passenger cars per hour. Thus, the traffic congestion at this construction zone can be predicted with the Kalman predictor method at each step of the prediction according to the following criteria:

If $\hat{f}(t+1|t) < 1612$ passenger cars per hour, then no congestion at time t+1 is predicted;
If $\hat{f}(t+1|t) \geq 1612$ passenger cars per hour, then congestion at time t+1 is predicted.

Conclusions

This study showed that using Kalman predictor in combination with the first-order autoregressive process of time series provided significantly improved traffic flow predictions over using only the time series method. This Kalman predictor model can predict traffic flow at construction zones dynamically with newly available traffic data at specified time intervals. Therefore, it can be used as an efficient tool for real-time construction zone traffic control and can be applied in such areas as highway construction planning and scheduling. A dynamic prediction of traffic flow rate at a construction zone with the Kalman predictor constitutes a dynamic prediction of traffic congestion as long as the traffic capacity at the construction zone is known.

Acknowledgments

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Appendix A

Comparison of Observed and Time Series Predicted Traffic Flow Rates

	Observed = *f(t)*	Time Series = $\hat{f}(t \mid t ? 1)$	Residual = *f(t)*- $\hat{f}(t \mid t ? 1)$
4:00	210	258.8	-48.8
4:10	237	235.3	1.7
4:20	328	260.4	67.4
4:30	218	344.6	-126.2
4:40	256	243.1	12.7
4:50	311	277.8	33.0
5:00	264	328.7	-65.0
5:10	321	285.1	35.4
5:20	226	337.8	-112.2
5:30	328	249.8	78.2
5:40	364	344.7	19.7
5:50	310	378.5	-69.0
6:00	300	327.6	-27.4
6:10	257	319.0	-61.8
6:20	449	279.0	169.9
6:30	348	456.7	-108.6
6:40	352	363.4	-11.2
6:50	413	367.1	46.1
7:00	434	423.7	10.4
7:10	351	443.0	-92.2
7:20	446	365.9	80.2
7:30	501	454.1	46.5
7:40	475	504.6	-29.3
7:50	494	481.3	13.1
8:00	535	498.9	36.3
8:10	668	536.7	131.7
8:20	595	660.2	-65.0
8:30	581	592.4	-11.9
8:40	719	578.8	140.3
8:50	678	707.2	-29.0
9:00	716	669.3	46.9
9:10	585	704.5	-119.9
9:20	736	582.6	153.3
9:30	784	722.8	61.6
9:40	633	767.6	-134.4
9:50	834	627.6	206.8
10:00	853	814.1	39.1
10:20	962	686.2	276.1
10:30	900	932.6	-32.6
10:40	889	874.9	13.8
10:50	675	864.3	-189.5
11:00	784	666.1	117.6
11:10	780	767.1	13.1
11:20	804	763.8	40.1
11:30	1026	785.8	239.9
11:40	735	991.4	-256.9
11:50	967	721.5	245.6
12:00	929	937.0	-8.4

Statistics of absolute values of residuals:

Mean=83.9 Standard Deviation = 72.9

Minimum = 1.7 Maximum = 276.1

Appendix B

Results of Time Series and Kalman Predictions

Time	Observed	Time Series	Kalman	Time-Series Residual (TR)	Kalman Residual (KR)	Abs(TR)-Abs(KR)
4:00	210	258.8	235.4	-48.8	-25.4	23.5
4:10	237	235.3	259.6	1.7	-22.6	-20.8
4:20	328	260.4	318.6	67.4	9.3	58.1
4:30	218	344.6	280.2	-126.2	-61.8	64.4
4:40	256	243.1	286.8	12.7	-31.0	-18.3
4:50	311	277.8	319.9	33.0	-9.1	23.8
5:00	264	328.7	305.8	-65.0	-42.1	22.9
5:10	321	285.1	332.4	35.4	-11.8	23.6
5:20	226	337.8	289.1	-112.2	-63.5	48.7
5:30	328	249.8	330.4	78.2	-2.4	75.8
5:40	364	344.7	366.0	19.7	-1.5	18.2
5:50	310	378.5	348.4	-69.0	-38.9	30.1
6:00	300	327.6	336.7	-27.4	-36.5	-9.1
6:10	257	319.0	308.3	-61.8	-51.2	10.6
6:20	449	279.0	405.0	169.9	43.9	126.0
6:30	348	456.7	384.3	-108.6	-36.2	72.4
6:40	352	363.4	379.0	-11.2	-26.8	-15.6
6:50	413	367.1	411.1	46.1	2.2	44.0
7:00	434	423.7	434.6	10.4	-0.5	9.9
7:10	351	443.0	396.7	-92.2	-45.9	46.3
7:20	446	365.9	436.0	80.2	10.1	70.1
7:30	501	454.1	480.9	46.5	19.7	26.7
7:40	475	504.6	483.3	-29.3	-7.9	21.3
7:50	494	481.3	494.8	13.1	-0.5	12.6
8:00	535	498.9	521.9	36.3	13.3	23.0
8:10	668	536.7	606.3	131.7	62.2	69.6
8:20	595	660.2	596.5	-65.0	-1.2	63.8
8:30	581	592.4	584.6	-11.9	-4.1	7.8
8:40	719	578.8	657.7	140.3	61.4	78.9
8:50	678	707.2	661.7	-29.0	16.5	12.5
9:00	716	669.3	684.5	46.9	31.8	15.2
9:10	585	704.5	619.3	-119.9	-34.7	85.2
9:20	736	582.6	679.8	153.3	56.1	97.3
9:30	784	722.8	729.2	61.6	55.2	6.4
9:40	633	767.6	662.9	-134.4	-29.7	104.7
10:00	853	814.1	793.8	39.1	59.4	-20.3
10:10	696	831.4	722.0	-135.0	-25.6	109.4
10:20	962	686.2	844.2	276.1	118.2	157.9
10:30	900	932.6	854.3	-32.6	45.7	-13.1
10:40	889	874.9	851.7	13.8	37.0	-23.2
10:50	675	864.3	731.2	-189.5	-56.4	133.1
11:00	784	666.1	747.8	117.6	36.0	81.6
11:10	780	767.1	751.9	13.1	28.3	-15.2
11:20	804	763.8	766.7	40.1	37.3	2.8
11:30	1026	785.8	896.0	239.9	129.7	110.2
11:40	735	991.4	780.9	-256.9	-46.4	210.5
11:50	967	721.5	868.5	245.6	98.6	147.0
12:00	929	937.0	879.2	-8.4	49.4	-41.0

Statistics of absolute values of residuals:

	Time Series	Kalman
Mean	83.9	37.1
Standard Deviation	72.9	29.0
Minimum	1.7	0.47
Maximum	276.1	129.7