DYNAMIC ADAPTIVE SHORT-TERM VEHICLE SPEEDS PREDICTION MODELS

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Abstract: This study presents various models for predicting short-term spot speeds of vehicles on a road section. The methodological approach is based on Multiple-Regression Analysis, Time-Series Forecasting (ARIMA), Artificial Neural Networks and Kalman Filtering. The critical point of predicting short-term speeds in this study is to use main deterministic factors as input or independent variables. Because a short-term prediction model needs to be flexible and easily adaptive to current traffic situations, it is important to determine the major factors that have important influence upon future traffic conditions directly. The objective of this study is therefore to predict average spot speeds of the subject location in the short-term periods of 5, 10 and 15 minutes respectively. In this study, field data were used to see the comparisons of the predictability of each model. These field data were collected from image processing detectors at the urban expressway for 17 hours including both peak and non-peak hours. Most of the results were reliable, but the results of models using Kalman Filtering and Neural Networks are more accurate and realistic than that of the others.

1. INTRODUCTION

Route guidance systems providing information for current and future traffic conditions to travelers play the most important role among all the functions of the Intelligent Transportation Systems (ITS). Most of the information is provided to travelers as reductive information about future traffic conditions after processing traffic data collected from various detectors.

Vythoulkas (1993) argued that "Traffic flow patterns observed in urban road networks are randomly varying with respect to time and space, to be efficient and accurate short term traffic forecasting, its procedures must ..... need to flexible and easily adaptive to current conditions." and used Kalman Filtering and Artificial Neural Networks/System Identification methods as prediction techniques. Okutain(1987) used Kalman Filtering as well. In addition to these studies many other methodological approaches have been studied about short-term prediction. However many short-term prediction procedures are analyzed as a black box. Therefore, in order to predict accurately the future traffic conditions that vary randomly with time and space, it is more efficient to use main factors that influence directly future traffic conditions rather than modify their procedures.

In this study, we present new approaches which can predict future traffic conditions more accurately and adaptively. The following section presents the structures of the proposed techniques such as Multiple regression Analysis, ARIMA, Artificial Neural Networks and Kalman Filtering. Section three focuses on determining the main factors, which explain traffic conditions accurately and adaptively, by using the correlation coefficient, partial correlation coefficient and part correlation coefficient. In sections four and five, the proposed techniques are tested using real data from image detector systems. In section six, we test the adaptability of each model. In the final section, a summarized conclusion based on the results of each model, and recommendations for future studies are provided.

2. MODEL IDENTIFICATION

There are many short-term predictive techniques. However, in this paper, Multiple-regression Analysis, a Time-Series Analysis (ARIMA), a Kalman Filtering technique and a method using Artificial Neural Networks are considered.

2.1 Multiple Regression Analysis

Multiple regression analysis is a statistical technique, which can be used to analyze the relationship between a single dependent variable and several independent variables. Therefore, the objective of the multiple regression analysis is to predict an unknown single dependent variable using the independent variables, whose values are known.

Let Y be a dependent variable and j, the number of independent variables; we denote these independent variables by $x_{i1},\dots,x_{ij}$.

The model is as follows.

$$Y_i = \alpha_i + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_j x_{ij} + E \tag{1}$$

Deviations around the regression line E are assumed to be independently normal distribution with a mean of zero and a standard deviation, which dose not depend on the levels of the independent variables.

By using the least square method, values of alpha and beta can be determined so as to minimize the error between prediction and observation. The error between prediction and observation is expressed as

$$L = \sum_i (Y_i - \alpha_i - \sum_j \beta_j x_{ij})^2 \tag{2}$$

where i is the number of observations, Y_i is the i *th* observation of dependent variable, j is the number of independent variables, and x_{ij} is the i *th* observation of the j *th* independent variable.

The first-order conditions for a stationary point of Eq.2 to minimize the error between observation and prediction are

$$\frac{\partial L}{\partial \alpha_i} = 0, \frac{\partial L}{\partial \beta_j} = 0 \tag{3}$$

And we solve the simultaneous Equation (3) to find parameters of α_i and β_j

2.2 ARIMA Technique

A Box-Jenkins method is used in predicting long-term and short-term information. Its strength is that it presents various models, which users can choose a model from a general theory of time series analysis.

General ARIMA(p,d,q) is described as below:

$$\phi(B)\Delta^d f(t) = \theta_0 + \theta(B)a(t) \tag{4}$$

Where, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$; AR operator

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

$f(t)$: the series value at time t

$\Delta f(t) = f(t) - f(t-1), \quad \Delta^d f(t) = \Delta[\Delta^{d-1} f(t)]$

$B(t) = f(t-1), B^m f(t) = f(t-m)$

when $d = 0$, the original process is stationary, but when $d \geq 0$, it is called the deterministic trend term and $a(t)$ is random noise.

Where, the optimal prediction time (D(t)) is decided as follows:

$$D(t) = f(t) - m(t) \tag{5}$$

m(t) : the historical smoothing value for time interval t

In the time series analysis, the critical procedure is to identify the model. This can be estimated by ACF, ρ_k and PACF, θ_{kk}. If the ACF tails off as exponential decay after lag(q-p) and if PACF tails off after lag(p-q), The model is determined as ARIMA(p,d,q).

2.3 Kalman Filtering Method

Kalman filtering is a recursive method, which estimates a temporary condition of linear dynamic system disturbed by Gaussian White noise. And it is a prediction process applied to dynamic systems that predict the optimal condition. This method is characterized as state average and covariance. In order to make this algorithm, first of all the state equation and observation equation should be made as follow:

$$X_{k+1} = \Phi_k X_k + w_k \qquad \text{(State equation)} \qquad (6)$$

$$Z_k = H_k X_k + v_k \qquad \text{(Observation equation)} \qquad (7)$$

where, X_k : $(n\times 1)$ state vector at time t_k

Φ_k : $(n\times n)$ transfer vector from time k to time k+1

Z_k : $(m\times 1)$ observation vector at time t_k

w_k : $(n\times 1)$ white sequence vector with known covariance that element's average is 0 and correlation with no other parameter

H_k : $(m\times m)$ connection vector between state vector and observation vector at time t_k

v_k : $(m\times 1)$ observation vector with known covariance and uncorrelated with w_k

The algorithm process is as follows and shown in Figure 1.

<Initialization> Input initial data

Former estimation $\hat{X}_{\bar{k}}$, covariance error vector $P_{\bar{k}}$

<Compute Kalman advantage> Compute Kalman gain by initial data

$$K_k = P_{\bar{k}} H_k^{\ T} (H_k P_{\bar{k}} H_k^{\ T} + R_k)^{-1} \qquad (8)$$

<Update state vector>

Update estimation state vector by using observation vector Z_k

<Compute covariance> Compute covariance about updated estimation

$$P_k = (1 - K_k H_k) P_{\bar{k}} \qquad (9)$$

<Predict the next value> The next former estimation

$$\hat{X}_{k+\bar{1}} = \Phi_k \hat{X}_k \qquad (10)$$

The next former covariance

$$P_{k+\bar{1}} = \Phi_k P_k \Phi_k^{\ T} + Q_k \qquad (11)$$

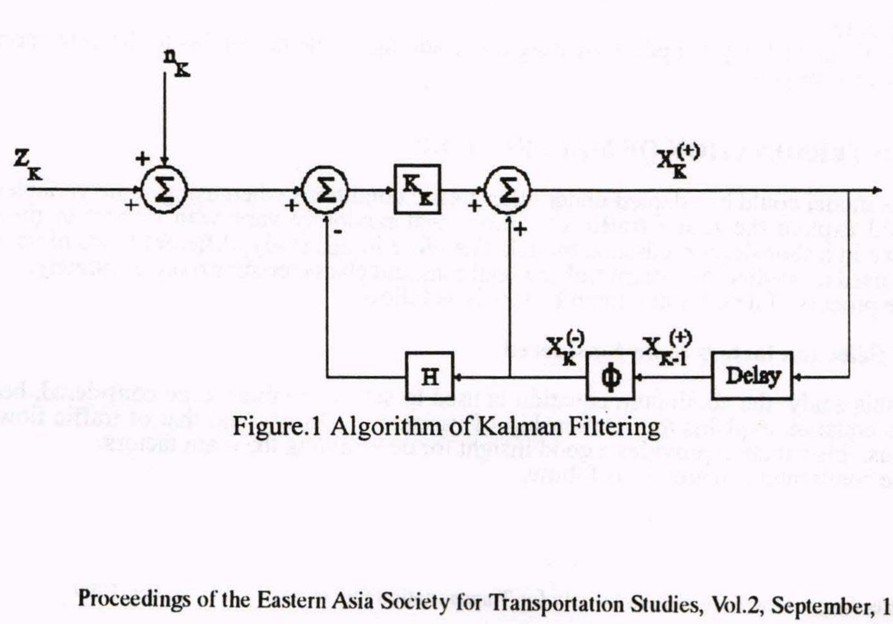


Figure.1 Algorithm of Kalman Filtering

2.4 Artificial Neural Networks Method

Artificial Neural Networks, which are made to imitate biological Neurons of human brain, are modeled mathematically to simplify connected relations of Neuron and realize to intelligently form a human brain. The most widely used model type is Multi Layer Feedforward(MLF). This Model uses Backpropagation that learns to control connection intensity of network from every input pattern to the direction where it minimizes error between output computed from input pattern and an objective value as a learning algorithm. Given input vector I, desired output vector D, the algorithm proceeds as follow.

<Pre-processing>
Remove the Noise in input data.
<Propagate >
Calculate output vector O by presenting input vector to the input layer

$$O^s{}_j = [\sum_i (W^s{}_{ji} O^s{}_i{}^{-1})] = f(I^s{}_j) \tag{12}$$

where, $O^s{}_j$: current output state of the j *th* processing element(PE) in layer s.

$W^s{}_{ji}$: weight on connection joining the i *th* PE in layer s-1 to the j *th* layers .

$I^s{}_j$: weighted summation of inputs to the j *th* PE in layer s .

<Calculate delta weight>
Calculate the scaled local error for each PE in the output layer.

$$e^0{}_k = -\partial E/\partial I^0{}_k = (-\partial E/\partial O^0{}_k)(\partial O^0{}_k/\partial I) = (D_k - O_k) f(I^0{}_k \_) \tag{13}$$

where E is global error $E = 0.5\sum_k (D^k - O_k)^2$

$e^s{}_j$ is the scaled local error of j *th* PE in layer s
k indicates the components of D, and O.

Then, calculate delta weight

$$\Delta W^s{}_{ji} = \eta e^s{}_j O^{s-}{}_i \tag{14}$$

$$(\because \partial E/\partial W^s{}_{ji} = (\partial E/\partial I^s{}_j)(\partial I^s{}_j/\partial W^s{}_{ji}) = -e^s{}_j O^s{}_i{}^{-1})$$

where η is a learning coefficient.

<Back-propagate>
For each PE in layer s,
Calculate the scaled local errors starting from output layer to input layer.

$$e^s{}_j = O^s{}_j(1 - O^s{}_j)\sum_k (e^{s+1}{}_k W^{s+1}{}_{kj}) \tag{15}$$

Then, calculate the delta weight

$$\Delta W^s{}_{ji} = \eta e^s{}_j O^{s-}{}_i \tag{16}$$

<Update>
For PEs in each layer, update all weights by adding the delta weights to the corresponding previous weights.

3. DETERMINATION OF MAIN FACTORS

This model could be adapted under other traffic conditions when using some variables that could explain the future traffic conditions that randomly vary with respect to time and space in a short-term prediction model. Therefore in this study, different kinds of variables are used to predict short-term traffic conditions and characteristics more accurately.
The process of determining main factors is as follow:

3.1 Selection factors to be considered

In this study, the continuum equation is used to select variables to be considered, because this equation explains the relationship of variance of density and that of traffic flow rate. Thus, this equation provides a good insight for determining the main factors.
The continuum equation is as follow.

$$k_j(n+1) = \frac{1}{2}[(k_{j+1}(n) + k_{j-1}(n)] - \frac{\Delta t}{2\Delta x}[q_{j+1}(n) - q_{j-1}(n)] + \frac{\Delta t}{2}[g_{j+1}(n) + g_{j-1}(n)] \quad (17)$$

in which,

$k_j(n)$: density on node j at the n *th* time step.

$q_j(n)$: flow rate on node j at the n *th* time step.

$g_j(n)$: generation rate at node j at the n *th* time step

(if no sinks or sources exist, $g_j(n) = 0$)

Δt, Δ : time and space increments, respectively.

This computation is proceeded by discretizing the space as small increments Δx and by updating the value of each traffic condition at every time increment Δi . Therefore, in this study, the proposed models are used to predict speed at the next time step. If it is assumed that speed has a linear relationship with density. Various explanatory variables (density of next nodes j+1 and previous nodes j-1 at the n *th* time step and flow rate of next nodes j+1 and previous nodes j-1 at the n *th* time step) could explain speed of node j at the next time step.

3.2 Determination of main factors

The basis for estimating all regression relationships is the correlation, which measures the association between two variables. If the independent variables are correlated, then they "share" some of their predictive powers. The shared variance must not be "doubled counted" by using direct correlation. The partial correlation coefficient, which is the correlation of an independent variable and dependent variable when the effects of the other independent variables have been removed from both independent variable and dependent variable.

Partial correlation of u ,k given v

$$= \frac{Corr\ \ of\ \ u\,k - (Corr\ \ of\ \ u\,v \times Corr\ \ of\ \ k\,v)}{\sqrt{(1.0 - Corr\ \ of\ \ u\,v)(1.0 - Corr\ \ of\ \ k\,v)}} \quad (18)$$

where, *Corr of u k* is simple correlation coefficient between k and u.

The part correlation represents the unique relationship predicted by an independent variable after the predictions shared with all other independent variables are taken out. Thus, the part correlation is used in apportioning variance among the independent variables. This process is to reduce the effect of multicollinearity. The part correlation between the dependent variable(u) and an independent variable(k) while controlling for a second independent variable(v) is calculated by the following equation:

Part correlation of u ,k given v

$$= \frac{Corr\ \ of\ \ u\,k - (Corr\ \ of\ \ u\,v \times Corr\ \ of\ \ k\,v)}{\sqrt{1.0 - (Corr\ \ of\ \ k\,v)^2}} \quad (19)$$

The calculation of shared and unique variance illustrates the effects of multicollinearity on the ability of the independent variables to predict the dependent variable.

4. APPLICATIONS

In this study, the proposed models were experimented and compared with results by using collected field data. These real data were collected from five image processing detectors (#3, 4, 5, 6, 7) in every one minute interval for 17 hours in the Olympic Expressway in Seoul, Korea, and these collected data consist of speed, flow rate and occupancy on April 2, 1998. The number and location of detectors is shown in Figure2.

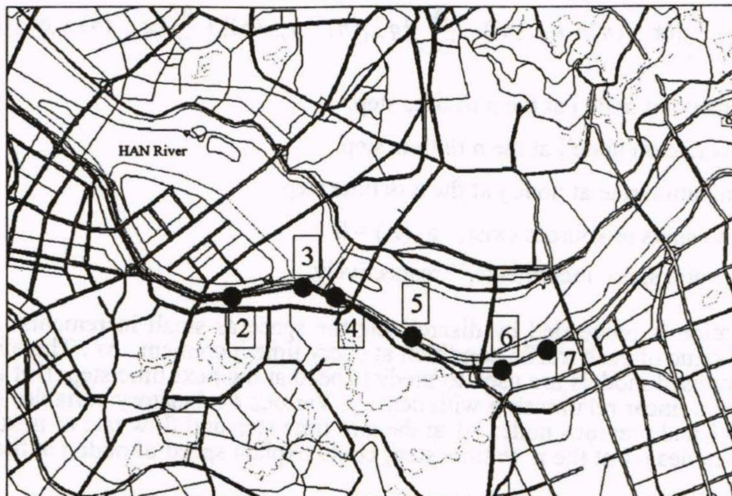


Figure 2. The Locations and Numbers of Image Processor Detectors

As shown in section 3.1, the continuum equation was used to select the variables to be considered. Therefore, in this section, the density, speed and flow rate collected from the

Table 1. The Simple Correlation coefficient between selected variables

	VOL_4	SPD_4	OCC_4	VOL_5	SPD_5	OCC_5	VOL_6	SPD_6	OCC_6	MIN1	MIN5	MIN10	MIN15	MIN30
VOL_4	1.00	-0.34	0.73	0.92	-0.41	0.64	0.89	-0.55	0.62	-0.41	-0.43	-0.45	-0.46	-0.50
SPD_4	-0.34	1.00	-0.79	-0.29	0.32	-0.33	-0.22	0.30	-0.27	0.34	0.37	0.41	0.44	0.47
OCC_4	0.73	-0.79	1.00	0.68	-0.42	0.57	0.62	-0.47	0.51	-0.43	-0.46	-0.50	-0.52	-0.58
VOL_5	0.92	-0.29	0.68	1.00	-0.42	0.66	0.90	-0.57	0.64	-0.42	-0.44	-0.45	-0.45	-0.48
SPD_5	-0.41	0.32	-0.42	-0.42	1.00	-0.90	-0.37	0.78	-0.76	0.91	0.86	0.82	0.80	0.66
OCC_5	0.64	-0.33	0.57	0.66	-0.90	1.00	0.61	-0.79	0.81	-0.87	-0.82	-0.79	-0.77	-0.68
VOL_6	0.89	-0.22	0.62	0.90	-0.37	0.61	1.00	-0.51	0.56	-0.38	-0.35	-0.37	-0.38	-0.40
SPD_6	-0.55	0.30	-0.47	-0.57	0.78	-0.79	-0.51	1.00	-0.95	0.78	0.78	0.77	0.75	0.68
OCC_6	0.62	-0.27	0.51	0.64	-0.76	0.81	0.56	-0.95	1.00	-0.76	-0.78	-0.76	-0.75	-0.68
MIN1	-0.41	0.34	-0.43	-0.42	0.91	-0.87	-0.38	0.78	-0.76	1.00	0.87	0.83	0.80	0.67
MIN5	-0.43	0.37	-0.46	-0.44	0.86	-0.82	-0.35	0.78	-0.78	0.87	1.00	0.86	0.82	0.72
MIN10	-0.45	0.41	-0.50	-0.45	0.82	-0.79	-0.37	0.77	-0.76	0.83	0.86	1.00	0.86	0.76
MIN15	-0.46	0.44	-0.52	-0.45	0.80	-0.77	-0.38	0.75	-0.75	0.80	0.82	0.86	1.00	0.80
MIN30	-0.50	0.47	-0.58	-0.48	0.66	-0.68	-0.40	0.68	-0.68	0.67	0.72	0.76	0.80	1.00

In table 1, and figure 2., VOL_j is flow rate of the j *th* node, SPD_j is speed of the j *th* node, OCC_j is occupancy of the j *th* node, and MIN_j is speed of the subject node at the j *th* time slice.

As shown in table 1 and figure 3, the simple correlation coefficient were calculated. The results show a symmetric pattern. In table 1, the higher value shows, the higher predictive power, and in figure 3, the more intensive along the line indicates, the higher the predictive power. Therefore, SPD_5, OCC_5, SPD_6 and OCC_6 show high predictive powers. But if the independent variables are correlated, then this that they are doubled counted. Therefore, partial and part(semi-partial) correlation coefficients must be calculated by equation(18) and (19) using simple correlation coefficient, as shown in the table 2. These values are part and partial correlation between the dependent variables that are in the column and an independent variable that is in the row while controlling for the others variables.

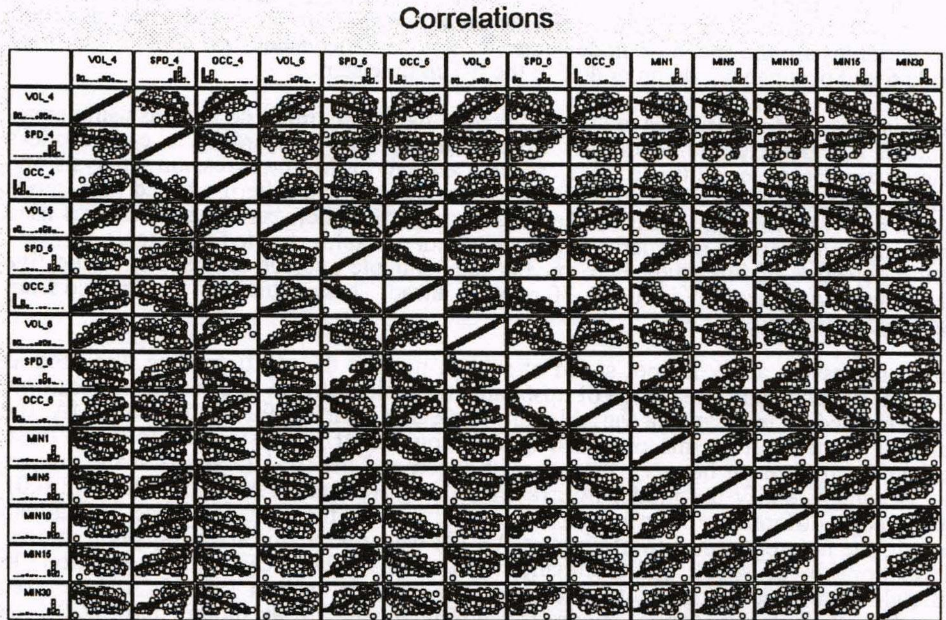


Figure 3. The Simple Correlation coefficient between selected variables

Table 2. The Partial and Part Correlation coefficient between selected variables

Controlled the others variables	Partial Correlation Coefficient					Part Correlation Coefficient				
	MIN1	MIN5	MIN10	MIN15	MIN30	MIN1	MIN5	MIN10	MIN15	MIN30
VOL_4	0.051	-0.037	-0.043	-0.062	-0.061	0.019	-0.017	-0.022	-0.033	-0.039
SPD_4	0.093	0.128	0.158	0.146	0.111	0.035	0.058	0.080	0.078	0.071
OCC_4	0.038	0.032	0.019	-0.019	-0.087	0.014	0.014	0.010	-0.010	-0.056
VOL_5	0.066	-0.017	0.015	0.022	0.015	0.024	-0.008	0.008	0.012	0.009
SPD_5	0.410	0.299	0.206	0.242	0.091	0.167	0.140	0.106	0.132	0.058
OCC_5	-0.290	-0.180	-0.158	-0.077	-0.058	-0.113	-0.082	-0.081	-0.041	-0.037
VOL_6	0.002	0.169	0.115	0.100	0.085	0.001	0.077	0.058	0.053	0.054
SPD_6	0.099	0.028	0.059	0.033	0.059	0.037	0.012	0.030	0.017	0.038
OCC_6	-0.027	-0.144	-0.116	-0.125	-0.088	-0.010	-0.065	-0.059	-0.067	-0.056

Table 3. The selected input variables for each models

Input Variables	Multi-regression Analysis & Artificial Neural Networks					ARIMA Model & Kalman Filtering				
	MIN1	MIN5	MIN10	MIN15	MIN30	MIN1	MIN5	MIN10	MIN15	MIN30
VOL_4										
SPD_4		V	V	V	V					
OCC_4										
VOL_5										
SPD_5	V	V	V	V	V	V	V	V	V	V
OCC_5	V	V	V			Where input variable is the differentiated value between nth time slice and n-1th time slice				
VOL_6		V	V	V	V					
SPD_6										
OCC_6		V	V	V	V					

As the value of partial and part correlation coefficient in table 2., variables shown the high explanatory value for speed of subject node at each time slice are presented with a dark cell. These variables are the speed on node 4, speed on node 5, occupancy on node 5, flow rate on node 6 and occupancy rate on node 6 at the n-1 *th* time step.

So, in this study, these variables are used to predict the future traffic conditions using every technique. But these chosen variables were used differently according to each model's characteristic. Because multi variables can be used only in Multi-regression Analysis and Artificial Neural Networks, but in ARIMA Model and Kalman Filtering based time-series analysis, only one variable, which is the difference of speed between time slices, was used as input variable. Table 3 summarized selected major variables resulted from table 2. And the objective of this study is to predict the 1 minute average spot speed of the five kinds of next time slice i.e., 5, 10, 15, 30 minutes ahead. These values can be detected from image processing detector No 5.

In multi-regression analysis spot speed of subject node at the nth time slice was used as dependent variable, and spot speed of upstream and subject stream node at the current time slice were used as independent variables In time-series analysis forecasting, ARIMA, the procedure carried out in this proposed model, consists of three steps as follows: First, calculate the difference between the nth spot speed and the (n+1)*th* speed at the subject node. Second, identify the model by examining into ACF and PACF as ARIMA(1,0,0). Third, predict differences of speeds of the subject node at the next time slice. In Kalman Filtering, the autoregression coefficient of AR (1) was used as the state-transition matrix, and relationship of speed and occupancy was used in the measurement equation. In Artificial Neural Networks, input vector was already determined in Table 3. And we used 0.2 as learning rate, sequential mode as learning mode, 0.2 as momentum, 9-20-1 as network designing, backpropagation as running rule and 20,000 as learning numbers.

To test the reliability and accuracy of the proposed model, the following various prediction error measures were used.

(1) Mean Absolute Relative Error; $\text{MARE}=\frac{1}{N}\sum_{t}\left|\frac{X_{real}(t)-X_{pred}(t)}{X_{real}(t)}\right|$

(2) Mean Absolute Error; $\text{MAE}=\frac{1}{N}\sum_{t}\left|X_{real}(t)-X_{pred}(t)\right|$

(3) Equality Coefficient; $\text{EC}=1-\frac{\sqrt{\sum_{t}\left[X_{real}(t)-X_{pred}(t)\right]^{2}}}{\sqrt{\sum_{t}X_{real}(t)^{2}}+\sqrt{\sum_{t}X_{pred}(t)^{2}}}$

(4) Mean Square Error; $\text{MSE}=\frac{1}{N}\sum_{t}\left[X_{real}(t)-X_{pred}(t)\right]^{2}$

5. RESULTS OF PREDICTION

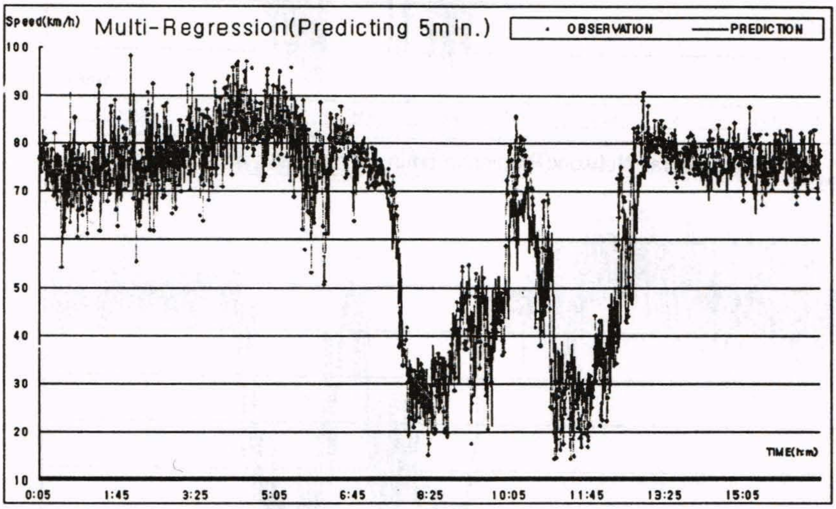
The previous section described both of each model's identifications and selecting major input or independent variables for prediction. This section presents the result of each model predicting speed for each prediction time interval. To compare results between models, results of proposed models were sorted in order of prediction time interval i.e., 5, 10 and 15 minutes. And in this section, each Figure and Table show predicted and observed spot speeds at every 1 minute for 17 hours in each proposed model. In addition, the value of speeds collected from detectors varied from 98 to 14 km/h. Therefore these data contain various states of traffic conditions.

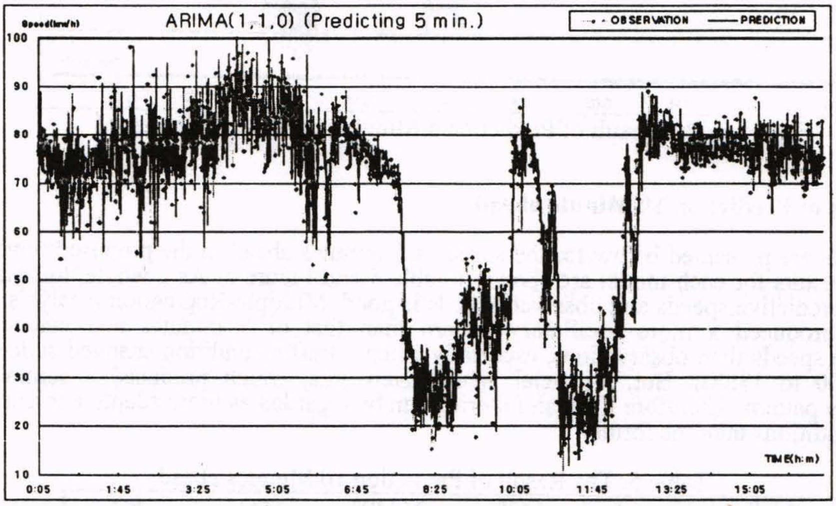
5.1 Result of Prediction 5 Minute ahead

The results for predicting the speed of 1 minutes ahead in proposed models. And Table 4 and Figure 4 show results for each model. As a whole, the matches are presented below between predictive speeds and observed speeds are good. But from 10:05 to 11:45, Multiple-regression analysis predicted lower than the observations, and produced a little oscillatory pattern than that of 1 min. As can be seen in these results, the decreasing rate of accuracy of Multiple-Regression and ARIMA Model was greater than those of the Kalman Filtering and Artificial Neural Networks, so the latter can be regarded to be more adaptive to current traffic conditions than the former.

Table 4. The Result of Prediction 5 Minutes ahead

Prediction interval	MSE	MARE	MAE	EC
Multi-Regression	76.025	0.127	6.483	0.951
ARIMA(1,1,0)	81.028	0.124	6.669	0.950
Kalman Filtering	43.286	0.073	4.381	0.967
Neural Networks	51.271	0.100	5.174	0.961





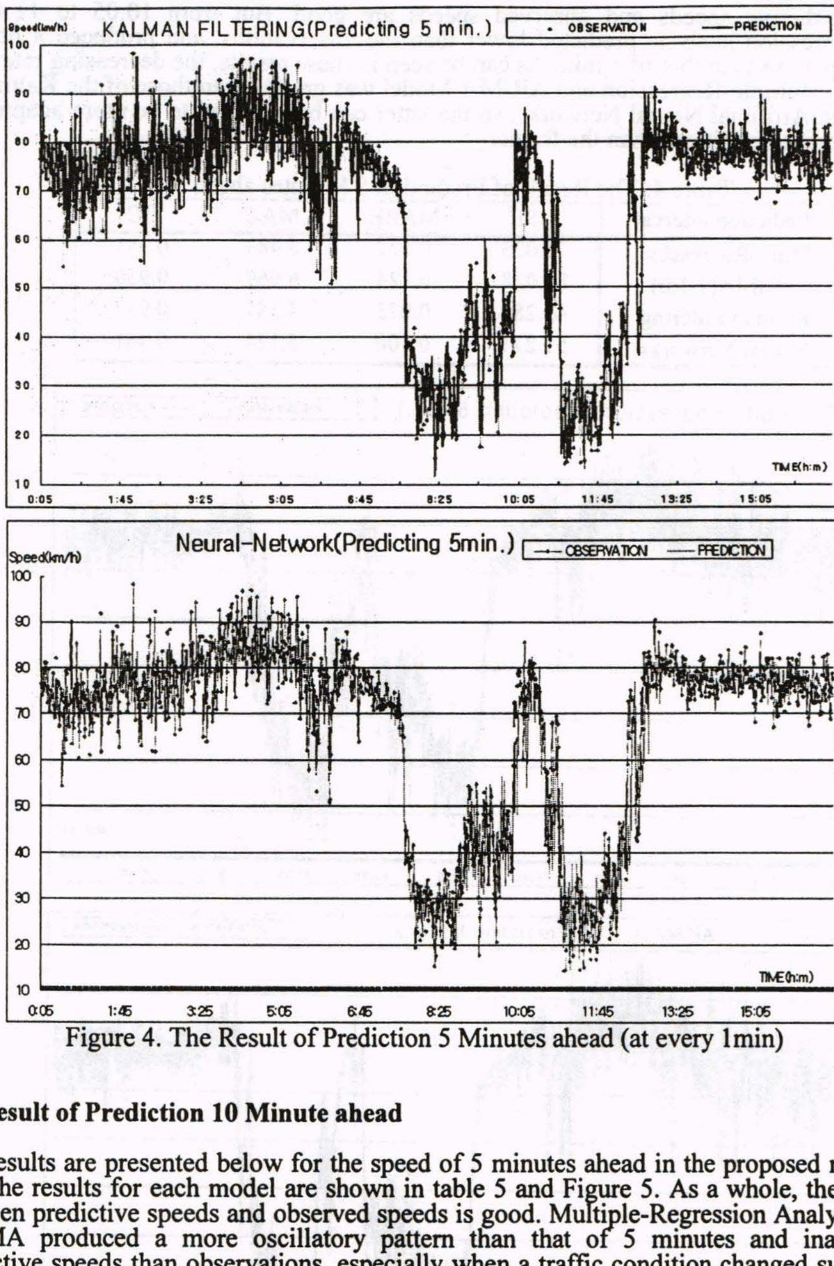


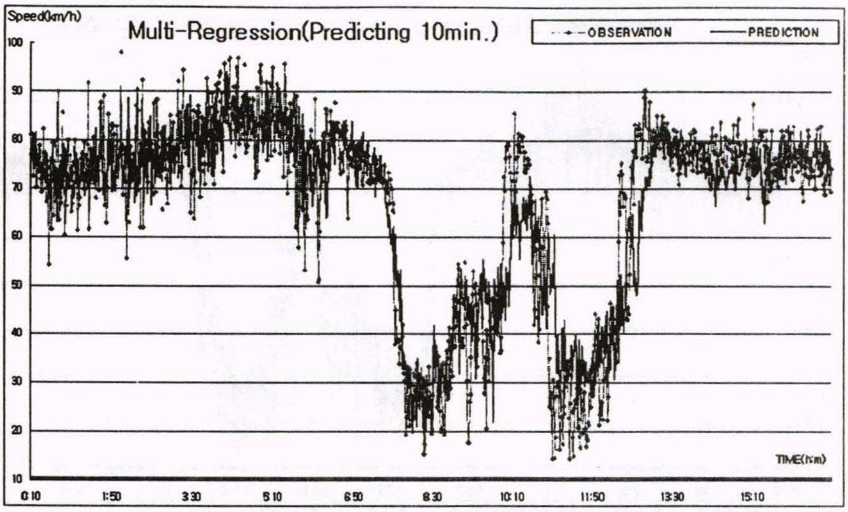
Figure 4. The Result of Prediction 5 Minutes ahead (at every 1min)

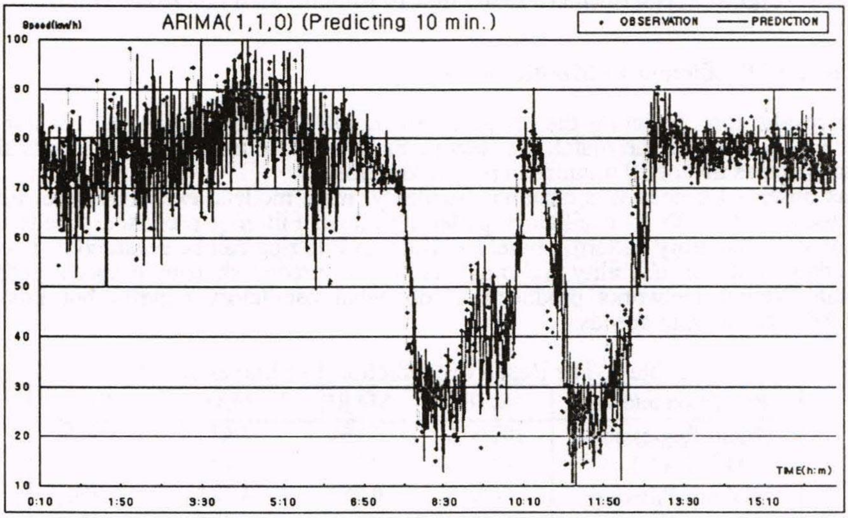
5.2 Result of Prediction 10 Minute ahead

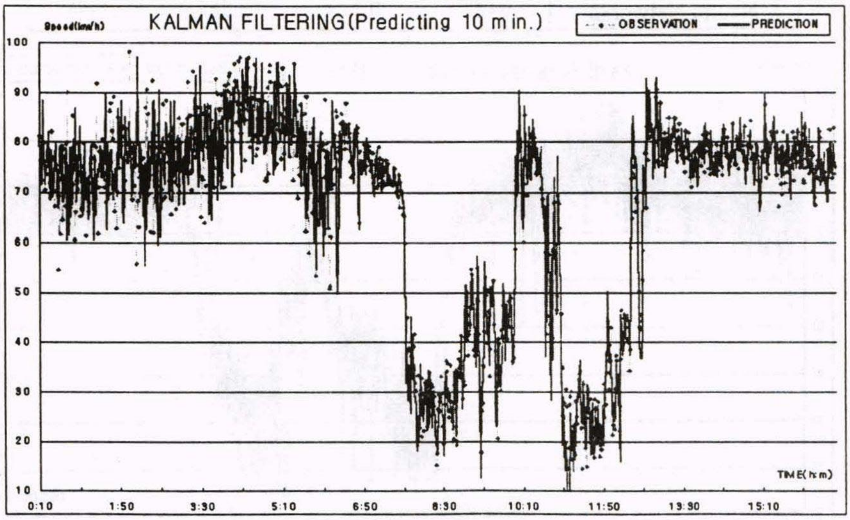
The results are presented below for the speed of 5 minutes ahead in the proposed models. And the results for each model are shown in table 5 and Figure 5. As a whole, the match between predictive speeds and observed speeds is good. Multiple-Regression Analysis and ARIMA produced a more oscillatory pattern than that of 5 minutes and inaccurate predictive speeds than observations, especially when a traffic condition changed suddenly (from 7:00 to 13:00). But, Artificial Neural Networks, which produced a somewhat oscillatory pattern. Therefore Kalman Filtering can be regarded as more adaptive to current traffic conditions than the former.

Table 5. The Result of Prediction 10 Minutes ahead

Prediction interval	MSE	MARE	MAE	EC
Multi-Regression	96.226	0.145	7.150	0.946
ARIMA(1,1,0)	91.911	0.133	7.088	0.946
Kalman Filtering	46.315	0.080	4.611	0.965
Neural Networks	58.294	0.105	5.518	0.958


Speed(km/h)
Multi-Regression(Predicting 10min.)
OBSERVATION
PREDICTION
100
90
80
70
60
50
40
30
20
10
TIME(h:m)
0:10
1:50
3:30
5:10
6:50
8:30
10:10
11:50
13:30
15:10


ARIMA(1,1,0) (Predicting 10 min.)
OBSERVATION
PREDICTION
100
90
80
70
60
50
40
30
20
10
TIME(h:m)
0:10
1:50
3:30
5:10
6:50
8:30
10:10
11:50
13:30
15:10


KALMAN FILTERING(Predicting 10 min.)
OBSERVATION
PREDICTION
100
90
80
70
60
50
40
30
20
10
TIME(h:m)
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1:50
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8:30
10:10
11:50
13:30
15:10

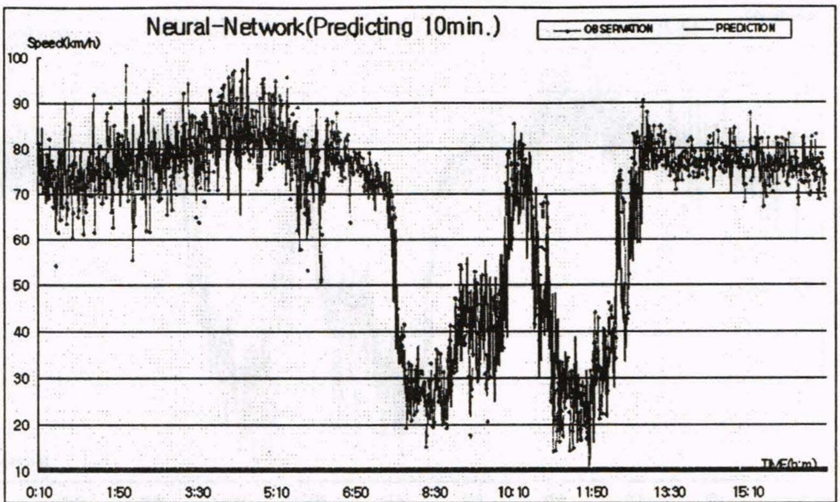


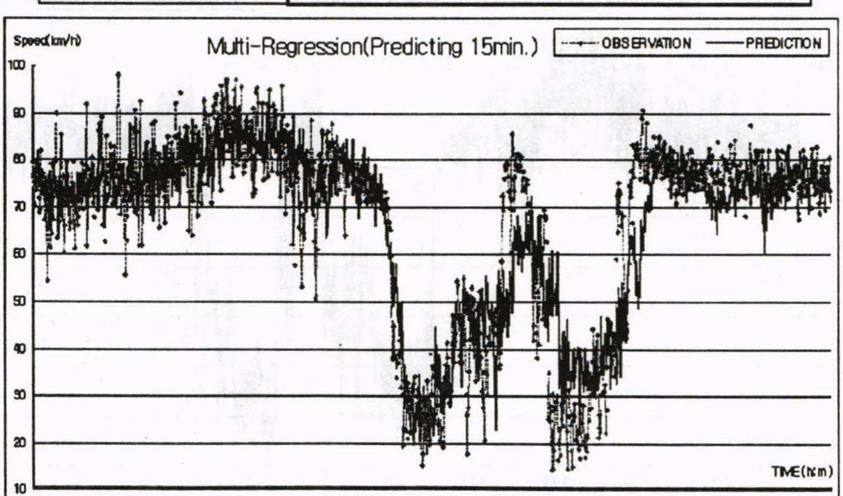
Figure 5. The Result of Prediction 10 Minutes ahead (at every 1min)

5.3 Result of Prediction 15 Minutes ahead

The results for Predicting the speed of 15 minutes ahead are shown in Table 6 and Figure 6. As a whole, the match between predictive speeds and observed speeds shows a similar shape as that of 10 minutes in proposed models.
And as observed speeds was changing suddenly, most models, except Kalman Filtering, predicted speeds with an oscillatory pattern. Kalman Filtering predicted speeds directly without any oscillatory pattern. Therefore, Kalman Filtering can be regarded as having the most adaptability in reliability and transferability to predict short-term spot speeds. And, Artificial Neural Networks produced a somewhat oscillatory pattern, but this model predicted accurate spot speeds.

Table 6. The Result of Prediction 15 Minutes ahead

Prediction interval	MSE	MARE	MAE	EC
Multi-Regression	107.616	0.161	7.682	0.942
ARIMA(1,1,0)	87.898	0.137	7.146	0.946
Kalman Filtering	46.068	0.084	4.724	0.964
Neural Networks	64.775	0.113	5.764	0.956



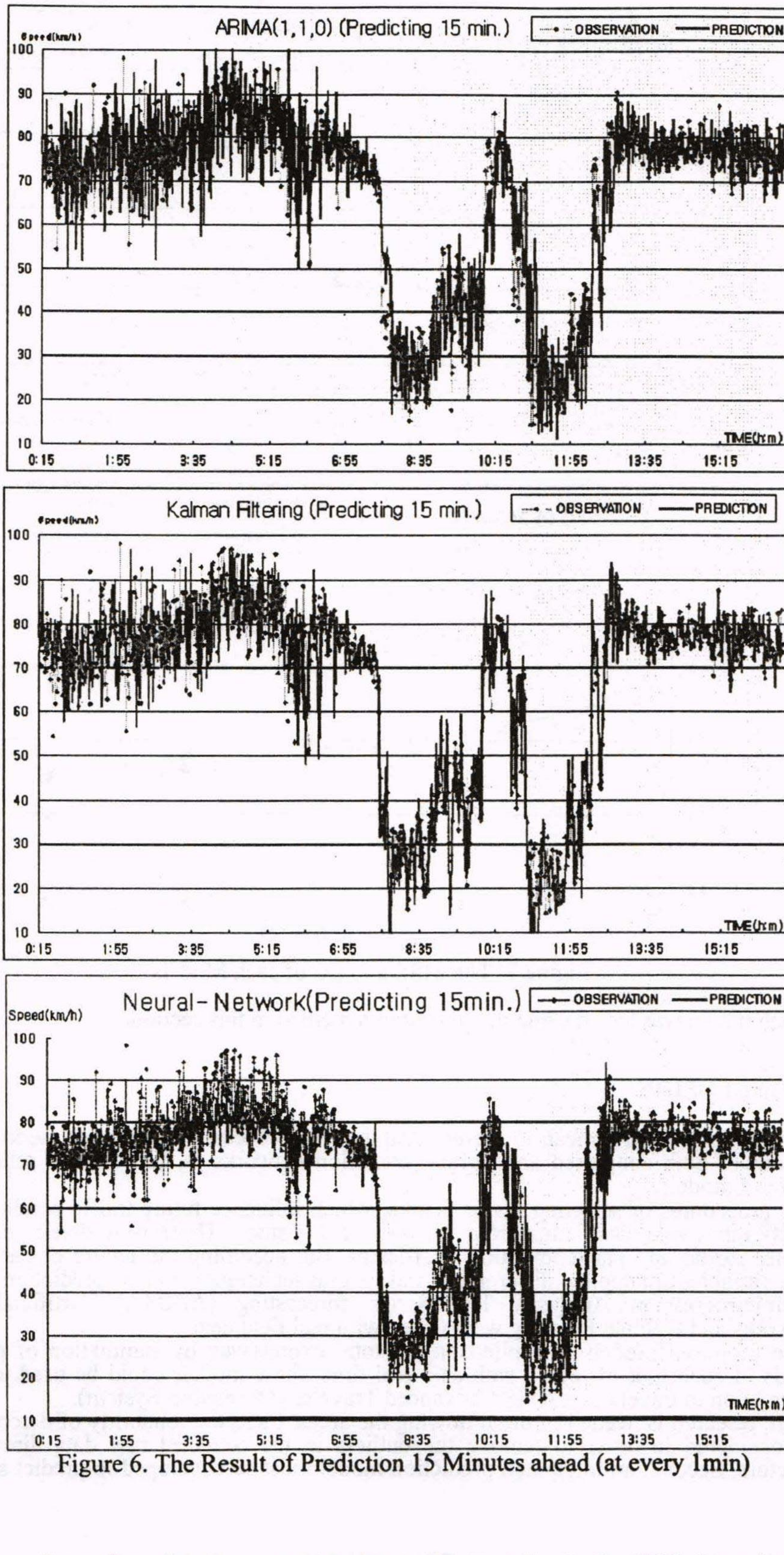


Figure 6. The Result of Prediction 15 Minutes ahead (at every 1min)

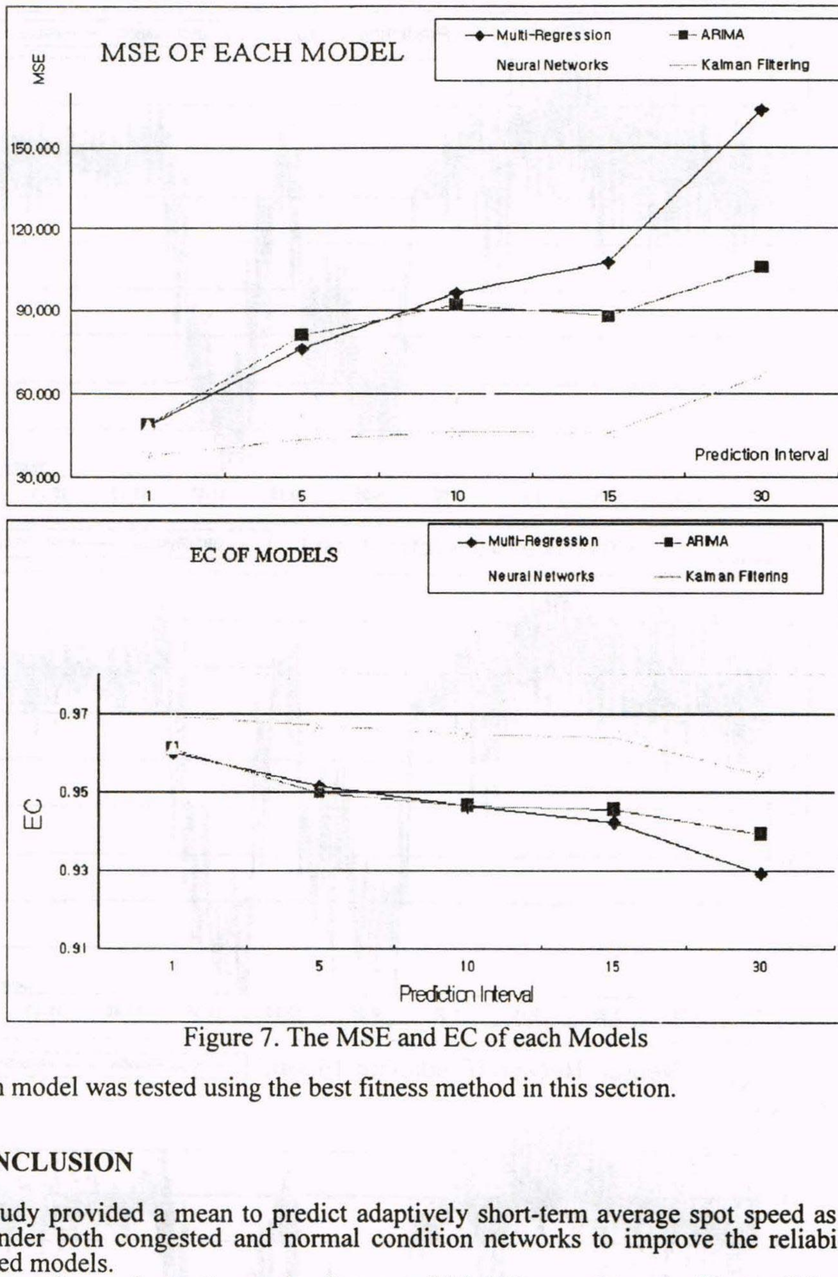


Figure 7. The MSE and EC of each Models

Each model was tested using the best fitness method in this section.

6. CONCLUSION

This study provided a mean to predict adaptively short-term average spot speed as a real time under both congested and normal condition networks to improve the reliability of proposed models.

The procedures of selecting major factors, which influence future traffic conditions, and modify input variables, is important analysis of this study. Those were determined by the simple, partial and part-correlation coefficient. But according the nature of each model, input variables are applied differently. And various techniques such as prediction based on Multiple-regression Analysis, Time-Series forecasting (ARIMA), Artificial Neural Networks and Kalman Filtering were tested with real field data

If the proposed models is applied on the total expressway by summation of predictive speeds of each link for every path as a real time, these models could be used to provide information to travelers in ATIS (Advanced Traveler Information System).

Future research is needed in the following the areas. First, the reliability of detectors must be considered in order to remove the outliers in the collected raw data directly from detectors. Second, an integrated prediction model must be developed to predict accurately in random situations such as incident and congestion.

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