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Traffic-Flow Forecasting Using a 3-stage Model

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Abstract –During the past few years, various traffic-flow forecasting models, i.e. an ARIMA, an ANN, and so on, have been developed to predict more accurate traffic flow. However, these strategies rest on the assumption that the pattern that has been identified will continue into the future. So ARIMA or ANN models with its traditional architecture cannot be expected to give good predictions unless this assumption is valid.
In this paper, we compared with an ANN model and ARIMA model and tried to combine an ARIMA model and ANN model for obtaining a better forecasting performance. In addition to combining two models, we also introduced judgmental adjustment technique that has an effect on correcting irregular and infrequent future events. Our approach can improve the forecasting power in traffic flow. To prove it, we have compared the performance of the models.

Keywords: Traffic Forecasting, ARIMA, Neural Network, and Judgmental Adjustment

1. Introduction

During the past few years, various traffic-flow forecasting models have been developed and forecasting accuracy has been improved substantially. Since a great deal of traffic data are observed in the form of a time series which is a collection of observations made sequentially, time series analysis is a valuable tool for traffic flow prediction. Furthermore, a variety of application on a high-speed digital computer enables us to consider the much more general and statistically based methods such as an Autoregressive (AR) model, a Moving Average (MA) model, an Autoregressive Integrated Moving Average (ARIMA), a Kalman Filtering model, and an Artificial Neural Network (ANN) model.

ARIMA models are, in theory, the most general class of models for forecasting a time series that can be stationarized by transformations such as differencing and logging. Box and Jenkins present a general methodology for developing an appropriate ARIMA time series model and using the model in forecasting. In the statistical field, the ARIMA models are said to be optimal forecasts. They are optimal in the sense that no other uni-variate forecasts have a smaller mean squared error (MSE). However, this comparison is valid only for those uni-vaiate models that are linear combinations of the past values in the time series, with fixed coefficients. Although non-linear regression techniques do exist, they require much more computational and intellectual efforts. This fact severely limits their practicality.

Since 1990, ANN models have been used in traffic flow forecasting and a vigorous campaign has been unfolded. Especially the use of ANN for forecast and even modeling of nonlinear dynamical systems has been successfully investigated. Many researchers have claimed that ANN models are superior to traditional statistical models in forecasting future events. Many experiments have been conducted on prediction accuracy of neural forecasting models and claimed much better performance than conventional models in stock price prediction, system operation forecasting, signal forecasting, and others. As a matter of fact, mathematical theorems have proved that a three-layer feed-forward ANN, with sigmoidal units in the hidden layer, can approximate a given real-valued, continuous multi-variate function to any desired degree of accuracy [1,2]. Furthermore, the consistency property of three-layer feed-forward networks has also been established in [3], which, in turn, implies that this kind of ANN possess non-parametric regression capabilities.
However, these models analyze historical data in an attempt to predict future value of a variable of interest. They make use of the following basic strategy. Past data are analyzed in order to identify a pattern that can be used to describe them. Then this pattern is extrapolated, or extended, into the future in order to make forecasts. This strategy rests on the assumption that the pattern that has been identified will continue into the future. So ARIMA or ANN models with its traditional architecture cannot be expected to give good predictions unless this assumption is valid [4].

A method to overcome this limitation can be observed from the forecasting experts practice of judgmental adjustment on the time series models. Judgmental adjustment is to make right for factors that cannot be fully incorporated into the time series models, and thus cannot be effectively identified by the extrapolation of past patterns in the data set [5]. For example, if significant internal and external changes cannot be reflected in the statistical model, forecaster or manager should incorporate subjective judgments to modify the statistical forecast. In fact, this judgmental adjustemnt approach has been widely used in practical fields more than theoretical forecasting. The reason of using judgmental adjustment technique is that we cannot construct a huge forecasting model due to difficulty in formulating mathematical form of irregular events, inefficiency of identification of huge mode and so on.

The characteristics of these factors are:

1. The factors occur irregularly and infrequently. Thus the number of data point is usually too small for statistical modeling.
2. Nevertheless, the impact is too significant to neglect.
3. The effect is transient
4. The occurrence of coming events can be recognized in advance although it is not easy to judge their impact precisely

In this study, we have attempted to combine with an ANN model and an ARIMA model, and to model judgmental adjustment processes to design more correct traffic-flow forecasting model than a single forecasting model. In the aspect of forecasting power, each model is compared with only linear statistical models such as the ARIMA model and traditional ANN model.

2. Proposed Architectures

The architectures that we propose and compare are described as Table 1.

Generally traffic flow data include several means such as travel speed, queue lengths, queue length ratio, and number of arriving vehicles per cycle. In this paper, we make only mention of travel speed on the interesting road because of other factors being able to take same approaches and travel speed representing other factors.

1339 times series data points in 5-minute intervals were collected for this research from 09:25 on Oct. 15th to 00:55 on Oct. 20th in 1999 between the East Kwang-ju interchange and the Hyu-juck crossing street.

Table 1. The architecture of Proposed models

	The architecture of models
Model 1	• A simple ANN model • Back-Propagation (BP) training method • Inputs: 1039 data points on road 28
Model 2	• A simple ARIMA model • Inputs: 1039 data points on road 28
Model 3	• ARIMA + ANN • Back-Propagation (BP) training method • Inputs - 1039 data points on road 28 - The output of ARIMA model
Model 4	• ANN + Judgmental Adjustment • Back-Propagation (BP) training method • Inputs - 1039 data points on road 28 - Near roads' impact on road 28
Model 5	• ARIMA + Judgmental Adjustment • Outputs = the outputs of ARIMA + the outputs of J.A
Model 6	• ARIMA + ANN + Judgmental Adjustment • Outputs = the outputs of (ARIMA + ANN) + the outputs of J.A

The distance between the East Kwang-ju interchange and the Hyu-juck crossing street is about 10 km, hence therefore vehicle's travel time is about from 5 minutes to 10 minutes under the real condition: most of the vehicles travel at a speed of about 40 km an hour. The rough map is sketched in Fig. 1.

Fig. 2 is to plot time series data of vehicle speed on the Dong-Moon Street during a day. In this figure, we can know the characteristics of the traffic data. Because a lot of traffic flows in the daytime (07:00-19:00) causes traffic jam, vehicles travel at a speed of below 20 km/h. On the other hand, few vehicles travel early in the morning (00:00-06:00), therefore vehicle speed varies from 50 km/h to 140 km/h according to only drivers' habit.

Figure 1. The rough map around an interesting road (Dong-Moon Street)

The deviation of vehicle speed at dawn occurs experimental uncertainty as well as no significance, so we convert the speed over 70 km/h to 70 km/h. On special case that no vehicle travels on the road, vehicle speed is recorded as 0 km/h. we also convert 0 km/h to 75 km/h.

1039 data points from 09:25 on Oct. 15th to 23:55 on Oct. 18th were used for learning. The remaining 300 data points from 00:00 on Oct. 19th to 00:55 on Oct. 20th, i.e. 25 hour-data points, were used for test.

The research develops six kinds of models to forecasting the traffic flow: predicting vehicle speed on target road for 5 minutes ahead. Each predicting data is used to the performance validation of an ARIMA, an ANN, and judgmental adjustment. As a result, we can identify whether an ANN model is superior to an ARIMA model in aspect to the traffic prediction or not, and whether judgmental adjustment has an effect on the forecasting or not. The evaluation criteria adopted were Mean Squared Errors (MSE) and Mean Absolute Errors (MAE).

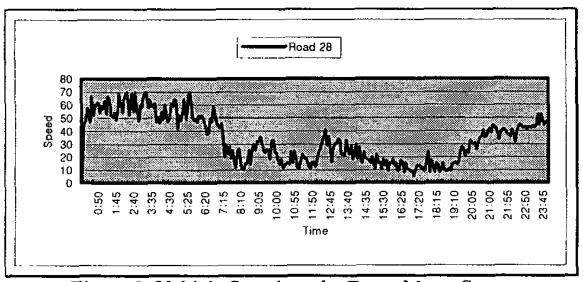

Figure 2. Vehicle Speed on the Dong-Moon Street

3. Experiments

3.1 A Simple ANN Model

These parameters decide the forecasting performance of the ANN, however there is no criterion for deciding optimal parameters. Thus the techniques of the deciding parameters base on only heuristic methods. One of the heuristic methods is the Hecht-Nielsen theorem by which we can determine the number of hidden nodes. The Hecht-Nielsen theorem is to guarantee that the number of hidden nodes does not need to exceed $2n+1$ where n is the number of input nodes [6].

In the paper, we designed several neural network architectures to determine the best on. As input variables, we selected three input variables (demand at ***t-1, t-2*** to reflect regency, and ***d-1*** to reflect the seasonal cycle) along with the optional ones from ***t-3, t-4, t-5, t-6, t-7***. For hidden nodes, we again selected even numbers of hidden nodes between ***1*** to ***2n+1***. In the experiments we don't consider weekend factor due to no significant difference with weekend and weekday in vehicle speed when 5% significance level is applied.

The designed neural network architectures and forecasting performance in aspect of MSE and MAE are shown in Table 2.

Table 2. The neural network architectures and forecasting performance[1]

Input Nodes		Number of Hidden Nodes	MSE	MAE
Number	Node's Time Tag			
3	t-1, t-2, d-1	2	36.3646	4.7749
		4	33.6902	4.7096
		6	34.0149	4.7090
4	t-1, t-2, t-3, d-1	2	33.7409	4.7391
		4	33.1635	4.6945
		6	33.7135	4.9070
		8	33.9533	4.7003
5	t-1, t-2, t-3, t-4, d-1	2	34.6072	4.7294
		4	33.7879	4.6593
		6	35.7071	4.8102
		8	36.5722	4.8214
		10	35.8964	4.8404
6	t-1, t-2, t-3, t-4, t-5, d-1	2	34.7143	4.7333
		4	34.4038	4.6983
		6	36.6942	4.8393
		8	35.9956	4.7962
		10	39.7751	4.9747
		12	38.2846	4.9133
7	t-1, t-2, t-3, t-4, t-5, t-6, d-1	2	34.4528	4.6877
		4	35.4224	4.7416
		6	34.5496	4.6591
		8	37.4167	4.8431
		10	38.3701	4.9843
		12	40.1798	5.0963
		14	38.4336	4.9541

We trained all of the neural networks for 2000 epochs with 1039 data points out of 1339. The trained neural network models were tested with the remaining 300 data points. Every experiment is repeated eight times and the least average MSE of eight values is chosen for preventing performance index from converging local minimum. Also changing the number of nodes is useful to prevent curve's underfitting or overfitting, which is caused by the use of few adjustable parameters or many parameters.

Among the best ones, the ANN (4-4-1) was selected as the ANN model because it had the minimum MSE.

The general characteristics of the ANN forecasting data are described as follows.

1. In the daytime, forecasting performance is relatively accurate due to stationary traffic-flow data, and vice versa early in the morning.
2. Forecasting data adhere to stationary flow against unexpected change.

[1] t-p: vehicle speed before $5*p$ minutes , d-1: vehicle speed before a day

3.2 A Simple ARIMA Model

We would like to develop a time series model for forecasting traffic flow using Box-Jenkins method and identify out time series as the ***ARIMA(0,1,2)*** process.
Our tentative model is

$$x_t = x_{t-1} + \varepsilon_t + 0.68661\varepsilon_{t-1} + 0.062871\varepsilon_{t-2} \qquad (1)$$

Based on the model, we generate forecasts of future observations (i.e. 5 minutes ahead) that are optimal in a minimum square error sense. The average forecasting performances are MSE=30.698 and MAE=4.456611.

We can find some characteristics of ARIMA forecasting as follows.

1. More training data, better forecasting performance.
   - We estimated vehicle speed using an ARIMA from 00:00 on Oct. 18^{th} to 00:55 on Oct. 20^{th}. The results say that an ARIMA has a better forecasting performance with time.
2. An ARIMA model can be superior to an ANN model when there are enough training data.
   - As we referred to the relationship between the forecasting performance of an ARIMA and time, an ARIMA produces the better forecasting performance than an ANN with the lapse of time. Although being inferior to an ANN from 00:00 on Oct. 18^{th} to 00:55 on Oct. 20^{th}, an ARIMA is superior from 00:00 on Oct. 19^{th} to 00:55 on Oct. 20^{th} in forecasting performance. The results are shown in Table 3.

Table 3. Comparison with an ARIMA and an ANN

	MSE	MAE
ARIMA forecasting performance (00:00 on Oct. 18^{th} -00:55 on Oct. 20^{th})	39.941	4.9390
ARIMA forecasting performance (00:00 on Oct. 19^{th} -00:55 on Oct. 20^{th})	30.698	4.4566
ANN forecasting performance (00:00 on Oct. 19^{th} -00:55 on Oct. 20^{th})	33.165	4.6945

3.3 An ARIMA + ANN Model

In this experiment, we try to combine ARIMA and ANN for reducing performance error. The model is the combination of the basic ANN model and the forecasting data obtained by ARIMA; ARIMA output is used for an input of an ANN. Some previous experiments argued that this model is superior to an ARIMA or an ANN model in aspect of forecasting ability [7]. Fig. 3 shows the rough architecture of the model.

We chose the neural network architecture that produced a better forecasting performance in ANN model: 3-4-1, 4-4-1, 5-4-1, 6-4-1, 7-2-1, and 8-2-1[1].

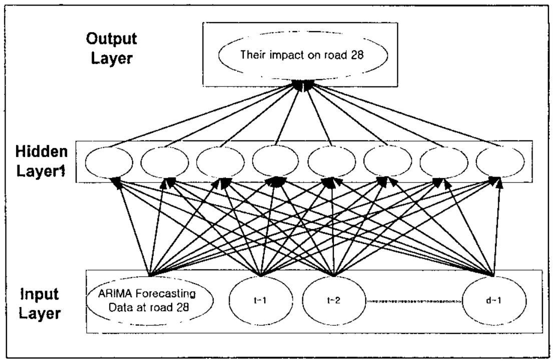

Figure 3. The architecture of ANN+ARIAM

The performance of each model is shown in Table 2. The best model is selected as the model with five-input factors (t-1, t-2, t-3, d-1, ARIMA output).

On the ground of the results, we can testify that the combination of the basic ANN model and ARIMA model is superior to a single forecasting model. Although we cannot say that this result is always correct in other applications, general cases are applicable.

Table 4. The architecture of ANN+ARIMA and their forecasting performance

Input factors	MSE	MAE
t-1, t-2, d-1, ARIMA output	28.7113	4.3369
t-1, t-2, t-3, d-1, ARIMA output	27.9322	4.1685
t-1, t-2, t-3,t-4, d-1, ARIMA output	28.3495	4.2628
t-1, t-2, t-3, t-4,t-5,d-1, ARIMA output	28.8632	4.3022
t-1, t-2, t-3, t-4,t-5,t-6,d-1, ARIMA output	27.9596	4.2197
t-1, t-2, t-3, t-4,t-5,t-6,t-7, d-1, ARIMA output	28.0852	4.1523

3.4 Judgmental Adjustment

Judgmental adjustment is to make right for factors that cannot be fully incorporated into the time series models as stated before. We produce judgmental adjustment data using an ANN whose inputs are vehicle speeds at road 4, road 9, and road 12 before 5 minutes and 10 minutes and output is their impact on road 28 (vehicle speed at target road). The road map is shown as Fig. 1. Vehicles spend between 5 minutes and 10 minutes in traveling from road 4, road 9, and road 12 to target road in real traffic condition. Therefore we can assume that vehicle speeds before 5 minutes or 10 minutes at road 4, road 9, and road 12 have an influence on vehicle speed at target road. The relationship between vehicle speeds near target road and their impact can be generalized by adopting an ANN as depicted in Fig. 4.

[1] The number of input node – The number of hidden node – The number of output node

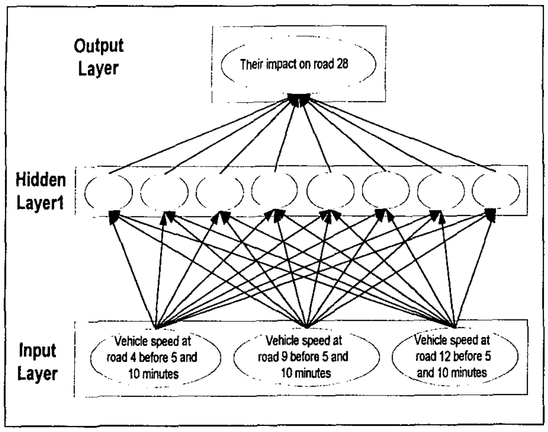

Figure 4. The procedure for producing J.A.

In the ANN, target factor is computed by delineating the difference between the forecasting data and its original data. The forecasting result of the model is shown in Figure 5.

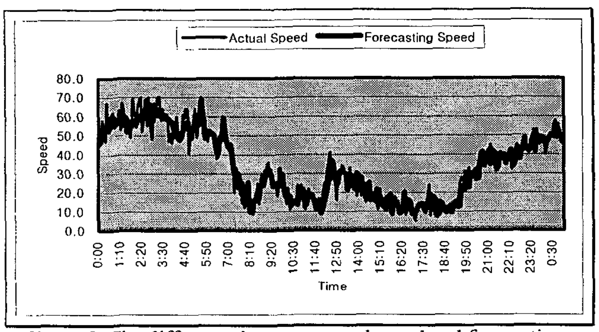

Figure 5. The difference between actual speed and forecasting speed using ANN + ARIMA +J.A.

The comparison between the forecasting performance applied to judgmental adjustment and not applied to judgmental performance is shown in Table 3.

To apply judgmental adjustment means that the last forecasting data is obtained by adding judgmental adjustment to the output of a single forecasting model; ARIMA, ANN, and ARIMA+ANN.

Table 5. The forecasting performance of the proposed models

Forecasting model	MSE	MAE
ANN	33.1635	4.6945
ARIMA	30.6980	4.4566
ANN + ARIMA	27.9322	4.1685
ANN + Judgmental Adjustment	29.8105	4.3975
ARIMA + Judgmental Adjustment	28.5425	4.1217
ANN + ARIMA + Judgmental Adjustment	25.7167	3.9200

In this data, we can identify the validation of judgment adjustment by comparing each forecasting performance. This result is proved statistically in the next chapter.

4. Comparative Performance Evaluation

Now let us evaluate the forecasting performance of each model in comparison with other models. Especially we focus on identifying the effect of the following experiments.

1. Comparing between an ARIMA model and an ANN model.
2. Validating the effectiveness of the combination with an ARIMA model and an ANN model.
3. Validating the effectiveness of judgmental adjustment.

We will use ***Z-test*** with two-sided tests as Statistical test method because we have a lot of samples

4.1 The comparison with an ARIMA and ANN model

Many studies have reported the superiority of ANN models over traditional time series model. But this situation occurs in the condition of a relative small number of observations or noisy data. Let us confirm whether their argument is always true or not.

Hypothesis 1 : The forecasting ability of the ANN models is equal to that of the ARIMA model.

The performance of each model is summarized in Table 3. We formulate the hypotheses as follows.

$$H_0 : Error_{ANN} - Error_{ARIMA} = 0$$
$$H_1 : Error_{ANN} - Error_{ARIMA} \neq 0.$$

Through the ***Z-tests*** of an ANN model versus an ARIMA model, we confirmed that the result of an ARIMA model is superior to that of an ANN because our experiments take many training data relatively to other studies. We can identify this result from Table. 3. ***p***-value for MSE and MAE were 0.2137 and 0.0883 respectively. Although the ***p***-values were not significantly low, we can say that an ARIMA forecasting model is better than an ANN model at least in this case.

4.2 The comparison with an ARIMA and ARIMA+ANN model

We want to check whether the combination of the basic ANN model and the ARIMA model is superior to a single forecasting model or not.

Hypothesis 2: The forecasting ability of the ARIMA+ ANN models is equal to that of the ARIMA model.

The performance of each model is also summarized in Table 3-4. We formulate the hypotheses as follows.

$$H_0: Error_{ARIMA} - Error_{ARIMA+ANN} = 0$$

$$H_1: Error_{ARIMA} - Error_{ARIMA+ANN} \neq 0.$$

We can confirme that the result of an ARIMA + ANN model is superior to that of an ARIMA from Table. 4. ***p***-value for MSE and MAE were 0.0244 and 0.0033 respectively. The p-values indicate that the forecasting performance of the ARIMA+ANN model is very significantly or significantly superior to a single model. From the result, we propose the use of an ARIMA+ANN model instead of a single model.

4.3 The comparison of the effectiveness of Judgmental adjustment method

Now we evaluate the performance of the models combined with judgmental adjustment in comparison with other models. Our concern is whether the judgmental adjustment contributed to the accuracy of forecasting.

Hypothesis 3: The forecasting ability of the ARIMA + ANN + Judgmental Adjustment models is equal to that of the ARIMA + ANN model.

We formulate the hypotheses as follows.

$$H_0: Error_{ARIMA+ANN} - Error_{ARIMA+ANN+J.A.} = 0$$

$$H_1: Error_{ARIMA+ANN} - Error_{ARIMA+ANN+J.A.} \neq 0.$$

Z-test result shows that ***p***-value for MSE and MAE were 0.1302 and 0.0469 respectively. The forecasting power is generally improved.

In the result, we can say that this model is the best model of six proposed models.

Table 6. The Z-test results of model comparison

Compared Model	*p*-value(MSE)	*p*-value(MSE)
ARIMA vs. ANN	0.2173	0.0883
ARIMA vs. ARIMA+ANN	0.0244*	0.0033**
ANN vs. ANN+ J.A.	0.1778	0.0074**
ARIMA vs. ARIMA+J.A.	0.0344*	0.0166*
ARIMA+ANN vs. ARIMA+ANN+J.A.	0.1302	0.0469*

4. Conclusions

In Intelligent Transportation System (ITS), a dynamic traffic flow prediction in road network is a basic component of many traffic monitoring and control systems. In-vehicle information, individual dynamic route-guidance, congestion management and incident detection are all systems requiring predictions of traffic flow on the given network. Such predictions could also make a useful contribution to bus management and passenger information system.

This paper can be summarized as follow:

1. In comparing an ARIMA and an ANN, we have confirmed that an ANN model is not always better than an ARIMA in forecasting power. In our experiment, the result of an ARIMA model is superior to that of an ANN because our experiments take many training data comparatively to other studies.
2. The effectiveness of combining two models have been identified: an ARIMA model and an ANN model. The result of our experiment says that an ARIMA+ANN model produce a better forecasting data than a single model.
3. Judgmental adjustment is able to reduce the performance error.

Finally we can reach a conclusion that the proposed model, i.e. ARIMA + ANN + Judgmental Adjustment, is superior to the other models.

5. References

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