# Dynamic Traffic Pattern Classification Using Artificial Neural Networks

JIUYI HUA AND ARDESHIR FAGHRI

Because of the difficulty of modeling the traffic conditions on a roadway network, little has been achieved to date in area control using dynamic traffic volume. The most commonly practiced method for timing control of area signals that takes into account traffic volume changes is *time-interval-dependent control.* This type of control strategy assumes that the traffic volume on each roadway of a network is constant over each time interval; it then determines different optimal sets of control parameters for each interval. Such a control strategy requires a procedure for determining appropriate time intervals. According to this investigation, one possible approach for determining proper time intervals for traffic control purposes is the dynamic programming (DP) method. This paper introduces an artificial neural network architecture called adaptive resonance theory (ART), which has demonstrated successful results when applied to different pattern classification problems. ART1 is applied to dynamic traffic pattern classification to determine appropriate time intervals and the starting times for those intervals. The results of a case study clearly demonstrate the feasibility of ART1 for time interval determination using network-level traffic patterns. A comparative conceptual analysis of the DP method and the ART1 neural network is also included. The computational experience describing the advantages and disadvantages of ART1 for general traffic pattern recognition and classification problems is summarized, and the conclusion that the neural network approach is feasible and efficient for network-level traffic pattern classification is reached. The methodology introduced in this paper may be applied to other transportation problems.

Traffic signal-timing control is realized mainly through the optimization of three important traffic signal-timing control parameters—cycle length, split, and offset. In general, this optimization is based on traffic volume information, since vehicle travel speed can be formulated as a function of traffic volume. *Cycle length* refers to the total time span of the green, yellow, and red phases of the traffic signal; *split* refers to the assignment of green and red time phases (yellow is usually deterministic) in one cycle length; *offset* refers to shifts of cycle starting time between different sets of signals. There are three major types of traffic signal-timing control: spot control, dealing with only one set of traffic signals for only one intersection; line control, dealing with several sets of signals for several intersections on one line; and area control, dealing with more sets of signals for a number of intersections on multiple lines.

Many sophisticated methods have been developed and are being used for spot control, line control, and static area control. However, little has been achieved for area control with dynamic traffic volume because of the difficulty in modeling the traffic status of a roadway network. At present, the most common area signal-timing control strategy for dynamic traffic is *time-interval-dependent control*, which splits a day (24 hr) into several time intervals such as rush-hour interval, normal daytime interval, and nighttime interval according to traffic volume. This control strategy assumes that the traffic volume on each roadway of the network is constant (normally the average traffic volume) over each time interval and then determines different optimal sets of control parameters for each time interval. Although in actual situations such an assumption is not true, it is perhaps the only feasible approach for implementing a network-level signal-timing control. In fact, one expects that traffic signal-timing parameters will remain fixed for a certain length of time because frequent changes in signal-timing parameters may cause traffic flow disorder (*1*). In order to obtain the minimum disutilities, it is necessary to minimize the difference between the average volume and the actual volume at each time point within the time interval. This can be achieved by appropriately dividing the time intervals.

Traffic patterns express the changes of traffic volume with time. It is believed that the appropriate time intervals can be found by using a traffic pattern classification procedure.

Following an in-depth investigation of the inherent nature of the problem, this paper introduces a neural network approach for area traffic signal-timing control through a network-level traffic pattern classification procedure. This study first focuses on the adaptability of the neural network paradigm to this particular problem with a case study using a hypothetical roadway traffic network. Subsequently, the effectiveness of the neural network approach is evaluated. Some of the advantages and disadvantages of using the neural network approach to deal with traffic pattern classification problems are also discussed. Finally, it is concluded that (*a*) the neural network can be used as a feasible and effective approach for classifying network-level traffic patterns, and (*b*) the methodology proposed in this paper can be used for general traffic pattern classification problems, traffic network monitoring, and evaluation of traffic control strategies.

Suppose that traffic volume is counted every 5 min; a traffic pattern can be formed in terms of the fluctuations of 5-min traffic, namely, the number of vehicles passing through some point on a roadway within 5 min. For a single link or single line, the term *traffic pattern* usually implies the curve of traffic volume on that link or line at each time point. If 5-min traffic is used, the term refers to the changes of traffic volume counted every 5 min with 5-min time intervals. Here, the term *network-level traffic pattern* is defined as the traffic volume on each roadway counted every 5 min. Thus, the traffic pattern at

Department of Civil Engineering, University of Delaware, Newark, Del. 19716.

time point $t$ is the 5-min traffic volume on each roadway in the time interval from time point $t$ to time point $t$ + 5 min.

## PROBLEM STATEMENT

Determining the appropriate time intervals for a single link, the roadway between two intersections in one direction, is simple because numerical differences in traffic volumes can be easily distinguished. However, with more than one link, the numerical comparison between traffic volumes becomes useless to the solution of the problem. Figures 1 and 2 show the failure of numerical traffic pattern classification. In the simplest situation, with only one intersection (Figure 1), the traffic comes from two directions, up and down and left and right. Suppose that there is no turning traffic and that both links have the same capacity. The traffic volumes are measured by the ratio of traffic volume to link capacity. At time $t_0$, traffic volumes on both are the same, namely, $v_0$. This forms Pattern 0. At time $t_1$, the traffic pattern is changed as shown in Figure 2(*a*), which is called Pattern 1. As the time moves on to $t_2$, the traffic pattern changes again (Pattern 2).

If these three patterns are compared by their numerical traffic volume differences, it is found that the difference between Patterns 0 and 1 is

$$D_{t1} = \frac{(V_1^{t1} - V_0)^2 + (V_2^{t1} - V_0)^2}{2} = 0.01 \tag{1}$$

where $V_1^{t1}$ is the ratio of traffic volume to the link capacity of Link 1 at time $t_1$ and $V_2^{t1}$ is the ratio of traffic volume to the link capacity of Link 2 at time $t_1$. The numerical difference between Patterns 0 and 2 is

$$D_{t2} = \frac{(V_1^{t2} - V_0)^2 + (V_2^{t2} - V_0)^2}{2} = 0.01 \tag{2}$$

where $V_1^{t2}$ is the ratio of traffic volume to the link capacity of Link 1 at time $t_2$ and $V_2^{t2}$ is the ratio of traffic volume to the link capacity of Link 2 at time $t_2$. The numerical difference between Patterns 1 and 2 compared with Pattern 0 is the same. If one classified Patterns 1 and 2 according to their numerical difference compared with Pattern 0, these two patterns would be in the same category. If the signal-timing parameters are kept the same as at times $t_1$ and $t_2$, such a numerical comparison leads to an obviously wrong classification. Therefore, at the network level, traffic patterns should be classified analogically.

In addition to the ability to classify analogic traffic patterns, traffic pattern classification should also be tolerant of small fluctuations in traffic volumes. Figure 3 shows two consecutive traffic patterns on a link. Traffic Patterns 1 and 2 are very similar in shape, though not exactly the same. For such a situation, it is still desirable that these two patterns be classified in the same category so that frequent changes of signal-timing parameters can be avoided.

From the foregoing discussion, the requirements for traffic pattern classification can be pinpointed as (*a*) the ability to recognize and classify analogic patterns and (*b*) some degree of tolerance to differences between traffic patterns.

## EXISTING APPROACH

One of the major methods that has been proposed for use in the determination of appropriate time intervals is the dynamic programming (DP) method. The DP method initially sets up $M$ sets of signal control timing parameters and then tries to find out the best time points for switching different sets of control parameters. If $Q(t)$ is the traffic pattern at time $t$; $P_i(t_i)$ is the optimal set of control parameters for $Q(t)$ in terms of

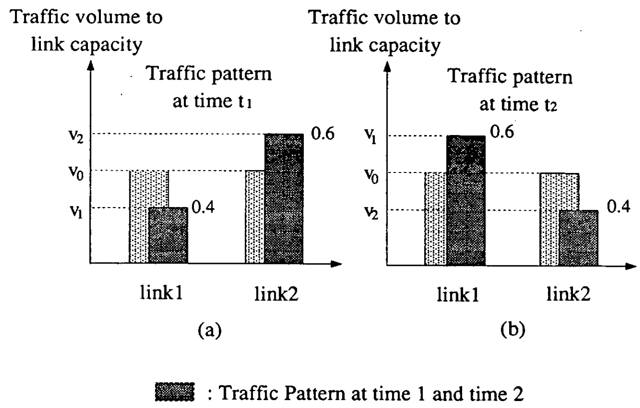


**FIGURE 2 Traffic patterns at (*a*) time $t_1$ and (*b*) time $t_2$.**

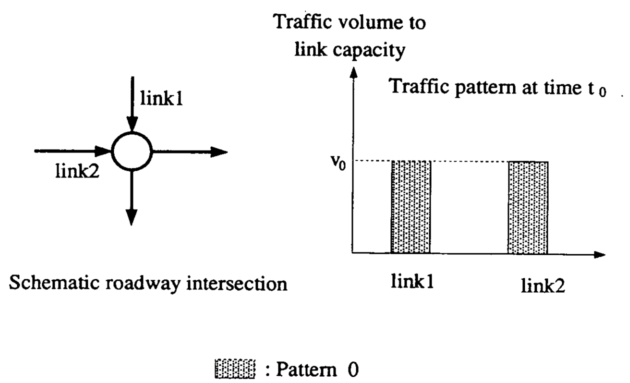


**FIGURE 1 Traffic pattern of Links 1 and 2 at time $t_0$.**

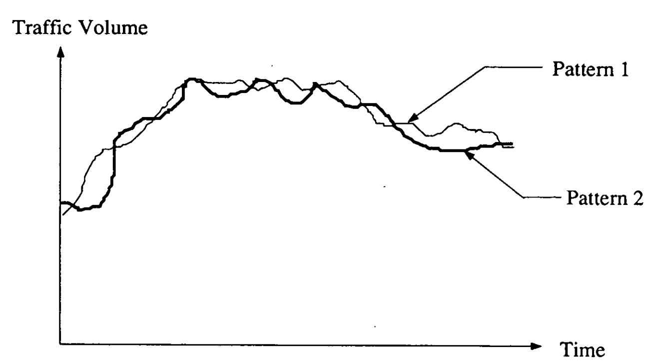


**FIGURE 3 Tolerance of traffic pattern classification procedure.**

a vector including cycle length, split, and offset; and $D[P_i(t_i), Q(t_i)]$ is the disutility, say, total delay, produced by $P_i(t_i)$ ($i = 0, 1, 2, \ldots, M$), then the following equation must be satisfied:

$$D[P_i(t_i), Q(t_i)] \leq D[P_j(t_j), Q(t_i)] \quad (3)$$

Equation 3 is tenable when $i = j$. The time intervals covered by these $M$ sets of control parameters will include a whole day. The number of switches of control parameters, $N$, can be calculated. To find the optimal switching time points for $N$ switches during a day, the following simple one-dimensional DP assignment procedure is used:

$$f_n(x_n) = \min \left[ \sum_{t=x_{n-1}+1}^{x_n} D(P_i,t) + f_{n-1}(x_{n-1}) \right] \quad (4)$$

where $f_0 = 0$ and $x_0 = 0$. In Equation 4, $f_n(x_n)$ is the total disutility over the time span from $x_0$ to $x_n$ under optimal control. Computing for $n = 1, 2, \ldots, N$, the optimal switching time $x_1^*, x_2^*, \ldots, x_N^*$ can be found.

For the DP method, it has been pointed out (*1*) that obtaining the value of $P_i$ that satisfies Equation 3 may not be easy, and determining cycle length and offset is difficult, especially when the difference between $Q(t_i)$ and $Q(t_j)$ is small. The difficulty of solving $P_i$ when $M$ is large has also been discussed. Obviously, the huge amount of computation required in the DP process is another drawback. With a large roadway network, this method may not be practical.

## NEURAL NETWORK APPROACH

It is apparent that the optimization of dividing appropriate time intervals can be achieved through a pattern classification procedure. When similar consecutive traffic patterns are grouped, the dynamic traffic volumes can be approximately dealt with as static over the time period in which there are similar traffic patterns.

A variety of artificial neural network models, such as backpropagation, Perceptron, and the Hopfield network, have proven to be applicable to classification problems (*2*). Some of them have recently been proposed for transportation engineering classification problems (*3*). After careful investigation into the inherent nature of the problem involved in this study, an Adaptive Resonance Theory (ART) neural network, ART1, was selected to complete the classification process. ART1 is compared with other neural network paradigms, and some of its unique characteristics for meeting the needs of the problem are discussed in the next section.

### Introduction to ART1

Three ART neural networks were developed by Carpenter and Grossberg of Boston University in 1987 (*4,5*). ART1 deals with integers, ART2 deals with continuous values between 0 and 1, and ART3 is a refinement of ART2. ART networks automatically stabilize pattern categories and automatically activate new processing units when they are needed to create new categories. The number of patterns being grouped into the same category and the number of groups are theoretically unlimited. The major considerations in deciding to employ ART1 were as follows:

- ART1 can classify analogic patterns into appropriate categories.
- ART1 can automatically set up the proper number of categories.
- ART1 is flexible in dealing with new patterns presented to it because it is a self-organizing network; that is, it can be trained on line.
- ART1 is tolerant of the differences between traffic patterns. This means that if traffic patterns are similar in shape but not exactly the same, they will still be classified into the same category.

### Operation of ART1

Figure 4 shows the schematic architecture of ART1. There are two layers of processing units, which are fully connected between the layers. Two types of weight sets are used in the network. The notation used in Figure 4 is defined as follows:

$n$ = number of inputs to the network,
$x_i$ = $i$th component of input vector (0 or 1),
$y_j$ = $j$th output,
$w_{ij}$ = weight for connection from $j$th output to $i$th input,
$w_{ji}^*$ = weight for connection from $i$th input to $j$th output,
rho = constant having a value between 0 and 1 (the "vigilance parameter"), and
$k$ = index that denotes winner of output element that has the largest value among the output elements.

The two types of weight vectors have a relationship that is always

$$w_{ji}^* = \frac{W_{ij}}{1 + \sum_{k=1}^{n} w_{kj}} \quad (5)$$

and initially, all $w_{ij}$ are set to 1 and all $w_{ji}^* = 1/(1 + n)$. $w_{ij}$ is the connection from input layer to output layer, and $w_{ji}^*$ is

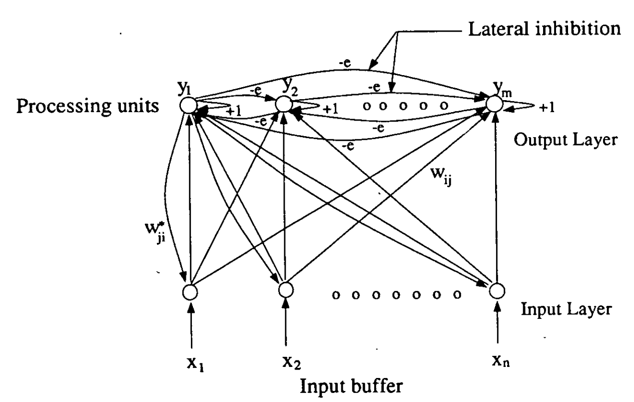


**FIGURE 4 Schematic architecture of ART1.**

the feedback connection from output layer to input layer. Note that in Figure 4 only two such connections are shown. The lateral connections are invisible, but they pass through the information between the processing units in the output layer so that a competition takes place to produce a winner of the processing units. The output of the winner is taken as the network output. ART1 operates as follows:

Step 1. Compute the outputs according to the formula

$$y_j = \sum w_{ji}^* x_i \tag{6}$$

Step 2. Determine the network output with a "winner take all" strategy; that is, let the output that has the greatest value be the output of the network for one run of computation and let the winner be $X_k$.

Step 3. Rate the input pattern match with the following formula:

$$r = \frac{\sum_{i=1}^{n} w_{ik} x_i}{\sum_{i=1}^{n} x_i} \tag{7}$$

Step 4. If $r <$ rho, set $y_i = 0$ and go to Step 2.

Step 5. If $r >$ rho, for all $i$, if $y_i = 0$ and $w_{ik} = 1$, set $w_{ik} = 0$ and recompute $w_{ik}^*$ for all $i$ if any weights have been changed.

ART1 can store vectors and check the committed processing units according to how well the vectors $[\mathbf{w}_{j1}^*, \ldots, \mathbf{w}_{jn}^*]$ being stored match the input pattern. If none of the committed processing units matches well enough, an uncommitted unit will be chosen. In other words, the network sets up certain categories for the input patterns and classifies the input patterns into the proper category. If the input pattern does not match any of those categories, the network will create a new category for it.

With ART1, similar traffic patterns can be grouped into the same category. Therefore, the proper length and starting and ending times of the time intervals can be automatically determined. Such an approach can also be used for on-line traffic pattern recognition and monitoring network traffic status changes.

## ASSUMPTIONS

In this study it was assumed that the traffic volume does not exceed the link capacity. The purpose of making such an assumption is very simple: all traffic volumes are below the corresponding capacities of the links such that the traffic volume can be described by the ratio of actual traffic volume to link capacity, which is a number between 0 and 1. Here the capacity of the roadway is defined as the number of vehicles passing a point on the road within a time unit if the traffic signal is green all the time. If one considers congested flow, imposing the ratio of the current density to the maximum density of the link, the traffic information can also be converted into a number with a value between 0 and 1.

## CASE STUDY

To verify the feasibility of neural networks in traffic pattern classification problems, ART1 is applied to a hypothetical roadway network.

### Data Base

A hypothetical roadway network containing six intersections and seven links is shown in Figure 5. For simplicity, all links are set to be one way. It is also assumed that there is no turning traffic in this network. Those links that are unnumbered are of no concern in this study, but they are considered as inflow or outflow links of the network. The roadway capacity is assumed to be 1,800 vehicles/hr for all links.

The traffic volumes are generated on the basis of a "mother traffic pattern," which is a typical street traffic pattern from 6:00 to 10:00 a.m. for one link. The traffic pattern of each link contained is derived from this mother pattern. The procedure followed is to suppose that the traffic volume of the mother pattern at time $t$ is $V_s$. Let $V_s$ be the mean of traffic volumes at time $t$ for all links of this hypothetical network. On the basis of normal distribution, the error of the traffic volume at time $t$ compared with that of the mother pattern is randomly generated for every link with a variance of 30 vehicles/hr.

Since ART1 takes only binary values, the traffic volumes are transformed into binary vectors. The procedure for transforming traffic volume into binaries is as follows:

- Compute the ratio of traffic volume to link capacity so that all traffic volumes are now represented by a decimal number between 0 and 1.
- Transform the ratios into a 10-element binary vector, for example, 0.8 ⇒ [1, 1, 1, 1, 1, 1, 1, 1, 0, 0].

After the transformation, traffic volumes are represented by 10-element vectors. Each vector will be a line of the input pattern. For all seven links, a 10 × 7 array was produced.

### Traffic Pattern Classification Process

With the traffic volumes represented by binary vectors, the data base is now adaptable to ART1. If ART1 is applied with

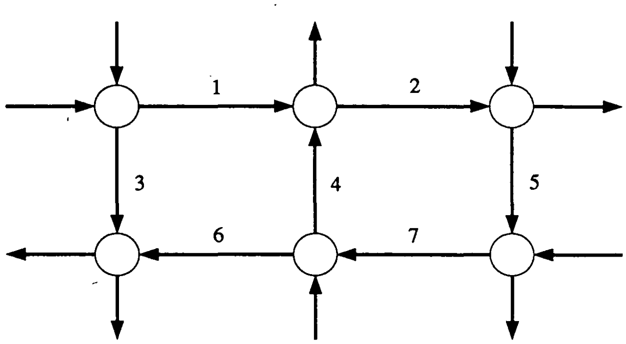


**FIGURE 5 Hypothetical roadway network.**

TABLE 1 Results of Time Interval Determination by ART1

| Time | 6:05 | 6:10 | 6:15 | 6:20 | 6:25 | 6:30 | 6:35 | 6:40 | 6:45 | 6:50 | 6:55 | 7:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Category to which current traffic pattern belongs | 0 | 0 | 1 | 1 | 2 | 4 | 3 | 2 | 4 | 4 | 4 | 5 |
| Time | 7:05 | 7:10 | 7:15 | 7:20 | 7:25 | 7:30 | 7:35 | 7:40 | 7:45 | 7:50 | 7:55 | 8:00 |
| Category to which current traffic pattern belongs | 6 | 6 | 6 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| Time | 8:05 | 8:10 | 8:15 | 8:20 | 8:25 | 8:30 | 8:35 | 8:40 | 8:45 | 8:50 | 8:55 | 9:00 |
| Category to which current traffic pattern belongs | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| Time | 9:05 | 9:10 | 9:15 | 9:20 | 9:25 | 9:30 | 9:35 | 9:40 | 9:45 | 9:50 | 9:55 | 10:00 |
| Category to which current traffic pattern belongs | 7 | 7 | 7 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |

a vigilance parameter value of 0.83, the traffic patterns are grouped as shown in Table 1. The grouping process is quite ideal. The "peak-hour" interval is successfully indicated by Category 7.

Figure 6 shows a three-dimensional plot of the traffic patterns. The section between the two boards indicates the "peak-hour" time interval for the entire network. To verify the performance of ART1 in traffic pattern classification, the variance of the "peak-hour" interval for a different starting time was computed. In Figure 7 the $x$-axis indicates the shifts of the "peak-hour" interval starting time: 0 is the case without shifting, the positive numbers indicate forward shifts, and the negative numbers indicate backward shifts. The unit for one shift is 5 min. If $x = -1$, the "peak-hour" interval starting time is shifted backward 5 min. If $x = 2$, the "peak-hour" interval starting time is shifted forward 10 min, and so on.

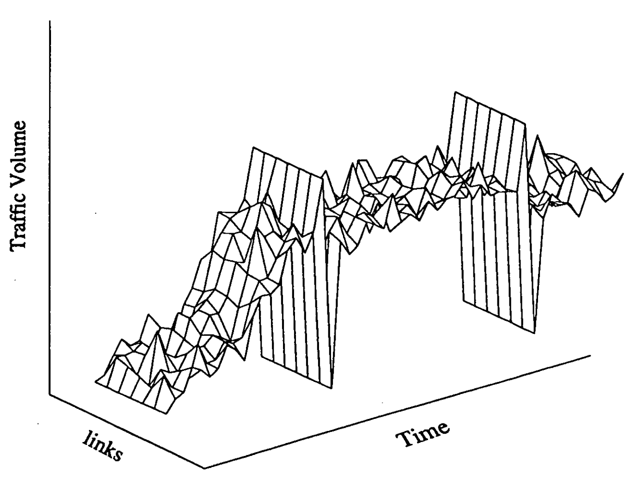


FIGURE 6 Three-dimensional drawing of network-level traffic patterns.

## DISCUSSION OF NEURAL NETWORK APPROACH

In classifying traffic patterns by their analogic differences rather than their numerical differences, the neural network approach seems to be more natural and reasonable than the conventional method. The neural network is also more effective and efficient in determining appropriate number of time intervals than the DP method since it performs on-line training. Both the number of time intervals and the positions of the intervals on the time axis are automatically determined by the neural network, whereas determining the appropriate number of time intervals is time consuming and inefficient in the DP method. The vigilance parameter of ART1 controls the tolerance of the classification process. It can adjust the degree of difference between traffic patterns belonging to the same category. With this property, the user is able to obtain the expected number of groups by adjusting the value of the vigilance parameter. However, there is no criterion for determining a proper value of the vigilance parameter in general. This leads ART1 to be problem dependent. Different values of the vigilance param-

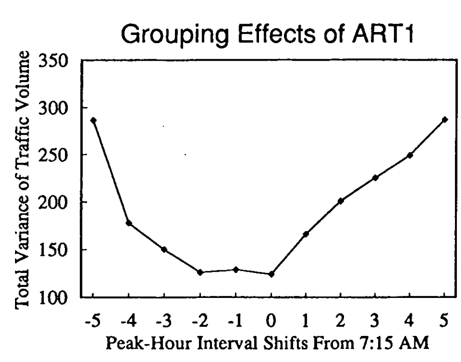


FIGURE 7 Verification of the effects of determination of "peak-hour" interval.

eter may be required for different roadway network and traffic patterns. The degree of tolerance must also be determined by the user's experience to arrive at an appropriate control strategy on a particular roadway network.

In summary, ART1 brings two remarkable contributions to traffic pattern classification problems: (*a*) a parallel process with an on-line training property that enables it to deal with large amounts and a dynamic data base, and (*b*) the ability to deal with an analogic input data base.

## CONCLUSION

In the case study, an optimization procedure for dividing appropriate time intervals for traffic signal-timing control is implemented. The feasibility of the neural network approach has been identified. Furthermore, it was demonstrated that ART1 is efficient in classifying traffic patterns in terms of computing cost, whereas the conventional approaches have serious shortcomings.

The significance of the neural network approach introduced in this study is not only in solving the traffic control problem, but also in dealing with general network-level traffic pattern classification problems. The capability of the neural network to classify network-level traffic patterns provides an effective means for transportation engineering to expedite traffic data collection and roadway network traffic status identification. The methodology discussed in this paper can also be used for other transportation problems such as traffic network monitoring by expressing the status of the entire traffic network with a single index and evaluation of traffic signal-timing control strategies.

As can be seen in this paper, the neural network accesses the traffic pattern classification problem from a totally different perspective than the conventional method. Some difficulties that exist in conventional methods were easily solved by the neural network approach. The extension of this work is planned to explore the applicability of ART2, which is able to deal with continuous values within a range from 0 to 1, as well as a deeper investigation of determination of the appropriate vigilance parameter.

## ACKNOWLEDGMENT

The funding for this project was partially provided by a grant from the University of Delaware Research Foundation.

## REFERENCES

1. K. Ichihara and T. Edamura. *Traffic Engineering* (in Japanese), 1976.
2. P. K. Simpson. *Artificial Neural Systems.* Pergamon Press, Inc., 1990.
3. A. Faghri and J. Hua. Evaluation of Applications of Neural Networks in Transportation Engineering. In *Transportation Research Record 1358*, TRB, National Research Council, Washington, D.C., 1992.
4. G. Carpenter and S. Grossberg. Invariant Pattern Recognition and Recall by an Attentive Self-Recognizing ART Architecture in a Nonstationary World. *Proc., IEEE First International Conference on Neural Networks*, IEEE, San Diego, 1987, Vol. 2, pp. 737–746.
5. G. Carpenter and S. Grossberg. A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition Machine. *Computer Vision, Graphics and Image Understanding*, Vol. 37, 1987, pp. 54–115.