Development of Neural Signal Control System—Toward Intelligent Traffic Signal Control

JIUYI HUA AND ARDESHIR FAGHRI

This study describes the process of developing a traffic signal control for isolated intersections using artificial neural networks. Currently existing signal control systems are briefly discussed and their shortcomings presented. Subsequently, a new multilayered neural network architecture is presented that diminishes many of the shortcomings in existing controllers. The new control system, called neural signal control system (NSCS), is more adaptive to the changes in traffic patterns that take place at isolated intersections. It also provides the traffic engineer more flexibility in terms of optimizing different measures of effectiveness. After describing the architecture and operation of this new system, a comparative analysis is performed by simulating different traffic patterns at a hypothetical intersection using both NSCS and a commonly used software—signal operations analysis package (SOAP). Measures of effectiveness produced by both NSCS and SOAP indicate NSCS's superiority in all aspects. This study concludes with some thoughts for further research in this area.

After disregarding static factors such as geometric conditions, the traffic signal control process for an isolated intersection deals primarily with two issues: the allocation of green time to each traffic movement and the duration of this allocation. From a pattern processing perspective, the signal control process is supposed to find the "best" phasing patterns and their display durations. In a natural sense, the phasing is not necessarily cyclic. Moreover, displaying phases according to traffic fluctuations makes more efficient use of green time from a microscopic point of view.

In the early development of traffic signal control studies, because even traffic flows were assumed, the most important control parameters for isolated intersection control were cycle length and green time split. The first computer traffic signal control concept was established by Webster (*1*), and it still influences current control operations, although many variations and enhancements have been made for different situations (*2–6*). However, there have been no substantial changes in the concept. After observing the variations in traffic flow at isolated intersections, some researchers (*7*) have tried to achieve better control performance by applying stochastic models to build control logics in order to accommodate the fluctuation in traffic flow caused by random arrivals. Conceptually, there is still some awkwardness. In stochastic models the distribution of random arrivals must be preassumed, however, this assumption may be proven to be unrealistic.

Current traffic signal control systems are primarily pretimed, semiactuated, fully actuated or volume-density responsive. The traffic signal operations currently used at isolated intersections fall short in the following ways:

1. In pretimed traffic signal control, the traffic arrival patterns are assumed to be uniform. Though this assumption provides the possibility of vigorous mathematical formulation to optimize the traffic conditions at an isolated intersection, it is obvious that the assumption is far from realistic. Thus, the control effects may not be achieved in a practical sense.
2. In actuated traffic signal controls including volume-density responsive operations, the control logics are made relatively reasonable for a specific range of traffic conditions. The traffic signal control system is then able to accommodate the changes in traffic conditions. The effects of the accommodation made by actuated control are, however, very limited because of the following reasons:

- The phases are displayed in order. The actual traffic conditions may not necessarily demand the preset phase sequence, though enhancements such as phase skipping, multisettings of maximum/minimum green intervals and multiring can be made.
- All decision making processes are based on thresholds such as maximum/minimum green time, passage time, and critical gap. These thresholds may not always lead to a satisfactory decision as traffic conditions change. More critically, in some cases fully actuated and semiactuated operations may fail, for instance, in oversaturated traffic conditions.

Almost all existing traffic signal systems are facing the problem of how to adapt operations to changes in traffic conditions using reasonable assumptions and the capabilities of on-line adjustments. Also, they all need a relatively large presetting effort for real-time implementation.

To achieve a signal control operation which is adaptive to traffic conditions, the neural signal control system (NSCS) has been developed. The NSCS identifies the most suitable phase pattern from among a set of prepared patterns, yet determines the duration of the pattern based on a "human-like thinking" mechanism. The performance of the proposed system is examined with a comparative analysis of computer simulation results obtained from NSCS and the signal operation analysis package (SOAP).

DEVELOPMENT OF NEURAL CONTROLLER

Artificial neural networks (ANNs) are mostly accredited in pattern processing tasks such as recognition and classification. The performance of ANNs in pattern processing strongly suggests their suit-

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

ability for addressing isolated intersection traffic control problems. In some ANN paradigms, such as Kohonen networks (*8*) and ART networks (*9,10*), the competition process among nodes is analogous to that of traffic demands of different movements. Based on the ANNs concepts, a paradigm suitable for isolated traffic signal control operation has been developed.

Concepts of NSCS

Inasmuch as it has been determined that phase patterns are associated with corresponding traffic patterns, signal operation can be treated as a pattern association process that includes traffic pattern recognition and classification procedures. There are theoretically *N!* combinations of possible phase patterns at any given time, if there are *N!* traffic movements at the intersection. However, there may be only several phase patterns out of the *N!* combinations necessary or applicable due to the constraints of conflict points, traffic patterns, and other mandatory control issues and policies. Therefore, in normal practice fewer phase display patterns will be applied for the different traffic patterns. In other words, traffic patterns can be classified into a number of types and each type of traffic pattern requests one specific phase pattern.

NSCS operates in such a way that approaches to the intersection are grouped to share one phase pattern in order to increase efficiency of green time usage and avoid conflict points. For example, in the five leg intersection shown in Figure 1, approaches can be grouped into two groups, A, B, and E form group 1; C, D, and E form group 2.

Thus, the determination of green time assignment is broken down into two steps:

1. Assign green time to an approach group which has a larger demand; and
2. Display suitable phase patterns according to the traffic patterns of this approach group.

These procedures reflect the principle that the phase pattern currently displayed is always, from among all available patterns, the one which carries the most traffic demand measured on a link group or a phase basis. These procedures will provide reasonable heuristics by increasing the efficiency of green time usage. Figure 2 presents the concept of green time assignment.

Duration of Phase Pattern

A selected phase pattern may not continue to be appropriate for traffic patterns which change over time and should therefore be reviewed for adjustment. There is, however, the possibility that the demand for changing a phase pattern occurs too frequently. In actual operations, too frequent changes in phase patterns are not acceptable because of time loss and disruption to the continuity of the traffic flow.

To avoid too frequent phase changes, the mechanism of human visual nerves is employed. The sensitivity of the human visual nervous system adapts to the circumstances it encounters. Suppose an individual has been outdoors on a sunny afternoon. When that person moves quickly into a dark room, he may temporarily lose his sight. At this point, his visual nerves may sense only luminous objects. As time passes, his visual nerves gradually begin to sense other objects in the room which are not luminous. Obviously then, the brightness sensoring range of the human visual nerves varies. Assuming all objects are competing to present themselves to the person's sight, the most luminous object will be the winner at the moment that the person walks into the room. However, the person may find all the other objects in an order of the degree of the brightness of those objects.

A similarity to the aforementioned scenario is also found in human traffic guidance. A human guide would first assign the phase which carries the largest demand. As time passes, the expectation to change to a new phase becomes stronger, even if the old phase is still carrying the largest traffic demand. Such a mechanism is employed in NSCS to determine the duration of a particular phase pattern. This phase pattern determination process is observed as a competition among different phase patterns. When a particular phase has just been chosen, the competition strength of this pattern will be at the strongest level and that of the others at the weakest level. As time

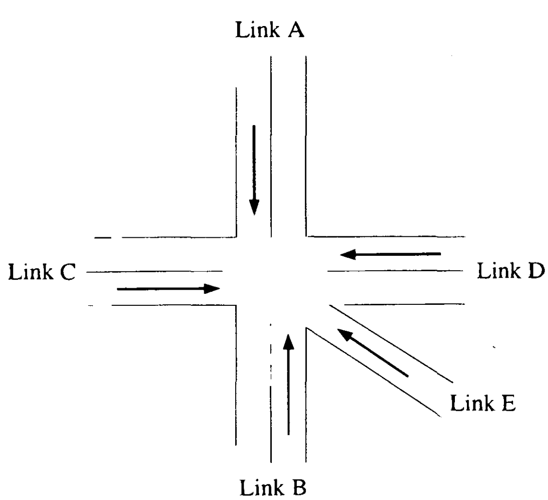

FIGURE 1 Link grouping process for a five-leg intersection.

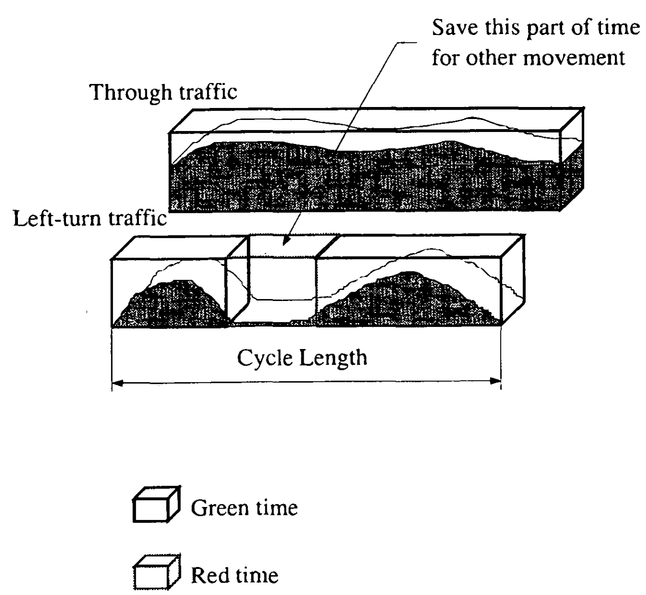

FIGURE 2 The green time assignment.

passes, the competition strength level of the winning phase decreases gradually and that of the losing phases increases gradually. This changing process continues until a new winner is found.

This "decay-enhance" process is conducted through an artificial neural network. The system in this case simulates the traffic control process of the human traffic guide with the ability to adapt to different traffic conditions without incorporating any of the conventional traffic signal operational parameters such as cycle length and split. The green time assignment is based only on the patterns of the traffic approaching the intersection.

Architecture of NSCS

The architecture of NSCS must be, as in most artificial neural networks applications, developed for the subject case to accommodate the geometric conditions of the intersection including number of approaches, number of lanes within each approach, and turning movements. Special attention should be given to avoid conflict points of the multiple traffic movements.

In its architecture, the NSCS contains a total of five layers, each layer containing a number of processing units, also called nodes or processing elements as shown in Figure 3. The first layer is used to hold traffic information about different movements. This layer works as an input buffer, and in normal cases, the information being fed into this layer is the number of cars. This layer must be divided into several slabs, each dedicated to one group of links.

Following this layer, there is a special layer containing several nodes, called "*G* nodes," each connected to all the nodes in a slab of the input layer. Thus each node in the second layer will take the traffic information of one link group. The connections between nodes in the second layer and those of the first layer can change during the operation.

The third layer is a mirror of the first layer except that the nodes in this layer must use transfer functions which are user-specified to compute the measures of effectiveness (MOEs) as their outputs. Nodes in the third layer are connected to the corresponding nodes in the first layer and also to those in the second layer.

The fourth layer contains a set of nodes that compute a value indicating the MOE, if a specific phase pattern was applied (this is discussed in more detail later). The number of nodes in this layer is adjustable by the user so that a variable number of phase patterns can be applied. The connections between this layer and the third layer are also changeable during the operation.

The fifth layer is simply the output of the phase pattern. All nodes in this layer connect to one of the fourth layer nodes.

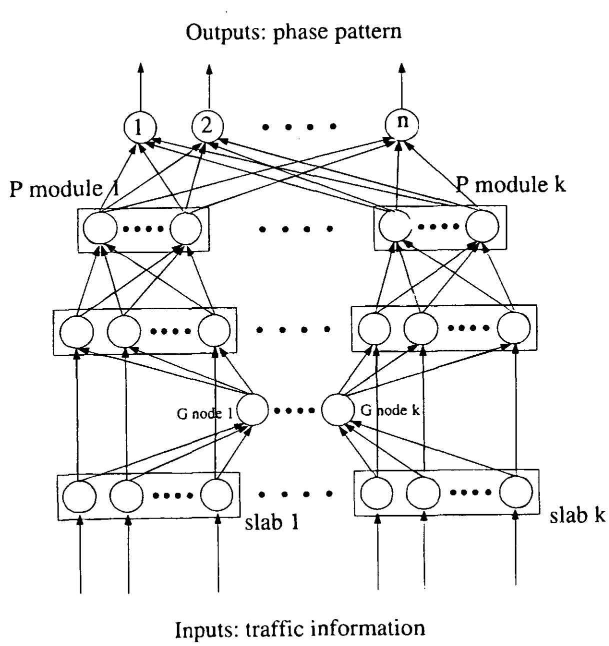

FIGURE 3 General architecture of NSCS.

Operation of NSCS

The NSCS is characterized as being highly dynamic in the sense of phase pattern changes. No specific or predetermined parameters such as cycle length and green time split ratio are required for the operation.

When a vector of traffic information is fed into the first layer, a value of output for every *G* node is first computed. This value implies the traffic demand for the link group. In the second layer, a competition takes place on a "winner takes all" basis. That is only the one whose output value is the greatest among the *G* nodes wins the competition, all other *G* nodes lose. The following simple equation is used to compute the output of *G* nodes.

$$Y_j = \sum w_{ij}^G X_{ij}$$

where

Y_j = output of *G* node *j*
W_{ij}^G = weight of connection from *I* node of *j* slab to *G* node *j*
X_{ij} = input value of *I* node of *j* slab; $X_{ij} = f(n)$, where *n* is the number of vehicles detected in the pocket.

The winning *G* node fires with a value of 1 and distributes this value to the nodes of its corresponding module in the third layer. The losing *G* node fires with a value of -1 and also distributes this value to the nodes of its corresponding module in the third layer.

In the third layer, the output of the node is computed as follows:

$$Z_{ij} = Y_{ij} H_j$$

where Z_{ij} is the input to the node *i* of slab *j* in third layer, and H_j is the output of *G* node *j*.

Adjustment of the Connection Weights

When competition takes place, the strength of the competition of each *G* node and *P* node changes as time passes. The competition strength of each node is reflected in the value of the weights of the connections from the nodes in the prior layer to this node. The weights of the connections change in an incremental or decremental manner as time is counted on a small incremental basis. The changing range of the weights is from 0 to 1. The step size of the weights adjustment is computed every time a new winner is found.

The initial determination of the step size of weight adjustment for each node is determined as follows:

$$\Delta = 1/(G_{max} - G_{min}) + M$$

where

Δ_k = step size of adjustment for G weights
G_{max} = maximum green time interval specified by the user
G_{min} = minimum green time interval specified by the user
M = an infinitely small real number used for the stability of the system
k = an index denoting the winning node.

Suppose there are n nodes in the phase layer and m nodes in its prior layer, and the current winning node in the phase layer is k. The procedure for adjusting the weights during the operation is determined as follows:

$$w_{ij}^{new} = \begin{cases} w_{ij}^{old} - \Delta_k & \text{for } i = k \\ w_{ij}^{old} + \Delta_k & \text{for } i \neq k \end{cases}$$

where

w_{ij}^{new} = new weight,
w_{ij}^{old} = old weight,
Δ_k = step size of weight adjustment for link group k, and
$i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$.

The same procedures are applied to determine the competition strength of P nodes.

DISCUSSION

NSCS's algorithm is flexible in many aspects. These flexibilities ensure the ability of the controller to perform in various traffic conditions. The operation can be fine tuned by adjusting several factors:

Expandability

The capability of NSCS, in terms of the number of phase patterns prestored, can be virtually expanded to the maximum number of possible combinations of the traffic movements, namely $N!$ phase displays. The expansion is reflected in the increase of the number of P nodes. But, this expansion does not increase the computational cost (computing time) if a parallel computing process is implemented on the hardware being used. This is an advantage of the neural network architecture. With the expansion, the controller should be able to perform a finer function in the sense that the phase pattern more precisely fits the traffic pattern.

Flexibility

NSCS offers the traffic engineer the flexibility of changing the optimization objective. For instance, mathematical formulae can be provided to optimize only the environmental MOEs. Here, we describe the optimization of two objectives.

If traffic demand is defined as the throughput, traffic demand should be calculated as follows:

$$U = \sum WF(X)$$

where

U = output vector
W = weights vector
$F()$ = vector of functions of x's
X = traffic volumes

In the algorithm of our system, the traffic volume is determined by using the Greenshield model.

If traffic demand is defined as the maximum queue length, it should be calculated differently as in the following equation:

$$U = \sum WN$$

where

U = output vector
W = weights vector
N = a vector of number of vehicles detected in the pockets.

Adaptivity

The system adapts to changing traffic patterns. This capability to adapt to different traffic behavior is accomplished through the competition strength function, the minimum/maximum green time thresholds, and the system sensitivity. Each is described below.

Competition Strength Function

The competition strength parameter, which is a function of time, can affect the operation significantly. It can also be given in numerous forms. For example, connection strengths of the losing processing units could be

$$w = t^u$$

where t is time elapsed and u is a real number.

The parameter u can be changed, by using the historical information of traffic arrivals to make signal operations more adaptive to traffic patterns.

Minimum/Maximum Green Time Thresholds

Minimum/maximum green time thresholds can affect the entire signal operation as well. Figure 4 illustrates that by changing the minimum/maximum green time thresholds, the signal flipping point will be different. In fact, these thresholds determine the proportion of stable operation of the signal. The signal display is fixed for the stable portion of a particular phase.

Adjustment of System Sensitivity

The system can be adjusted to be more or less sensitive to the fluctuation of traffic for both assignment of green time to link groups and traffic movements. The operators can fine-tune the system by adjusting the system sensitivity to accommodate their own traffic patterns.

The adjustment of the system sensitivity is accomplished simply by assigning the value of s, where s is the sensitivity index shown in Figure 5. The variable s has value ranging from 0 to 1. When $s = 0$, the system is most insensitive and when $s = 1$, it is most sensitive. The sensitivity can be adjusted in both competition among G nodes and P nodes.

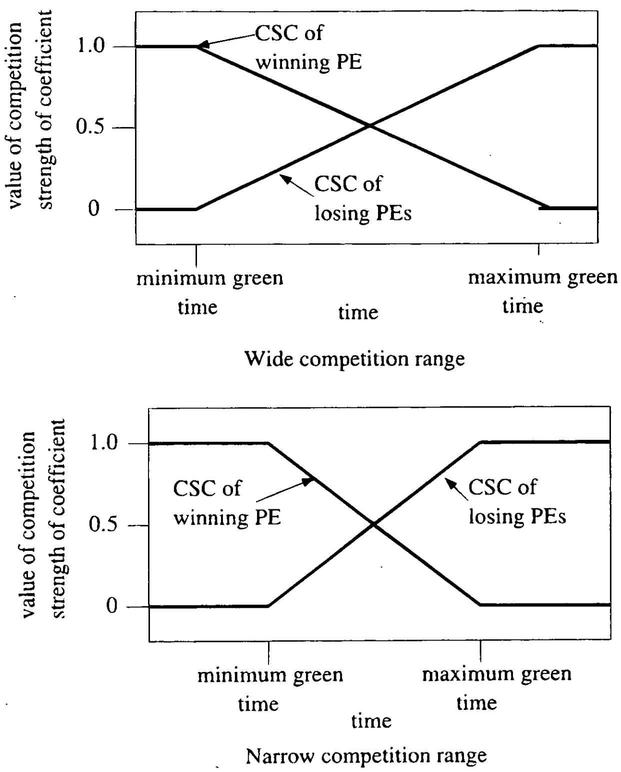

FIGURE 4 Adjustment of maximum/minimum green time interval.

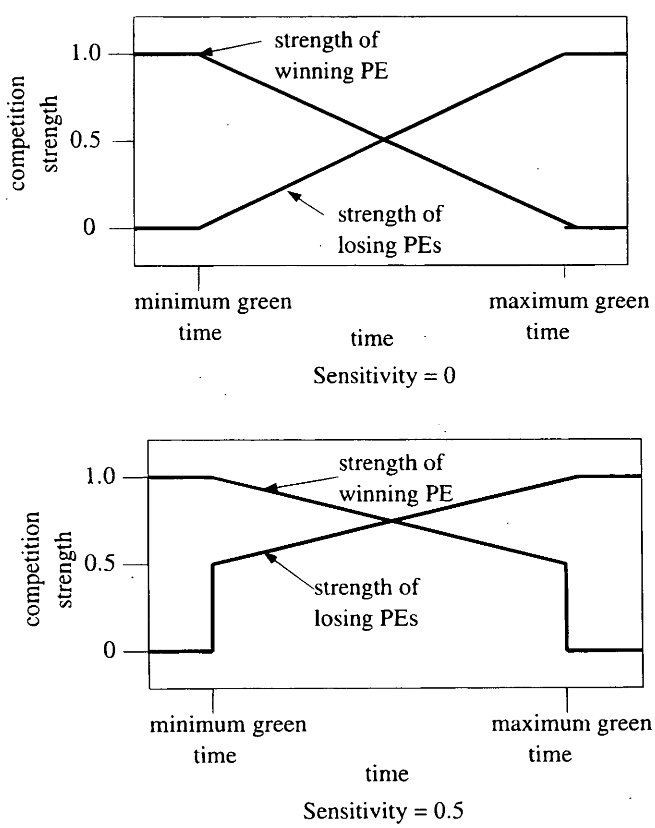

FIGURE 5 Adjustment of system sensitivity.

Unlike conventional traffic control strategies, NSCS approaches the problem by considering the traffic fluctuation microscopically. The optimal control strategy used in NSCS provides a set of sequential phase patterns in a heuristic manner in order to optimize the user specified MOEs, instead of a conceptually defined exact optimal phase sequence. The competition features of both *G* and *P* node groups used when assigning green time is a process of simulating the human traffic guide thinking process that is assumed in this study. Thus, when different traffic movements demand green time, the assignment is accomplished on a relative competition basis instead of on simple threshold criteria.

The entire operation of NSCS is conceptually more natural for isolated intersection control. It is expected that an adaptive control process can be realized through NSCS's operation and less effort required for NSCS operators in practical applications.

COMPUTER SIMULATION CASE STUDY

Case Study

A case study is made for examining the performance through comparative analyses of simulation results by NSCS and a popular commercial software, SOAP.

A hypothetical case containing an isolated intersection and different traffic conditions is used for this case study. The intersection has four approaches. All approaches are made with two pockets for exclusive left-turn and through traffic movements. Because it is easier for right-turn traffic to be carried in signal control problems, this study assumes no right-turn traffic on all approaches. A schematic drawing of the hypothetical intersection is shown in Figure 6. A flowchart of the simulation program based on NSCS is presented in Figure 7.

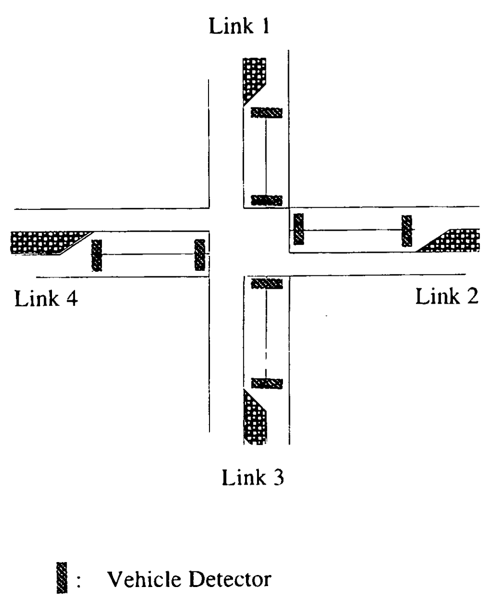

FIGURE 6 Subject intersection of case study.

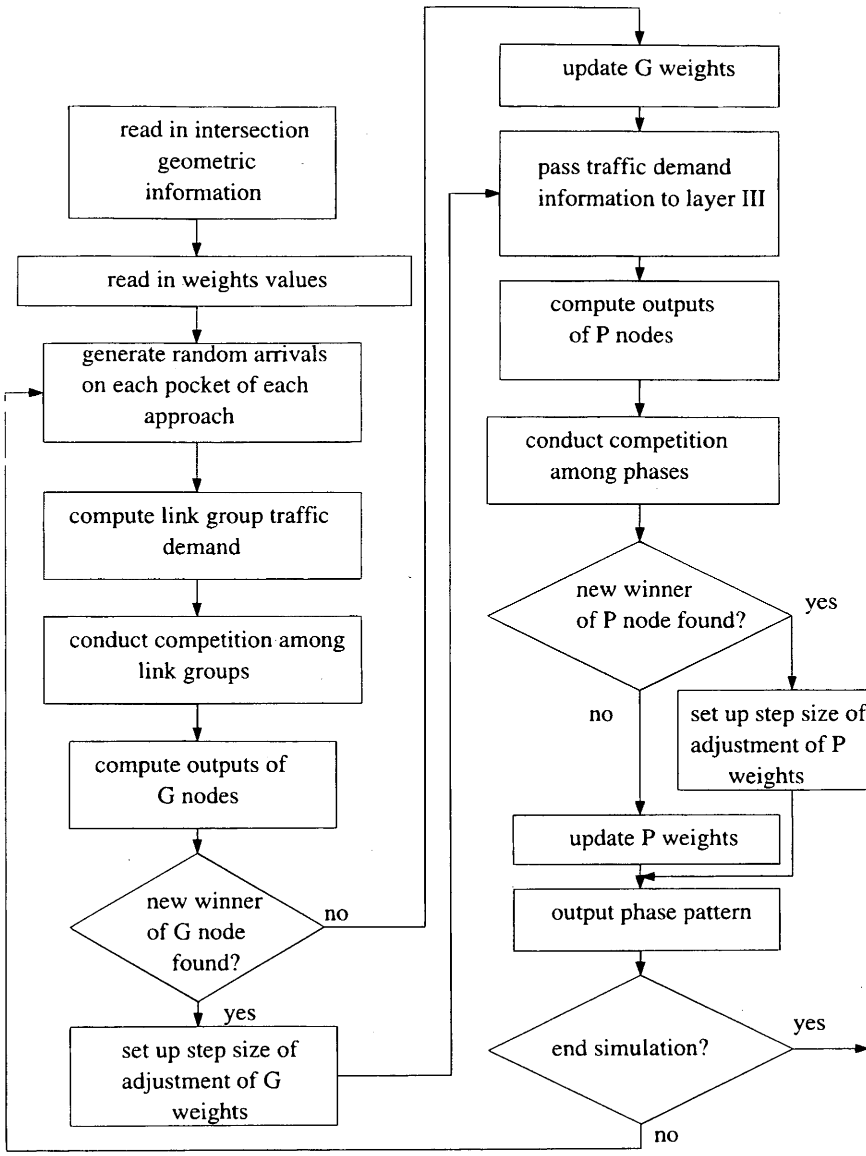

FIGURE 7 Simulation process.

Comparative Analysis of Simulation Results

The foregoing study case is input into both NSCS and SOAP for seven runs under different traffic conditions. When comparing the results generated by the two computer simulation programs, several interesting findings are discovered. The nature of NSCS is also explored.

Simulation Results

Table 1 lists a collection of MOEs recorded from the simulation results by NSCS and SOAP. It shows that in almost all MOEs, NSCS's performance was superior to SOAP's fully actuated mode. Emission pollutant MOEs are not available in SOAP. By investigating NSCS's outputs of emission pollutants, the user can adjust the operation by changing the system sensitivity, the minimum/maximum green time, the competition strength coefficient curves, or the optimization objective to obtain the best environmental MOEs.

Three comparative plots illustrating MOEs of average delay, percentage of stopped vehicles, and fuel consumptions are presented in Figures 8, 9, and 10 respectively.

Findings of the Case Study

By comparing the simulation results produced by NSCS and SOAP respectively, several findings can be summarized as follows:

1. At extremely low traffic volumes, the performance of both SOAP and NSCS are almost the same. This is so, because if waiting traffic is always low enough to be cleared within a single time interval, there should not be any difference in operation between the

TABLE 1 Simulation Results by SOAP and NSCS

Simulation run	Average delay (secs/veh)		Number of stops (%)		Fuel consumed(gals/hr)		Level of service	
	SOAP	NSCS	SOAP	NSCS	SOAP	NSCS	SOAP	NSCS
1	4.68	4.60	54.7	38.3	5.00	2.56	A	A
2	4.93	5.39	66.9	44.1	12.37	7.14	A	B
3	8.68	5.89	79.3	43.5	22.50	12.25	B	B
4	19.66	6.83	91.4	45.6	39.72	22.08	C	B
5	72.40	8.03	97.7	53.3	87.36	37.68	F	B
6	96.21	11.50	97.4	82.8	123.71	51.03	F	B
7	144.86	12.24	100.0	103.0	191.20	53.11	F	B

two programs. The comparative competition of NSCS does not make sense at this point, because such competition often takes place between one nonvoid traffic movement and other void movements. The left portion of Figure 8 indicates this fact.

2. In this particular case, NSCS seems to perform better when the number of stopped vehicles falls within a range of traffic volume from 400 VPH to 1000 VPH. This is in accordance with the basic concept of NSCS analyzed earlier. NSCS always assigns green time to the group of movements in which the traffic is heaviest. Therefore, the number of stopped vehicles can be significantly reduced. If the traffic is too low, the phenomenon described above in Finding 1 takes place. If the traffic is too high, the queue length of vehicles will exceed the detectable length so that a maximum number of vehicles is recognized by NSCS as the maximum detectable number of vehicles. Consequently, the difference among varied movements of traffic is less recognizable by NSCS. This may affect the correct competition strength computation of NSCS. Under very heavy traffic conditions, the NSCS loses its adaptivity and the operation remains constant.

3. NSCS can basically follow the arriving pattern of traffic to assign green time. Figure 11 demonstrates all phase patterns displayed for through traffic on link 1 during the simulation. As observed, the green time pattern is basically a projection of a traffic arrival pattern.

4. The performing range of NSCS is broader than that of SOAP's fully-actuated mode. In Figure 9, when traffic is in excess of 800 VPH, SOAP's actuated mode fails in optimization. Average stopped-delay in SOAP increased dramatically, whereas NSCS maintained a reasonable increase in average stopped-delay.

5. Because of producing lower stopped-delay in heavy traffic conditions, NSCS's fuel consumption is much less than that of SOAP, as displayed in Figure 10.

6. Environmental factors are taken into consideration in NSCS. This will provide practitioners more power in improving the environment through traffic operation.

7. In Table 1, the total number of stopped vehicles produced by NSCS is higher than that of SOAP at the 7th run. This conforms with the adaptivity of NSCS to changing traffic conditions. In cases that generate maximum throughput, NSCS will sacrifice the continuity of traffic flow whereas in SOAP if a preset gap is not detected then the phase will not change from one ongoing traffic movement to another.

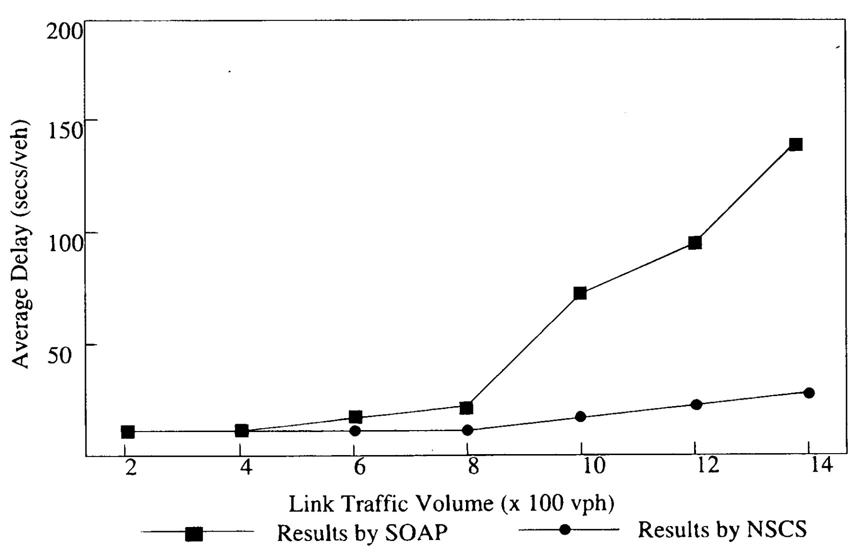

FIGURE 8 Comparison of average stopped delay. Results by SOAP (■) and (●) NSCS.

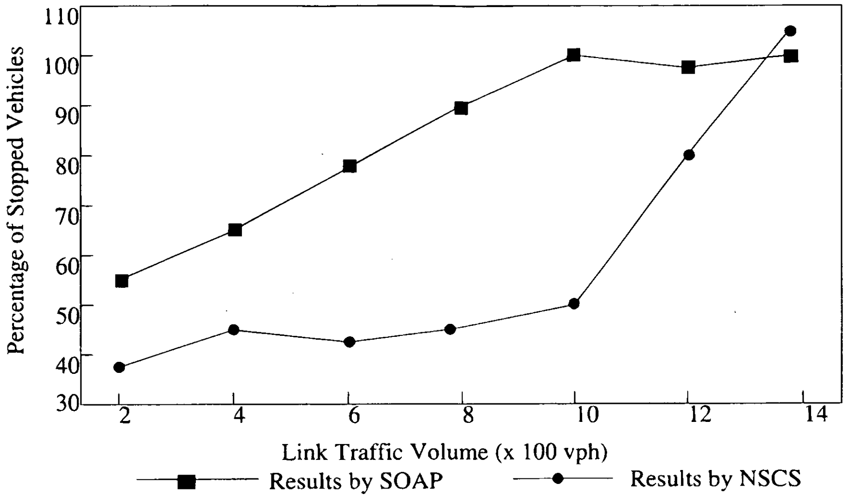

FIGURE 9 Comparison of percentage stopped vehicles. Results by SOAP (■) and (●) NSCS.

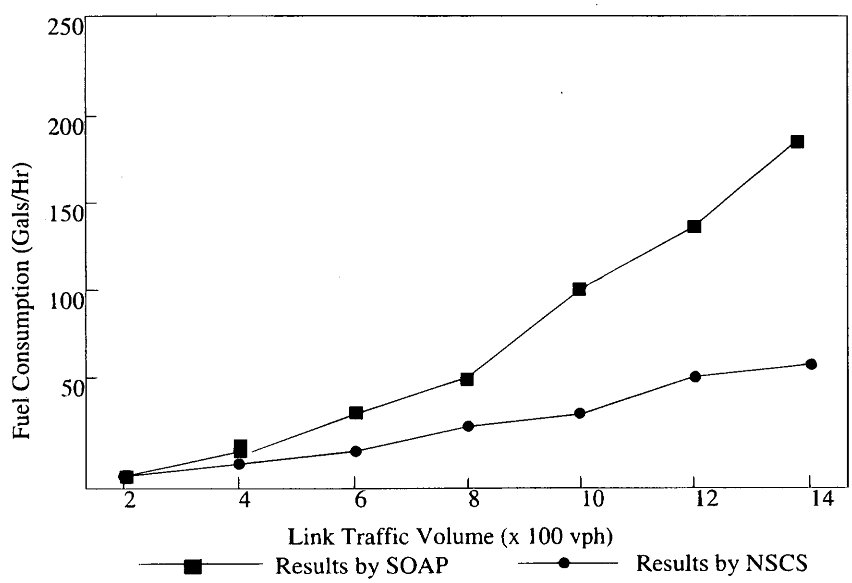

FIGURE 10 Comparison of hourly fuel consumption. Results by SOAP (■) and (●) NSCS.

8. Less presetting effort is needed to operate NSCS. In general, HCM claims that three types of information, geometric conditions, signalization conditions, and traffic conditions, must be understood by human signal designers for setting a conventional signal control system. NSCS requires only the geometric information of the intersection.

CONCLUSIONS

After describing the shortcomings of existing controllers, this paper presented a new concept based on ANNs for optimizing timing at isolated intersections. The chief advantage offered by this multilayered ANN is its adaptiveness to the constantly changing traffic pattern. As a result, this new system does not function through a cyclic operation, instead, it provides the right-of-way with the same approach that a human traffic guide would. Because of the system's adaptivity and flexibility for optimizing different MOEs, less presetting effort is required. There is virtually no need for traffic and signalization information. Therefore, NSCS is expected to overcome malfunctions of traffic signals due to missing or false information provided in the presetting procedure.

In multiple MOEs comparisons, NSCS's performance was superior to a fully actuated control operation simulated by SOAP. The operation offered by NSCS appeared to be adaptive to the fluctuations of traffic approaching the intersection. This feature will be suitable for isolated intersections where larger traffic fluctuations take place.

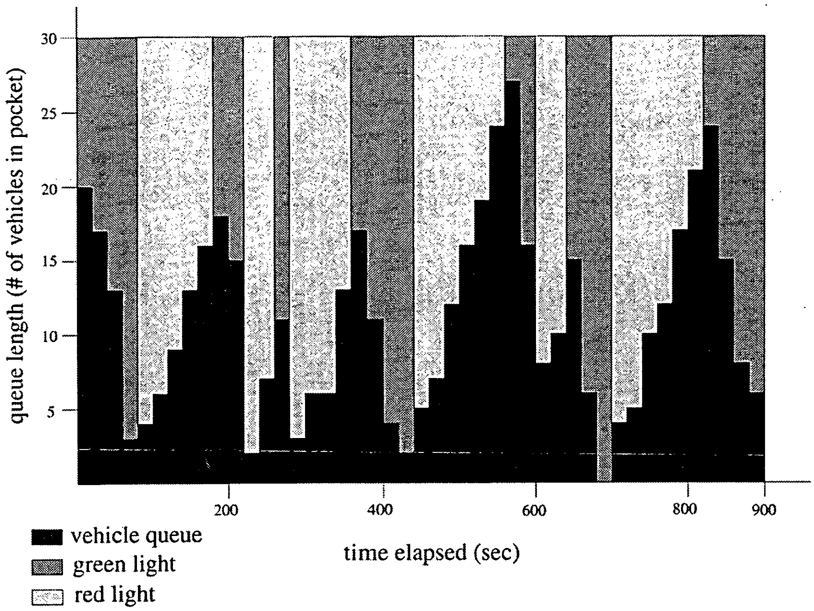

FIGURE 11 Projection of phase patterns to traffic patterns.

The performance investigation of NSCS by computer simulation confirms the methodologies presented in this study. The simulation results also indicate that NSCS stresses several features in its operation:

- Adaptiveness to traffic conditions;
- "Human thinking-like" process;
- A generic ability that allows the process to be applied to virtually any type of isolated intersection; and
- Self-organizing control logic.

It is clear that the NSCS has a much wider operable range and performs better than a fully actuated mode simulated by SOAP for heavier traffic flow.

The control system presented in this paper is a completely new non-cyclic approach to intersection control operations. The preliminary validation tests explained in this study indicate promising results. However, evaluation of the system's capabilities in real life conditions as well as comparison with other sophisticated controllers such as a demand-responsive one are recommended for further research in this area.

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