Applications of Artificial Neural Networks to Intelligent Vehicle-Highway Systems

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The potential applications of artificial neural networks (ANNs) to intelligent vehicle-highway systems (IVHS) are evaluated, and the extent of use and the position of ANNs in future IVHS implementations are discussed. The state of the art and the potential implementation needs of IVHS are reviewed, and the characteristics, properties, limitations, and application domains of ANNs are discussed from a technical perspective. On the basis of review and discussion, potential application domains of ANNs to IVHS are evaluated. A technical demand-supply matrix is provided to indicate the most possible potential application domains of ANNs to IVHS. As an application case study of ANNs in the implementation of IVHS, an ANN-based model is established for vehicle travel time estimation. The results and findings associated with the development of the neural network-based travel time estimation model are also reported. It is concluded that (*a*) ANNs can provide most techniques needed by IVHS, and (*b*) for some IVHS implementation domains, ANNs may be superior to conventional techniques. The case study demonstrates the modeling feasibility of ANNs for potential IVHS implementations.

Today's vehicle-highway systems face a variety of problems, including increasing congestion, rising accident rates, alarming environmental pollution, and depletion of energy sources. Building more highways, the traditional solution, is no longer effective because building involves intensive development for which there are limited financial resources. Instead, upgrading existing vehicle highway systems by making them "intelligent" is being considered as one way to curtail or resolve those problems. Such upgrading is made feasible by the computerization of existing facilities and operations with applications of a series of advanced technologies, such as expert systems, neural networks, and fuzzy set theory. Unlike traditional transportation systems, intelligent vehicle-highway systems (IVHS) will possess more power in dealing with dynamic and uncertain problems. It is anticipated that advanced technologies will be a large share of the technical base for future IVHS development.

Inspired by the success of initial efforts, many attempts have been made to apply various advanced technologies to IVHS. Nevertheless, it is also true that each of these advanced technologies has its own proper application domains and limitations. As a branch of artificial intelligence, artificial neural networks (ANNs) are considered useful techniques for a wide variety of IVHS implementations. There is, however, less literature work available for a systematic discussion about the domains, extents, and limitations of ANN applications in IVHS implementations. Being a tool of problem solving, ANNs have been highly recognized for certain tasks in several areas, such as financing, business, and computer science. It is important to the future of IVHS programs to understand how far and to what kind of applications ANNs can be applied to IVHS implementations.

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In the past, there have been few reports in the literature about the application of ANNs to IVHS programs (*1,2*). Nevertheless, the successful application of ANNs in various areas strongly implies great potential for the application of ANNs in IVHS. This paper focuses on a comprehensive evaluation of the application of ANNs to IVHS. The technical needs of IVHS and the technical properties of ANNs are analyzed and summarized. On the basis of on an in-depth investigation of the characteristics of IVHS and ANNs, the interface between IVHS and ANNs is drawn in terms of the technical demand-supply relationship. As a result, the technical conjunction of IVHS and ANNs is reclarified. Several matrices that indicate the technical requirements of IVHS, the technical properties, and the potential application domains of ANNs to IVHS are provided. A simplified version of ANN application to a potential IVHS problem is also presented to demonstrate an application of ANNs in a modeling process. Results of the application example also are discussed.

TECHNICAL REQUIREMENTS OF IVHS

IVHS is a collection of advanced applications for information processing and computer technologies. The major benefits provided by IVHS are greater mobility for highway users and a higher level of safety. So far, several implementations of IVHS already have been achieved or are in progress. To illustrate the technical needs of IVHS, the following IVHS technologies have been implemented and are summarized.

- Leit- Und Information System of Berlin (LISB) (*3*),
- Autoscope (*3*),
- Advanced Mobile Traffic Information and Communication System (AMTIC) (*3*), and
- Automatic Vehicle Identification (AVI) System (*4*).

LISB (*3*) is a route guidance information system that encompasses about 500 vehicles and a network of approximately 3000 km of roadways. The network covers 4,500 intersections and about 1,300 signals. Approximately 250 beacons set along the roadside provide information to the vehicles. This is an information processing intensive system.

AUTOSCOPE (*3*), a driver navigation system, was codeveloped by the Minnesota Department of Transportation and the University of Minnesota. AUTOSCOPE uses video cameras and computers to analyze images and extract traffic flow information for surveillance and control purposes. The system includes roadside image sensors and closed-circuit television devices. The computer vision system processes images and generates data identifying congestion and incidents. Artificial intelligence systems are used to aid in the analysis of alternatives for congestion control.

AMTIC (*3*) was developed in Japan. Traffic information is sent to the system's center from a guide terminal and sign posts through a cable network installed along the ground. The sign posts and guide terminal also relay signals from the system's automobiles through the ground network. The automobiles have on-board signal-receiving equipment and advisory display systems.

The AVI system (*4*) identifies vehicles without stopping or even slowing the traffic flow, thereby improving highway mobility. Its most promising application at this time is in toll booth functions. With the success of the AVI system, toll booths are expected to become highly automated by providing nonhuman operation for nonstop toll charge services. A prototype of AVI was set up on the Dallas (Texas) North Tollway in 1988. Another three AVI-equipped highways are also under construction in Orange County, California.

As seen in the aforementioned programs, IVHS makes intensive use of information processing, control, image processing, pattern recognition, optimization, classification, prediction, and knowledge-processing techniques.

IVHS is composed of four elements. Each element is a system that contains a variety of advanced hardware implementations and software technologies. The four elements are as follows:

- Advanced traffic management system (ATMS),
- Advanced driver information system (ADIS),
- Advanced vehicle control system (AVCS), and
- Commercial vehicle operation (CVO).

ATMS consists of several procedures, including detection, classification, prediction, optimization, communication, and control technologies. The information about traffic conditions on the highways is detected and transmitted to a central management processor. After processing the input information, the central management processor sends commands or advisory information back to the vehicles in the traffic flow.

ADIS provides information to individual motorists. The information could be travel related, such as traffic conditions, advice on route selections, or travel costs, or nontravel related, such as the location of a theater, if an extensive ADIS is established. Intensive information processing, massive transportation data, data compression, and knowledge-processing technologies are required because of the wide variety of information communicated to individual drivers.

AVCS enhances the performance of motor vehicles. The implementation of AVCS is expected to bring significant improvements in highway safety, fuel efficiency, and elimination of air and noise pollution. It is also expected to affect some human limitations in driving, such as perception/reaction time, thereby changing the basic models and designs of highway transportation systems. Prediction, classification, detection, and control techniques are used intensively in AVCS.

CVO applies to commercial and emergency vehicles. The implementation of CVO provides faster, more reliable, and more efficient services, such as the collection and delivery of goods through the monitoring of fleet vehicles. Communication, optimization, and control techniques are necessary for the implementation of CVO.

In summary, the major technical requirements involved in IVHS implementation should be in accordance with intelligent techniques; that is, they are capable of performing well even under uncertain or dynamic circumstances, or both, giving heuristic solutions when exact solutions are unnecessary or impossible; and reasonably ignoring noises that exist in the input data. Figure 1 indicates major techniques required for IVHS implementation on a category basis. These techniques could be applied through either hardware implementation or software programming.

IVHS Elements / Technical Requirments	ATMS	ADIS	AVCS	CVO
prediction	●	●		●
classification	●			
control	●		●	●
pattern recognition	●	●	●	
optimization	●			
noise cancellation	●	●	●	
image processing			●	
knowledge processing	●	●		
signal processing			●	
data compression		●		
natural language processing			●	●
speech recognition			●	●

● Useful technique for the corresponding IVHS element

FIGURE 1 Technical requirements of IVHS.

PROPERTIES OF ANNs

ANNs are parallel computing techniques that conceptually mimic human mental neural structure and functions. The number of ANN applications in different fields has been expanding rapidly since the middle 1980s because of their attractive characteristics and capabilities such as learning, abstraction, and generation. Although it is preferable that they be operated on parallel computing devices, ANNs problem-solving abilities are still impressive in their performance of many tasks from a noncomputing speed point of view. Although limited in number, ANN applications have covered a variety of problem domains in transportation engineering (*5*). ANN applicable problem domains include prediction, classification, control, optimization, and modeling. Some of the ANN uses most frequently encountered in transportation engineering are summarized.

Prediction

Prediction is a basic technique of transportation planning. It determines the "appropriate" actions to be taken in the future on the basis of historical data and reasonable logic or inferences. The perceptron types of ANNs can be trained to form appropriate architectures for the prediction procedure. Training data can be obtained in the same way, from either an historical data base or a current survey. The modeling of the input-output relationship is completed by training the ANN. The advantages of applying ANNs to prediction problems are (a) no programming or formulation effort is required; and (b) to some degree the noise existing in the data base can be removed. Neural network models such as ADALINE and backpropagation have been applied to zonal trip production prediction (*5*). The backpropagation model also has been applied to the prediction of short-term traffic volume on a highway segment (*6*).

Control

Control is an important procedure in traffic management and transportation operations such as vehicle driving. Control logic is defined as giving an appropriate output when an input is presented to the controller. The output of a control logic model could be an action to take, the amount of an adjustment, or some other measurements. It is often difficult, however, to formulate the input-output logic model mathematically. Sometimes irregular requirements, such as insensitivity of an output value with a specific range of input values, are necessary. Ordinary mathematical approaches are unlikely to form an arbitrary curve. In most cases, the control logic model could be complicated even more by providing multiple inputs and producing multiple outputs. In contrast, a multilayered nonlinear perceptron ANN is able to approximate any reasonable continuous function to an arbitrary degree of accuracy (*7*). A number of control applications have been reported in the area of transportation engineering. These applications are widely scattered in a variety of domains, including roadway network traffic signal control (*8,9*), vehicle control (*10*), in-vehicle device control (*11*), and air traffic control (*12*).

Optimization

Neural networks in general provide heuristic optimization. A typical optimization application is the traveling salesperson problem. A recurrent network called the Boltzman machine is used to determine the salesperson's optimal route. A simulated annealing technique is incorporated in the architecture of the neural network. The network attempts to discover the global minimum. It allows, however, for an alternative point that is near the true optimal point in the solution space to be the ultimate solution.

Classification

ANNs can perform classification in various fashions. Some of the neural network approaches provide better classification than do conventional approaches. For instance, an application that uses ART1 (adaptive resonance theory), an ANN model designed to solve the stability-plasticity dilemma, to classify dynamic traffic patterns at a network level is much more efficient than an ordinary dynamic programming approach (*8*).

Pattern Recognition

Perhaps the most remarkable property of ANNs is that of pattern recognition. Much success has been reported in this application domain (*13*). The pattern recognition abilities of ANNs are especially useful for computer vision because of their capability for dealing with incomplete, noisy, or distorted patterns. Such properties could be extended to obstacle detection, pedestrian detection, and even traffic incident detection problems.

ANNs possess a wide variety of properties, and although the performance of each ANN property has not yet been fully evaluated, ANNs are most certainly able to provide transportation engineering, including IVHS, with many useful problem-solving approaches. Figure 2 lists some major ANN properties that are frequently needed in transportation engineering.

POTENTIAL APPLICATION OF ANNs TO IVHS

The four IVHS elements—ATMS, ADIS, AVCS, and CVO—are implemented primarily through the use of two advanced techniques: advanced information processing and advanced modeling. Advanced information processing includes numerous techniques such as data acquisition, data arrangement, knowledge processing, classification, and transportation data processing. Modeling techniques are used to build desirable relationships between given inputs and the outputs of models, such as the control logic model and the prediction model. Neural networks provide numerous versions of these two types of techniques as a technical basis for IVHS. In this section, several major technical properties provided by ANNs and their potential applicability to IVHS are discussed. The limitations of ANNs for use in IVHS are discussed at the end of this section.

Data Acquisition

In this study, the term data acquisition does not refer to the capability of hardware to obtain information but instead to the capability of software to correctly and precisely obtain the desired information. For instance, for the purpose of pattern recognition the preferred data acquisition technique should be able to correctly catch patterns that may be incomplete or noisy because one of the major advantages offered by ANNs is recognizing noisy, incomplete, or distorted patterns. Many such ANN applications have proven to be successful (*14–18*). For IVHS implementations, ANNs can be applied to computer vision to acquire information through pattern recognition. They also can provide reliable and feasible input information to other processors such as algorithms for obstacle detection (*19*) or an autonomous driving system (*10*).

Knowledge Processing

ANNs are useful in dealing with abstract information. In real life, including IVHS systems, many pieces of information are abstract, that is, it may not be possible to represent them by a single, clearly defined concept. Sometimes, their definition varies, depending on who is doing the defining. An example of such a case is making a judgment about whether a specific congested traffic condition is recurrent or nonrecurrent. An ANN can store different opinions and summarize them to give a single-valued reasonable "standard." This characteristic of ANNs can be utilized as a decision-making procedure with the varying-input information needed for such IVHS applications as incident detection systems.

Classification

A number of ANN models can be used as classifiers (*20–22*). An interesting ANN model, ART, has been identified as a good tool for distinguishing different attributes of roadway segments on the basis

ANN Applications / ANN paradigms	control logic modeling	pattern recognition	prediction	noise cancellation	knowledge processing	classification	image processing	optimization
(M)ADALINE	●		●	●			●	
Backpropagation	●	●	●		●		●	●
ART	●				●	●	●	
Hopfield Network	●	●				●	●	
Boltzman Machine		●			●		●	●
Neocognitron / Cognitron		●					●	
Counterpropagation						●		
Kohonen Net						●		
Neural GMDH								●
BSB					●	●	●	
LVQ	●						●	●
BAM	●						●	

FIGURE 2 ANN application domains.

of traffic patterns taking place on those roadway segments. The sensitivity of ART in detecting the differences between traffic patterns is adjustable. It is also capable of on-line training, that is, no predetermined classification algorithm is required. The classification is largely based on the analog similarity among the patterns instead of numerically computed error values. Another advantage of using ART is that the haphazard, unseen irregular traffic patterns will not affect the memory before it is stored.

Data Compression

Because intensive information and data on transportation are required for IVHS applications, such as in ADIS and ATMS, the collection of accurate data is extremely important. Also, because IVHS serve dynamic systems and require massive communication with time limits, the efficiency of information transmission becomes a key issue affecting the success of many IVHS applications. Data compression is one way to improve efficiency. ANNs are good tools to compress data for quickening data transportation (*23*). The utilization of data compression by ANNs should be expected soon for ADIS.

Modeling

As mentioned earlier, the neural network (multilayered perceptron with nonlinear transfer function) can approximate any reasonable function. It can be applied to virtually any modeling problem if sufficient data are provided for the training. Especially when the system to be modeled is very complicated, conventional mathematical approaches are often impossible to use for completion of the procedure. In IVHS, many tasks such as control and forecasting need to be completed through models that compute or react reasonably to external stimulus. In the real world, relationships between the external stimulus and the outputs of the model are frequently unknown. Multiple inputs/outputs is another often-seen situation in which the relationships are difficult to be expressed mathematically. For example, travel time in a weaving section of highway can be affected by many factors, such as number of lanes, driver characteristics, and visibility of the highway section. Some of those factors are known, some are unknown. The travel time should be a function of these factors, however, it is difficult to tell how these factors will affect travel time. To deal with such a complex problem using conventional mathematical approaches, in most cases, is establishing empirical equations that require a great deal of effort in calibration and model validation. Similar problems are encountered even more often in control logic modeling. Nonlinearity often prevents building a reasonable model or even the ability to build that model. ANNs can be trained to obtain appropriate architecture that functions desirably. As long as reasonable and sufficient data are available, models can be established. With an ANN approach, it is not necessary to identify how every factor affects the output of the model. The importance of each factor is automatically identified through the training. Therefore, less knowledge about the nature of the problem is required.

Limitations

Although ANNs provide many useful properties that meet IVHS needs, there are several drawbacks to the use of ANNs that should be noted.

- Many ANN paradigms have not yet been well examined;
- In most cases, ANNs can provide only heuristic solutions;
- Some inherent drawbacks, such as determining the proper learning parameter during backpropagation training remain unsolved; and
- Computing speed is highly dependent on hardware implementation.

There is still a long way to go to fully exploit the advantages of ANNs implementation for IVHS. For control IVHS applications, hardware implementations are needed to accompany software development for the full utilization of the ANNs advantages.

In summary, as seen in Figure 1 and Figure 2, the technological requirements of IVHS and the technological contributions made by ANNs meet at many points. Figure 3 indicates the potential application domains of ANNs to IVHS. Many ANN properties can be directly applied to IVHS implementations such as classification, pattern recognition, image processing, knowledge processing, and control logical modeling. Some, such as speech processing (*24*), and natural language processing (*25,26*) are expected to be applicable in cooperation with other supplementary approaches in future applications.

ANN APPLICATION EXAMPLE—ANN TRAVEL TIME ESTIMATION MODEL

As indicated earlier, ANNs could be used for numerous IVHS implementations. In specific circumstances, various IVHS tasks may be completed by various ANN models or their combination with other approaches. In this case study, a limited demonstration is presented to explore the applicability of a specific ANN model, backpropagation (BP) network, in modeling problem. An experiment was undertaken to create an ANN travel time estimation model. The computational details will not be presented here because this is a demonstration version.

As known, travel time estimation is an important process in many decision-making procedures in traffic management. In IVHS, travel time is a basic piece of information needed for ATMS and ADIS. On the other hand, the travel time estimation process is complex because any of a large number of factors could affect motor vehicle travel speed. This case will examine a neural network travel time estimation model for a two-lane roadway segment that is assumed to be an urban roadway with a Class 2 ranking and a 30-mph free flow speed (Figure 4). The model will deal with the following situations: normal condition, blockage in the left lane, and blockage in the right lane.

Problem Statement

Roadway condition is considered the most important factor affecting travel time in an urban network. Many studies have examined travel time estimation for a particular roadway segment under normal conditions. The problem becomes much more complex under abnormal conditions such as a lane blockage. The complexity is the result of several factors:

- The reduction in the number of available lanes,
- Weaving movement,
- Positions of weaving taking place,
- Length of the blockage, and
- Position of the blockage.

It is difficult to determine which and by how much these factors will ultimately affect the average travel time. Empirical mathemat-

ANN Application Domains / IVHS Applications	control logic modeling	pattern recognition	prediction	noise cancellation	temporal pattern recognition	classification	image processing	speech & language
route guidance			●					
vehicle identification		●					●	
neural suspension	●							
obstacle detection		●					●	
driving control	●						●	●
navigation				●				
collision avoidance	●			●				
traffic control		●	●	●	●	●		
incidence detection		●				●	●	
traffic information			●	●				

FIGURE 3 Potential applications of ANN.

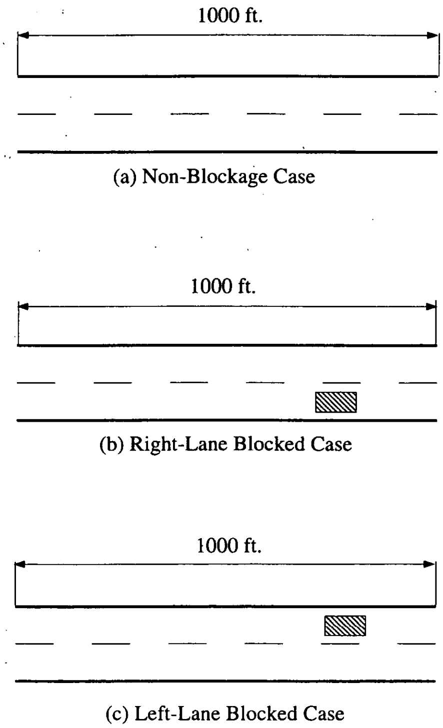

FIGURE 4 Schematic drawing of street segment for simulation of TRAF-NETSIM.

ical modeling has been the primary approach used to express the relation between travel time and the group of influencing factors. However, the method of determining the basic form of the equation, that is, to approximate the curve of travel time versus the influencing factors, is still nondeterministic. Although some mathematical processes such as Fourier transformation are theoretically able to model any curve, it is virtually impossible if the polynomial equation is large.

Establishment of ANN Model

As mentioned earlier, the BP ANN is in wide use to reasonably approximate any curve on a multiple input-output basis. It is also convenient to update simply by feeding new data into the system. For these reasons, the BP is considered to be a flexible neural network paradigm for travel time estimation modeling.

The raw data for training the BP for this case study is obtained from a simulation run on the TRAF-NETSIM software, which was developed for urban traffic network simulation. The simulation was divided into three groups: Group 1, normal roadway conditions; Group 2, right lane blockage; Group 3, left lane blockage. Each group contains 32 cases with different average traffic volumes. The simulation period for each case is 5 min. After running those cases, the simulation results for 5-min traffic volume and average through time for every case was recorded as if for BP training use.

The BP has a two-layered architecture with five hidden processing units. It requires three inputs: 5-min traffic volume, blockage index for the right lane, and blockage index for the left lane. The latter two inputs are binary, that is, set to 0,0 if the roadway is not blocked, 1,0 if the right lane is blocked, and 0,1 if the left lane is blocked. Only one output is given by the BP—the average through time in seconds.

The total of 96 data sets was divided into two groups with a random order. One of the groups was used to train the network and the other was used to test the training effect. In the training, the BP reached the error minimum on the testing data group at Training Iteration 4900. The total squared errors generated by the BP on the training data group and the testing data group were 1,225.08 and 1,449.68 sec ^{2}, respectively.

Figures 5 through 7 indicate the performance of the neural travel time estimation model under three different roadway conditions. The line is drawn by the neural network estimation model, and the dots are the simulation results.

Results and Discussion

The application example shown in this study is simple, but it is detailed enough to show the feasibility of the modeling process. Many factors affecting travel time were not taken into consideration because of the simulation program used. The BP neural network estimated the travel time on a specific roadway segment for all the three scenarios with an average error of 5.5 sec compared with the results obtained by TRAF-NETSIM. Such a result is considered conceptually reasonable because no other models are available with which to compare it. Figures 5 through 7 indicate the performance of the neural network travel time estimation model under three different roadway conditions. The lines were drawn by the neural network estimation model, and the dots are the simulation results. In addition to not having any requirements for addressing explicitly the characteristics of the input-output relation such as polynomial, exponential, and logarithmic, for concepts and operations of the model, the following are possible extended advantages of using ANN modeling.

- More complex traffic and roadway situations can be dealt with,
- Updating the ANN model is simple, and
- The ANN model requires less mathematical effort.

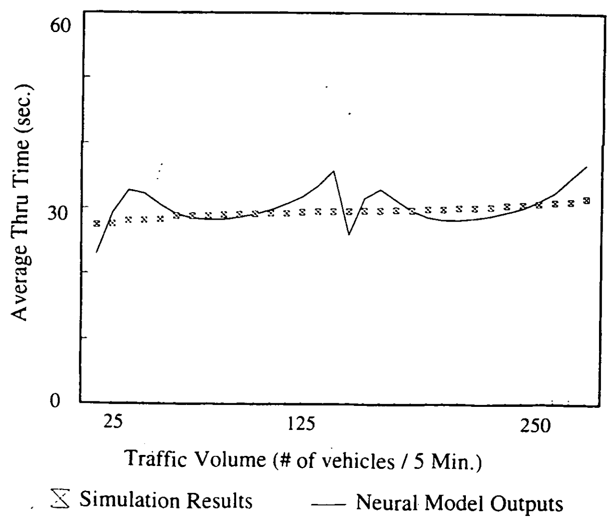

FIGURE 5 Traffic volume versus travel time for nonblockage case.

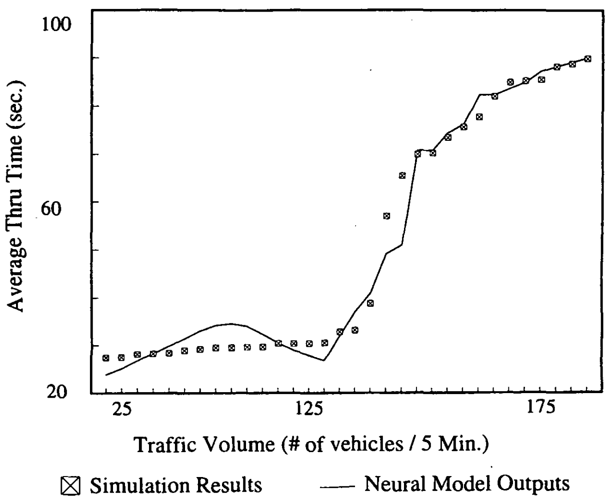

FIGURE 6 Traffic volume versus travel time for right lane-blocked case.

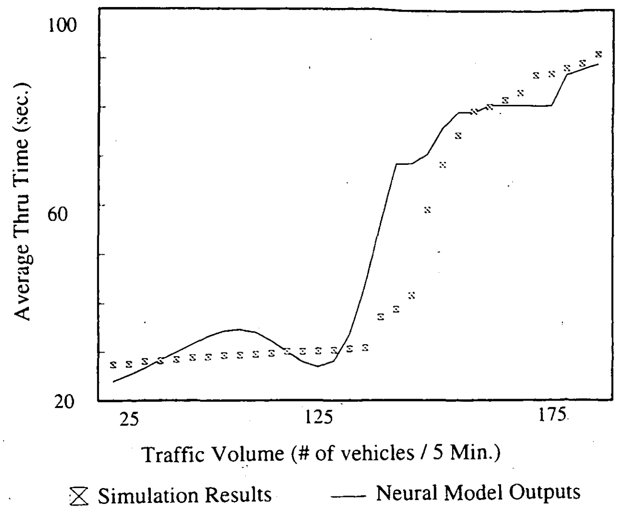

FIGURE 7 Traffic volume versus travel time for left lane-blocked case.

The ANN models provide heuristic solutions instead of exact solutions. Because ANNs are operated on a vector basis and each element of the vector can be treated independently, more complex problems can be dealt with. Furthermore, the relationship between each element in the input vector and the outputs are allowed to be unknown. Therefore, ANNs are considered to be particularly useful for those estimation or prediction problems in which accuracy is not necessary or not guaranteeable.

SUMMARY AND CONCLUSIONS

ANNs provide many properties that meet a number of technological requirements of IVHS, especially in information processing and modeling. The intelligent operations provided by ANNs are, in many aspects, in accordance with the application orientation of IVHS. Some ANN techniques, such as pattern recognition and control logic modeling, are expected to contribute excellent performances when used in IVHS. There is a great potential for ANN techniques to be superior to conventional techniques in such areas as pattern operation and modeling process in certain IVHS applications. The vector-level operations of ANNs—handling multiple input-output—also will better meet the complexity of transportation systems. As seen in Figure 3, numerous direct and indirect applications of ANNs to IVHS should be expected.

In the application example, the BP formulated a model that was able to reasonably estimate the average travel time on a given roadway segment on the basis of two types of information—the traffic volume and lane-blockage index. This model takes into consideration irregular roadway conditions. With the neural network, the complex procedures of formulating traffic weaving movement, car following movement, and tourist lane-blockage detection/reaction behavior could be avoided. The average estimation error was 5.5 sec, whereas the simulation result of travel time at free flow is 27.3 sec for going through the roadway segment (on the basis of results obtained from the Highway Capacity Manual).

Overall, the application potential of ANNs to IVHS is significant. Suitability to IVHS is found in the ANN properties of pattern recognition, classification, data compression, prediction, and control logic modeling. Although superiority to other technologies is not identified in this study, it is possible to expect that ANNs are feasible alternatives to conventional techniques in numerous IVHS application domains, and their use is expected to be extended further in the future.

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