Simulation-Neural Network Model for Evaluating Dilemma Zone Problems at High-Speed Signalized Intersections

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The commonly used traffic control devices or techniques used to address dilemma zone problems at low-volume, isolated, high-speed signalized intersections include detector configurations, advance warning signs with or without flashers, and timings of change intervals or green extensions. The levels of effectiveness of these devices or techniques are sensitive to roadway geometric, speed distribution, and traffic volume. The measures of effectiveness of traffic control at a high-speed intersection approach are expressed as the (a) probability of being caught in a dilemma zone, (b) speed of a vehicle in different segments of the intersection approach, and (c) vehicle conflict rate. A simulation model has been developed to dynamically represent each element of the traffic control system such as roadway geometric, traffic control devices (advance warning signs, flashers, detectors, and signals), and vehicular movements. Artificial neural networks have been developed to estimate vehicular speeds in different segments of the intersection approach in response to different advance warning signs, flashers, and signal indications. The simulation model has been integrated with the neural networks to provide better accuracy of the simulation. A case study showed that the results of the simulation-neural network model compared well with the field data collected at several low-volume, high-speed signalized intersections in Ohio. The model can be used as a non-accident-based safety evaluation procedure for high-speed signalized intersections.

At an isolated high-speed signalized intersection, a high potential for an accident exists in a roadway section close to the stop line, called the *dilemma zone,* where a driver, on seeing a yellow light, may have a difficult time in making a decision whether to stop or to proceed through the intersection. The driver may not be able to stop in advance of the stop line at an acceptable deceleration rate or to clear the intersection during the change interval.

A schematic representation of the dilemma zone is shown in Figure 1, where X_s is defined as the minimum distance from the stop line that would ensure that a vehicle would stop before the stop line at an acceptable deceleration rate, and, similarly, X_c is the maximum distance from which a vehicle can clear the intersection during the yellow interval at current speed. If X_s is greater than X_c, a dilemma zone is formed within which neither the distance from the stop line is adequate for a safe stop nor the yellow interval is adequate for clearing the intersection. When a vehicle is caught in the dilemma zone, the driver is exposed to a potentially unsafe and indecisive situation. A rear-end collision may occur if the driver stops abruptly during the yellow interval, or a right-angle collision may occur if the driver attempts to go through the intersection during the red interval. These conditions commonly exist on rural, low-volume highways where vehicle speeds are high and signals are unexpected or hidden by horizontal or vertical curves.

Some researchers (*1*) have defined the dilemma zone as that area of the approach between a point where 90 percent of the drivers will stop on yellow and a point where 90 percent of the drivers will go (i.e., 10 percent will stop). The boundaries of a dilemma zone for various speeds are shown in Table 1.

To reduce dilemma zone problems at high-speed signalized intersections, various types of traffic control devices or techniques have been used. These include advance warning signs with or without flashers, vehicle detectors, and yellow interval timings. An advance warning sign informs the driver about potentially hazardous conditions on the roadway, and the active flasher on the sign tells the driver whether to expect a yellow or a red indication when he or she arrives at or near the stop line. Vehicle detectors that are strategically placed at the entrance point of a dilemma zone may extend the green interval while there are vehicles traveling within the dilemma zone. A proper yellow interval may provide reasonable yellow timing to minimize the dilemma zone problem. The levels of effectiveness of these traffic control devices are sensitive to roadway geometric, speed distribution, and traffic volume. Hence the design and evaluation of a traffic control system should incorporate these factors to minimize dilemma zone problems.

In the past several methods have been used for the design and evaluation of traffic control at high-speed signalized intersections. These methods can be classified into the following three groups:

1. Field study: conducting experiments such as before-and-after studies (*2,3*),
2. Laboratory simulator: providing simulated driving environment and having subject drivers use a simulator to get results (*4*), and
3. Judgments of experts: conducting a survey or interviewing experts to obtain their engineering judgments (*5*).

However, some of the following difficulties have been experienced with these methods:

1. Limitations on the number of field experiments with different detector configurations, advance warning signs, flashers, change intervals, and green extensions because of the long time, high risks, and high costs of the experiments;
2. Inability to model a traffic control system at the microscopic level because driver behavior is not adequately understood; and
3. Inability to conduct a comprehensive system analysis because the existing methods generally allow for the analysis of only one

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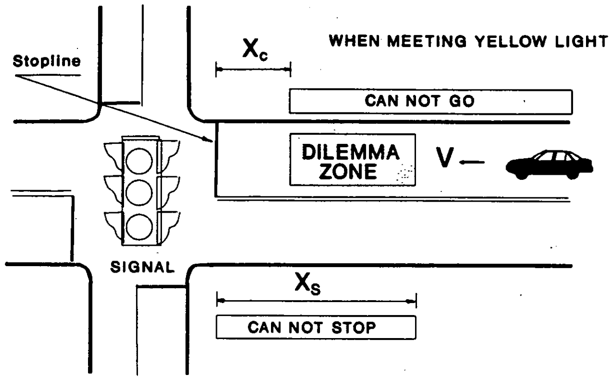

FIGURE 1 Schematic representation of a dilemma zone.

type of traffic control device at one time. The effects of specific traffic control strategies involving detectors, advance warning signs with or without flashers, change intervals, green extensions, and so on are not fully understood.

The objective of the study described here was to develop a simulation-neural network model for examining the dilemma zone problems at rural, low-volume, isolated high-speed signalized intersections. It consisted of

1. Developing a simulation model that can dynamically represent each element of the traffic control system such as roadway geometric, traffic control devices (advance warning signs, flashers, detectors, signals), and vehicular movements;
2. Developing artificial neural networks that can estimate a vehicular speed in response to different advance warning signs, flashers, and signal indications;
3. Integrating the model by developing an interface between the simulation model and the neural network and supporting programs for data input or output and statistical analysis; and
4. Testing and validating the model.

METHODOLOGY

As stated previously a major safety concern at rural, low-volume, isolated high-speed signalized intersections is the accident potential in the dilemma zone. The probability of a driver being caught in a dilemma zone can be interpreted as the chance or frequency of encountering a driver who meets a yellow light and can not proceed through the intersection on yellow at the current speed or stop in advance of the stop line at an acceptable deceleration rate. A high probability of being caught in a dilemma zone will indicate a high accident risk at the intersection and vice versa. Therefore, the effectiveness of a traffic control system can be expressed as the probability of being caught in a dilemma zone (PBCDZ). In the present study PBCDZ was defined as one of the measures of effectiveness for the design and evaluation of a traffic control system at high-speed signalized intersections. The major parameters that affect PBCDZ are

1. Type of advance warning signs; the following four types of advance warning signs are included in the study:
   –Passive symbolic signal ahead (PSSA) sign. This is a commonly used sign with green, yellow, and red circles. Flashers are not used.
   –Prepare To Stop When Flashing (PTSWF) sign. The flashers are activated a few seconds before the onset of the yellow indication. Some agencies [for example, the Ohio Department of Transportation) (DOT)] use the PTSWF sign in addition to the PSSA sign.
   –Flashing Symbolic Signal Ahead (FSSA) sign. The flashers act like the PTSWF sign. However, the written message is replaced by green, yellow, and red circles.
   –Continuously Flashing Symbolic Signal Ahead (CFSSA) sign. It has three circles as for the FSSA sign. However, the flashers are active all the time.
2. Location of advance warning signs; the signs are usually located a few hundred feet upstream of the intersections. The location of an active advance warning sign is related to the vehicular speed (usually the 85th percentile speed) for maximum effectiveness.
3. Configuration of detector loops; two or more detector loops are commonly used for high-speed signalized intersections. In a previous study (*3*) five detector loops were recommended to accommodate high vehicular speeds. Some other loop configurations for high-speed signalized intersections were also recommended (*1*). Proper loop configuration will reduce the chances of "gap out" or "maximum green time out."
4. Change interval and green extension; the length of the yellow interval is generally 3 to 5 sec (*6*). ITE has specified a formula for the calculation of yellow intervals (*7*). In theory a long change interval seems to be a possible solution to the dilemma zone problem.

TABLE 1 Dilemma Zone Boundaries (*1*, p71)

Approach Speed		Distance from Intersection for Probabilities of Stopping			
		Feet		Meters	
mph	kph	90%	10%	90%	10%
35	56	254	102	77	31
40	64	284	122	87	37
45	72	327	152	100	46
50	80	353	172	108	52
55	88	386	234	118	71

However, in practice it may cause other problems, like encouraging drivers to use the change interval as part of the green interval or proceeding into the intersection from a longer distance upstream. The green extension is timed to permit a vehicle to travel from a detector to the next detector or to the stop line, subject to the preset maximum green interval. A short green extension results in a relatively snappy operation.

In practice it is difficult to record PBCDZ in the field because the boundaries of a dilemma zone vary with individual vehicular speeds (*1*) and the effect of each traffic control device cannot be separated. In the present study, in addition to the PBCDZ the speed of a vehicle in various segments of the intersection approach was used as a measure of effectiveness. In a previous study (*2*) the authors found that the signs with flashers described earlier had a strong influence on speeds at or near the intersections, and the speed of an individual vehicle in different segments of an intersection approach was related to the type and location of advance warning signs, flasher indication (active or inactive), and signal indication.

The speed of a vehicle was recorded in four segments along the high-speed intersection approach. Each segment was called a *speed zone.* Zone 1 was the segment of the intersection approach just upstream of the advance warning sign. Zone 2 was the segment just past the advance warning sign but in advance of the dilemma zone for an average speed of 55 mph. Zone 3 was the final segment of the intersection approach, measured from the beginning of the dilemma zone to the stop line. If the intersection approach had a PTSWF sign, a PSSA sign existed at an upstream location (per current practice in some jurisdictions). In this case an additional zone, called Zone 4, was used (Figure 2). The speed profiles along the approach were obtained from the recorded data and used later for simulating vehicle movements.

Finally, in the present study vehicular conflict rate was used as an additional measure of effectiveness in the design and evaluation of traffic control systems at high-speed signalized intersections. The following types of conflicts (*8*) were examined:

1. Run red light: a proceeding vehicle is upstream of the stop line when the signal turns red.
2. Abrupt stop: at the last instant a driver decides to stop. The deceleration, particularly within 100 ft of the stop line, causes the front end of the vehicle to dip noticeably.
3. Acceleration through yellow: the driver guns the engine to proceed through the intersection on a yellow light.

In the past several traffic simulation software programs have been developed, such as TEXAS for intersection analysis and NETSIM for network analysis. However, no existing simulation model can be used to effectively address dilemma zone problems and particularly to calculate PBCDZ or estimate the effects of advance

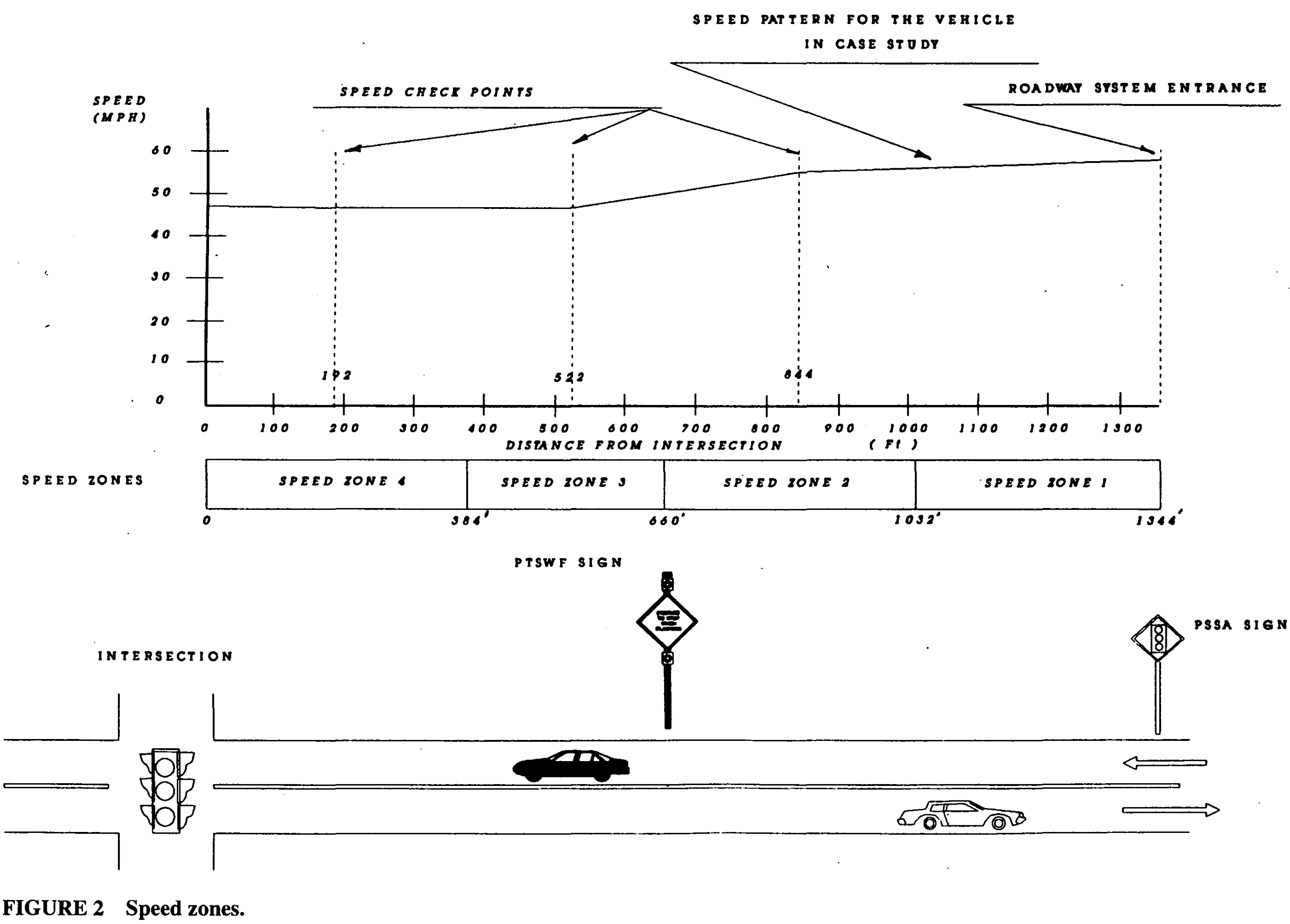

FIGURE 2 Speed zones.

warning signs, flashers, detectors, change intervals, and so on on speed and vehicle conflict rate. Hence, a personal computer–based simulation model was developed for evaluating dilemma zone problems at rural, low-volume, isolated high-speed signalized intersections. The simulation model was interfaced with a set of neural networks and supported by a graphic user interface and programs for data input/output, statistical analysis, and reporting. The neural networks allowed for a better representation of the changes in driver behavior as a result of different traffic control strategies implemented at the intersections, which is not available with the existing simulation models. In this way better experiments could be conducted in short time periods at low cost. In the present study the simulation system SLAM II (*9*) and Neuralworks Professional II/Plus (*10*) were chosen for use in the development of the simulation model and the neural networks, respectively.

SIMULATION MODEL

The simulation project involved many complex activities including building models, executing simulations, collecting data, generating alternatives, analyzing outputs, and interpreting results. The philosophy in developing the simulation model was first to make the simulated system closely represent the character of a real-world system under various conditions and then to enable the model to generate PBCDZ and other results for further analysis.

The simulation model contains the following four major subsystems: (a) vehicle subsystem, (b) traffic control subsystem, (c) driver behavior subsystem, and (d) roadway subsystem. Several simulation processors were developed to process each vehicle and to process the system information. Figure 3 shows the structure of the model, the relationships of the processors within the model, and the information flow from and to each processor. The subsystems are briefly described in the following paragraphs.

The vehicle subsystem is a key component of the model, which contains vehicle arrival and attribute processors to simulate vehicles traveling through the system. Each vehicle is represented by several attributes such as vehicle type, current speed, location, and headway to leading vehicle. Each vehicle is generated at an entry point on the roadway, which is sufficiently in advance of the intersection, and is removed from the system after crossing the intersection.

The traffic control subsystem is represented by traffic signal indications, loop detectors, and advance warning signs with or without flashers. It has a traffic control processor to coordinate the functions of all traffic control devices. Signal indications, detector calls, advance warning signs, and distance to traffic control devices are important factors that affect driving behavior. If a vehicle is passing over a loop near the end of the green phase, a detector call is sent to the controller, which then gives several seconds of green time extension (depending on the detector configuration and the speed limit). This process can be repeated until the maximum green time is reached. The flashers on the active advance warning sign are timed with the controller so that the flashers begin to flash shortly before the end of the green phase and continue to do so until the next green phase begins.

The driver behavior subsystem consists of a speed update processor and a set of trained neural networks, which take the current vehicle position, flasher and signal indications, and related factors as inputs and estimate the response of the driver, which is represented by the vehicular speed in the next time unit or speed zone. This processor provides communications between the vehicle subsystem and the neural networks.

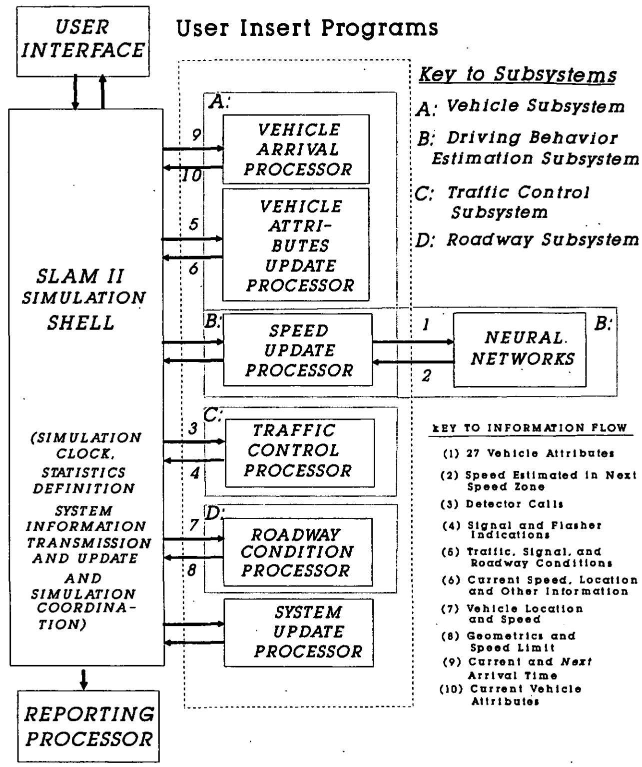

FIGURE 3 Model structure.

The roadway subsystem was represented by a roadway segment that begins in advance of the intersection (called an entry point) and ends at the stop line, which includes the number of lanes, roadway curvature (if any), width of lanes, and existence of exclusive left turn lanes (if any).

Additionally, the system update processor scans all activities in the system, compiles data for generating statistics, and updates the system information, including the number of vehicles in the system, average speed, queue length, volume, and traffic delay in the system. Finally, the reporting processor generates printed outputs of the simulation results.

NEURAL NETWORK DEVELOPMENT

In the past the neural network technology has been found to give good results in engineering applications owing to its capability to learn and recall (*11*). In the present study neural networks were trained and tested to estimate speeds in various speed zones of high-speed signalized intersections, which could be recalled for specific applications by the simulation model. The speeds are estimated in response to the current driving environment such as geometric conditions (tangent or curved approach), signal indications, flasher indications, distance of the vehicle to the intersection, and type and location of the advance warning sign(s) (Figure 2).

A neural network works on a learn and recall basis and is different from conventional computer programs. The basic component of a neural network includes a processing element (PE) that has the ability to learn the relationship between the given inputs and the correct output and to use the relationship to estimate an output when a set of new input data is given. A typical neural network usually consists of one input layer, one output layer, and one or more hidden layers. Detailed descriptions on the theory and practice of the neural network have been provided previously (*12,13*).

Field data were needed for the training and testing of neural networks. The data used in the study were collected for a research project on active advance warning signs at four rural, low-volume, isolated high-speed signalized intersections in Ohio (*2*). The data contained the following information:

1. Vehicle type: light or heavy;
2. Geometric condition: curved or tangent approach, with or without exclusive left turn lanes;
3. Travel time or speed in each speed zone;
4. Advance warning sign: four types of signs as described before;
5. Flasher indication: active or inactive (when the vehicle arrived at the advance warning sign);
6. Turning movement: through, left, and right;
7. Signal indication: green, yellow, and red (when the vehicle arrived at the beginning of the dilemma zone or at the stop line);
8. Stop: whether the vehicle stopped or proceeded;
9. Conflict: run red light, abrupt stop, and acceleration through yellow; and
10. Time period: morning, midday, afternoon, and night.

The intersections where the data were collected consisted of roadways with different geometrics and advance warning signs. For a detailed description of the data collection and results of the study see Pant and Huang (*2*).

Figure 4 shows the structure of a neural network that was developed by the study. It has an input layer with 27 input PEs, an output layer, and two hidden layers. The 27 PEs represent the coding for the different variables affecting the speed of a vehicle in a given zone. All variables except speed and distance were of the categorical type and were coded in the 1-of-*N* forms as shown,

- Input variables
  1. Current speed (ft/sec).
  2. Vehicle type: truck = 0,1; passenger car = 1,0.
  3. Existence of flashers: yes = 1,0; no = 0,1.
  4. Flasher indication when vehicle reaches advance warning sign: active = 1,0; inactive = 0,1.
  5. Signal indication when vehicle reaches beginning of dilemma zone: green = 1,0,0; yellow = 0,1,0; red = 0,0,1.
  6. Signal indication when vehicle reaches stopline: green = 1,0,0; yellow = 0,1,0; red = 0,0,1.
  7. Turning movement: left = 1,0,0; through = 0,1,0; right = 0,0,1.
  8. Vehicle stopped or proceeded: proceeded = 1,0; stopped = 0,1.
  9. Tangent or curved approach: tangent = 1,0,0; modest curve = 0,1,0; high curve = 0,0,1.
  10. Existence of additional PSSA sign: yes = 1,0; no = 0,1.
  11. Existence of CFSSA sign: yes = 1,0; no = 0,1.
  12. Distance of flasher from stopline (ft).
  13. Distance of PSSA sign (if any) from stopline (ft).
- Output variable was the speed in the next speed zone (ft/sec).

Three neural networks—one each for estimating speed in Zones 2, 3, and 4—were developed. The back-propagation method (*10*) was used to develop the neural networks. In all cases the best results were obtained with the hyperbolic tangent transfer function and the normal-cumulative-delta rule. The root mean square error varied between 1 and 5 percent, and the number of iterations required for training the neural networks varied between 5,000 and 15,000. The sample consisted of 8,900 observations at the four high-speed signalized intersections. In a random selection process, 6,200 observations were used for training the neural networks and the remaining 2,700 observations were used for testing. The estimated and actual speeds were tabulated for each neural network, and *t*-tests were performed at the 5 percent level of significance. The tests showed that there were no significant differences between the estimated and observed speeds. Hence, the trained neural networks were accepted. They were translated into FORTRAN codes, compiled within the SLAM II simulation shell, and interfaced with the simulation model.

SIMULATION PROCEDURE

The model begins simulation with a randomly selected initial condition, processes the data after a warm-up period of 500 sec in simulation time units, and terminates the simulation when the statistics reach a stable status. At each time unit all vehicles in the system are scanned, beginning with the first vehicle closest to the intersection and ending with the last vehicle at the most upstream segment of the approach. All vehicle attributes and system information are updated and statistics are computed. A sample of tracing data is listed in Table 2, which provides records of a light vehicle traveling in the through direction on a tangent approach of a high-speed signalized intersection system with an exclusive left-turn lane.

The inputs required for running the simulation model are listed as follows:

1. Traffic conditions: traffic volume, headway distribution, traffic composition, and time of day.
2. Roadway conditions: number of lanes, width of lanes, curvature, exclusive turn lane, and posted speed limit.
3. Traffic control:
   –Number and location of loop detectors;
   –Active advance warning signs—type, location, and timing of flashers; and
   –Signal timing—cycle, phase split, sequence, change interval, green extension, maximum green.

The available outputs are

1. Total number of vehicles simulated,
2. Probability of being caught in dilemma zone,
3. Average speed in each speed zone,
4. Acceleration or deceleration in each speed zone,
5. Vehicle conflict rate,
6. Queue length and delay,
7. Number of maximum green time-outs and gap-outs, and
8. Other user specified statistics and graphic outputs.

SUMMARY OF FUNCTIONS OF ARTIFICIAL NEURAL NETWORKS AND SIMULATION MODEL

The PBCDZ is defined as a major measure of effectiveness for the evaluation of dilemma zone problems, because PBCDZ is related to

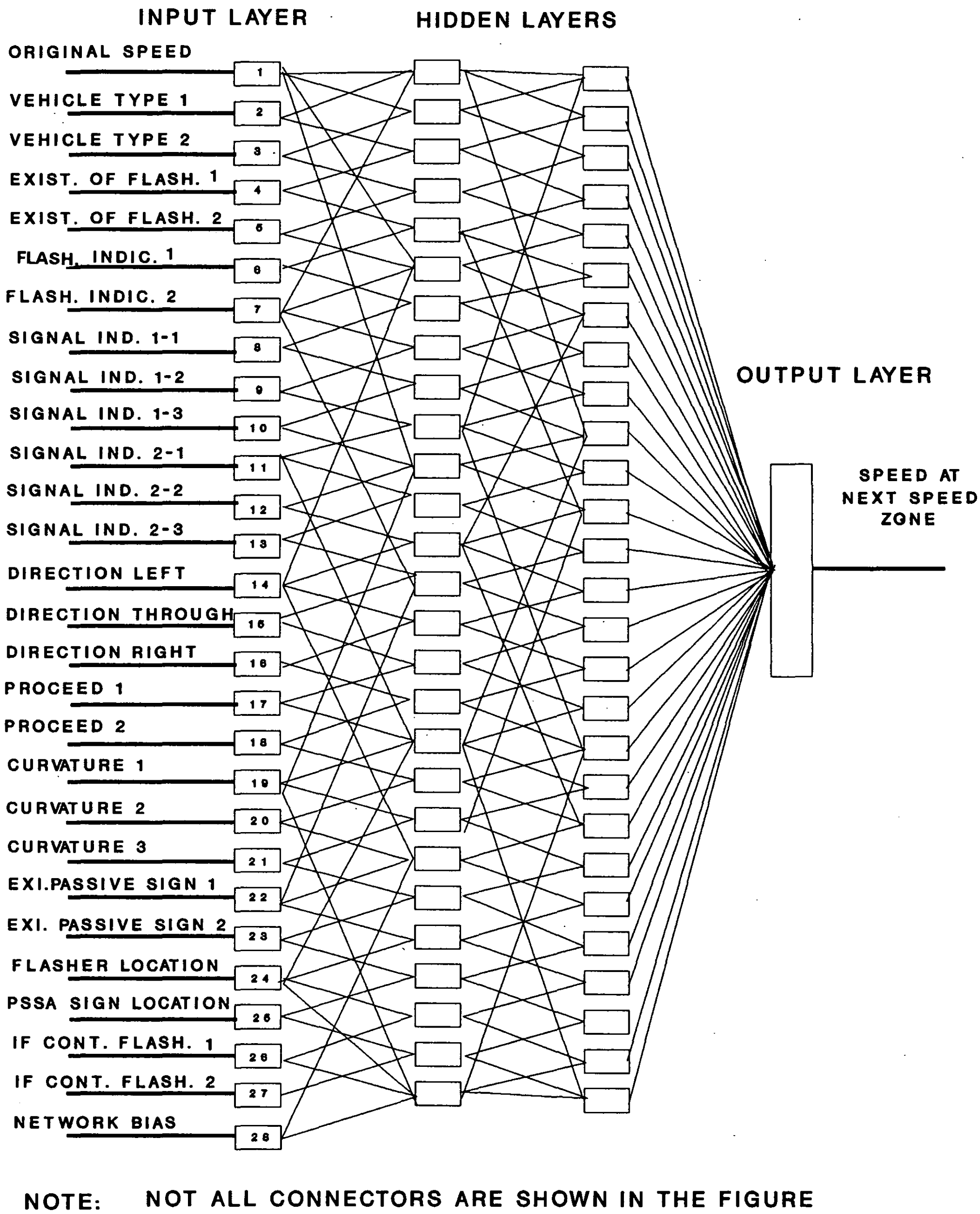

FIGURE 4 Structure of neural network.

the potential of accidents at high-speed signalized intersections (HSSIs).

A simulation-neural network model was developed in the study to obtain PBCDZ and other statistics for the evaluation of dilemma zone problems. The model consists of a simulation model, a set of artificial neural networks, and a group of supporting programs.

A microscopic simulation model was developed. It can precisely simulate traffic flow, traffic control devices, and roadway conditions in HSSI systems, trace every vehicle that has been caught in the dilemma zone, and calculate PBCDZ and other statistics needed for further analysis.

The artificial neural networks (ANNs) are used to estimate vehicle speeds at different segments of the intersection approach during simulation. The ANNs are trained and tested by field data and interfaced with the simulation model to provide the speed estimation for each vehicle in the simulation. For example, if a passenger car is traveling at 55 mph under free-flow condition during a daytime nonpeak hour on a tangent approach equipped with a PTSWF sign, the neural network would allow for estimation of the vehicle speeds along the remaining segments of the intersection approach under these conditions. First, a program sends the current information on the vehicle, roadway, and signal and flasher indications to the ANN. Then the ANN estimates the vehicle speeds at the downstream segment (for instance, 50 mph) and sends the result back to the simulation model. The estimated speeds are used to guide the movement of the vehicle through the system. The applications of the ANNs

TABLE 2 Simulation Tracing Data

Simulation Clock Time (sec)	Current Speed (ft/sec)	Current Location (ft to HSSI)	Headway (ft)	Activity Description
5938	85.2	1340	577	Next vehicle arrival in 14 seconds; current vehicle filed in system; speed estimated 81.3 fps at 844 ft by neural network; and unit speeds reduced according to this speed pattern.
5944	81.3	844	559	Vehicle in free flow, no signal change; speed reduced at each simulation time unit; speed estimated 68.7 fps at 522 ft. by neural network.
5949	68.7	522	NA	PTSWF sign is flashing, signal is still green, decision made to process on yellow, speed estimated 70.6 fps at 192 ft; controller not accepting detector calls.
5951	67.9	350	NA	PTSWF is flashing, signal still green, the vehicle begins accelerating.
5954	70.6	192	NA	Signal is yellow, the vehicle continues accelerating.
5957	71.5	0	NA	The vehicle proceeds through the intersection on yellow interval.

Note: This is the tracing data of one vehicle when at least one major event took place.
NA = no headway available.

allow improvements to be made in the quality of the simulation model, through which PBCDZ is calculated. For a detailed description of the applications of the ANNs refer to Huang (*14*).

The integrated simulation-neural network model is capable of evaluating various traffic control plans by using a non–accident-based procedure and providing traffic control design options with minimum PBCDZ.

CASE STUDY

Several case studies were conducted to test the model and to compare the outputs of the model with field data. The case studies were performed to cover various types of high-speed signalized intersections including those with tangent and curved approaches, different posted speed limits, and traffic control strategies (advance warning signs, flashers, detector configurations, change interval, etc.). The result of a case study performed at the westbound approach of the intersection of US 33 at US 127 in Mercer County, Ohio, is described in the following paragraphs.

The intersection approach under study was a tangent section of a high-speed signalized intersection with an unusually high percentage (about 39 percent) of truck traffic and a posted speed limit of 55 mph. First, a PSSA sign existed at 1,340 ft upstream of the intersection. Later, the Ohio DOT installed a PTSWF sign 660 ft upstream of the stop line. The flashers were activated 9 sec before the end of the green interval, and the detection system was temporarily shut down during the flashing period. One detector loop existed near the stop line and another 554 ft upstream of the intersection, from which each call would give a 5-sec green extension. US 33 and US 127 are important arterials; however, the study approach was considered minor and received 15 sec of minimum green to 45 sec of maximum green, depending on detector calls. The intersection was located in an isolated area, was surrounded by cornfields in a flat terrain, and had a history of higher-than-average accidents before the active advance warning sign was installed. The mean traffic volume was 192 vehicles per hr, with a standard deviation of 32.6 vehicles per hr. Thirty-nine percent trucks was included in the traffic composition.

The estimated speeds of light vehicles in the through direction were tested against the observed speeds for each of the following groups (Table 3):

1. Speed at the entry point to the roadway system (1,340 ft upstream),
2. Speed at the first speed checkpoint (844 ft upstream),
3. Speed at the second speed checkpoint (522 ft upstream),
4. Speed at the third speed checkpoint (192 ft upstream), and
5. Speed at the exit point of the roadway system (at stop line).

The result showed that the relative error between the observed and estimated speeds in each group was less than 5 percent. *t*-tests were performed to test the differences between the observed and estimated speeds, which showed that they were not significantly different at the 5 percent level of significance. The result indicated that the neural networks performed well under each specific condition.

Vehicle conflict rates estimated by the simulation model were compared with those observed at this intersection (Table 4). However, the result was not conclusive because a previous study (*2*) indicated that in the short term vehicle conflict rates at an intersection could vary by a wide margin (as much as 60 percent) without any change in the advance warning sign or other traffic control devices. In the present study the relative error between the simulated and observed vehicle conflict rates was found to vary between 22 and

TABLE 3 Analysis of Selected Speeds for Case Study of US 33 Westbound at US 127

signal indication[a]	travel direction[b]	proceeding without stop[c]	observed speed (ft/sec)	simulated speed (ft/sec)	speed check point[d]	relative error[e]	significance in t-test[f]
G	TH	Y	87.7	87.6	ENT.	0.1%	NS
G	TH	Y	80.1	79.4	CHK1	0.9%	NS
G	TH	Y	61.4	60.6	CHK2	1.3%	NS
G	TH	Y	62.3	61.4	CHK3	1.4%	NS
G	TH	Y	62.6	62.5	EXIT	0.2%	NS
Y	TH	Y	83.0	83.1	ENT.	0.1%	NS
Y	TH	Y	71.1	72.5	CHK1	1.9%	NS
Y	TH	Y	59.8	60.0	CHK2	0.3%	NS
Y	TH	Y	66.9	65.4	CHK3	2.2%	NS
Y	TH	Y	72.0	70.1	EXIT	2.6%	NS
R	TH	N	79.9	80.3	ENT.	0.5%	NS
R	TH	N	69.8	70.1	CHK1	0.4%	NS
R	TH	N	59.9	58.0	CHK2	3.2%	NS
R	TH	N	33.7	35.1	CHK3	4.2%	NS
R	TH	N	0	0	EXIT	0.0%	NS

Note: Only light vehicles are selected.

[a] Signal indication: G=Green, Y=Yellow, R=Red
[b] Travel direction: TH=Through direction
[c] Vehicles proceeding without stop: Y=Yes, N=No
[d] Location where speeds were checked:
ENT.=Entrance of system, 1344 ft upstream of intersection
CHK1=Check point1, 844 ft upstream of intersection
CHK2=Check point2, 522 ft upstream of intersection
CHK3=Check point3, 192 ft upstream of intersection
EXIT=exit point of system
[e] Relative Error: (observed - simulated)/(observed)*100%
[f] NS=Not Significant in T-Test, S=Significant at 5% level

TABLE 4 Observed and Simulated Vehicle Conflict Rates for US 33 at US 127

Vehicle Conflict	Observed Conflicts per 1000 Vehicle	Simulated Conflicts per 1000 Vehicle	Relative Error
Abrupt Stop	1.8	2.2	22 %
Acceleration on Yellow	28.0	40.1	43 %
Running Red Light	1.7	2.5	47 %
TOTAL	31.5	44.8	42 %

Note: Relative Error = (observed - simulated)/(observed)

47 percent. The factors contributing to the errors can be summarized as follows:

1. Instability of field data: the conflict rates may not be stable for a day or even for several days. Hence, it was not clear whether the model or the field data were causing the errors.
2. Human judgment: the conflicts were manually recorded at the site by observers. Because these observations involve subjective judgments, some differences between the observed and estimated rates may exist.
3. Logit model: the logit model was developed by a previous study (*15*) with limited field data. In the future it may be possible to improve the accuracy of the logit model by calibrating it with a significantly larger data base.

The simulation study showed that PBCDZ was 2.7 percent. Because PBCDZ was not observed during the field study the model could be validated only by examining the estimated and observed speed profiles and conflict rates. The result showed that the PBCDZ was sensitive to the traffic control devices on the intersection approach. For example, PBCDZ was reduced by about 19 percent when the PTSWF sign was installed 100 ft upstream of the original location or was reduced by about 28 percent when 1 sec of additional flashing time and a 1-sec longer yellow interval was provided. A user-inserted subroutine was developed to trace back, upon request, the characteristics of speed patterns and related traffic conditions for vehicles caught in the dilemma zone (Table 2). Hence, the most likely causes of a vehicle being caught in the dilemma zone can be examined by tracing back the records. The results indicated that the simulation model could be used to evaluate potential traffic control strategies that could result in a lower PBCDZ at the intersection approach.

CONCLUSION AND RECOMMENDATION

Presented in this paper is a simulation-neural network model for evaluating dilemma zone problems at high-speed signalized intersections. The measures of effectiveness were PBCDZ, vehicle speeds in various segments of the intersection approach, and vehicle conflict rate. The advantage of using PBCDZ in the study is that it reflects the potential of accident risk, because it represents the chance of rear and right-angle collisions. It also represents the effects of various traffic control devices including advance warning signs, flashers, detectors, and signal timing. Therefore, the model can be used as a non–accident-based safety evaluation procedure for high-speed signalized intersections. It is particularly important to use a non–accident-based method for evaluation if an intersection lacks a sufficient number of accidents within a specified period for conducting a rigorous statistical analysis. Because PBCDZ is available through the model, an algorithm for searching the traffic control strategy that would result in the minimum PBCDZ should be developed. In this way the model can provide help to the user in finding optimal traffic control alternatives that conventional simulation models usually cannot provide.

The use of the neural networks made the simulation of vehicle movements more closely resemble the situation observed in the field. By interfacing the neural network with the simulation model, the quality of the simulation was improved. The method used in the present study has significance for future traffic simulation studies because it can better reflect drivers' responses to various traffic control strategies and can improve the accuracy of simulation. The technique of simulation interfaced with a neural network can be extended to other traffic control studies, for example, traffic control for urban signalized intersections or highway work zones. The technique can be used in intelligent vehicle-highway system (IVHS) projects that involve new technologies including detection, real-time control, and communication that would influence a driver's behavior. Because large amounts of traffic data are required for neural network training and testing, future efforts should include collection of traffic data by automatic traffic detection systems. With the development of IVHS technology, such data collecting systems are increasingly available. For additional information on this research, the reader is referred to the work of Huang (*14*).

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