CHAPTER 6　RESULTS OF RTFNN

This chapter develops a rolling-trained fuzzy neural network (RTFNN) approach for freeway incident detection. The core logic of this approach is to establish a fuzzy neural network and to update the network parameters in response to the prevailing traffic conditions through a rolling-trained procedure. The simulation results of some thirty-six incident scenarios in a two-lane freeway mainline case study show that the proposed RTFNN approach can improve the detection performance over the FNN approach, which is based on the same network structure but without updating the parameters through a rolling-trained procedure. The highest detection rate is found at a rolling horizon of 45 minutes and a training sample size of 90 samples in this case study. Section 6.1 illustrates the off-line test results of RTFNN. The comparison of incident detection performance between RTFNN and FNN is shown as section 6.2. Furthermore, the sensitivity of RTFNN is elaborated in section 6.3 and a brief discussion is presented in section 6.4.

6.1 Off-line Test Results

The RTFNN approach is using lane-based fuzzy neural network (see Figure 3-2) to enhance the accuracy of the incident detection algorithms. The validation of off-line tests are performed by simulating various incident scenarios, which is based on the 30-second traffic flow data observed from 6:00 to 12:00 covering a typical morning peak hours and two off-peak periods before and after that peak at the experimented site. As a base for comparison, we set the rolling horizon with 60 minutes and 30-second traffic data as one sample, thus the training sample size is 120 samples. Table 6-1 presents the detection performance, based on the 100 evaluation sets, of 36 incident scenarios. Note that the six data rows in Table 6-1 represent six different incident locations within the same simulation hours. According to Table 6-1, the RTFNN approach has performed quite well with average DR 93.95%, FAR 0.0754%, and TTD 68.39 seconds. The best DR is 98.12%, the best FAR is 0.05%, and the shortest TTD is 59 seconds. From Table 6-1, we find that the detection performance for RTFNN approaches consistently depend on the location of the incident. In general, if the incident takes place near the detector, either upstream (the 250-meter scenarios) or downstream (the 750-meter scenarios), the DR is higher and the TTD is shorter than the one occurring farther away from the detector (the 500-meter scenarios). The overall detection performance for an inner-lane incident is slightly better than that for an outer-lane incident because more traffic volumes are observed in the inner lane than in the outer lane.

Table 6-1 The detection performance of RTFNN for 36 incident scenarios

(rolling horizon = 60 minutes, training sample size = 120)

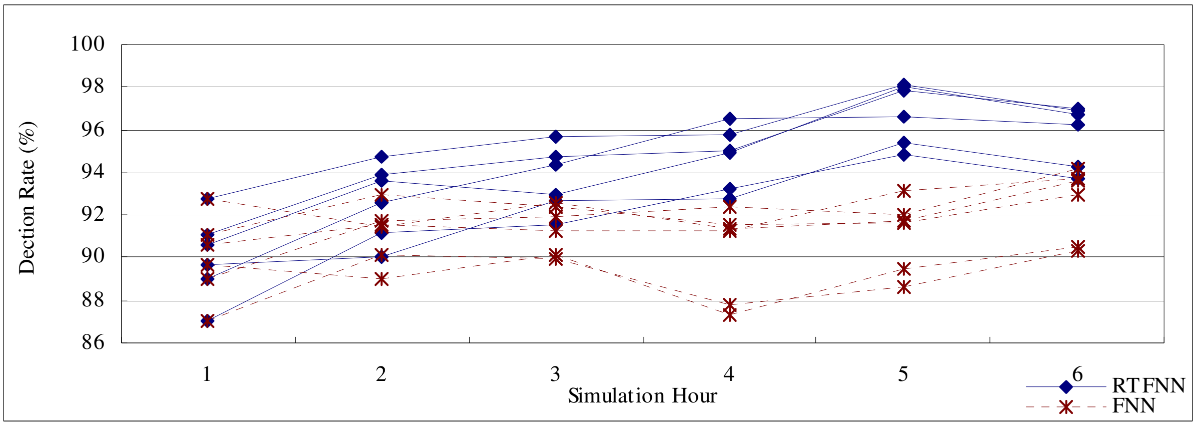
Simulation hour (time of day)	Hourly volume (vph)	Incident location		RTFNN approach		
		Lane position	Distance from upstream detector (meter)	DR (%)	FAR (%)	TTD (sec)
1 (6:00-7:00)	2,403	Inner	250	92.78	0.08	73
			500	89.68	0.05	88
			750	91.11	0.09	74
		Outer	250	88.98	0.08	79
			500	87.05	0.07	83
			750	90.62	0.08	76
2 (7:00-8:00)	2,919	Inner	250	94.70	0.08	74
			500	90.01	0.07	78
			750	93.89	0.09	72
		Outer	250	92.56	0.08	71
			500	91.17	0.06	80
			750	93.58	0.08	73
3 (8:00-9:00)	3,664	Inner	250	95.66	0.09	66
			500	92.71	0.09	72
			750	94.76	0.08	61
		Outer	250	94.33	0.08	65
			500	91.58	0.07	69
			750	92.98	0.09	66
4 (9:00-10:00)	4,514	Inner	250	95.78	0.06	66
			500	92.77	0.07	65
			750	95.02	0.07	67
		Outer	250	96.53	0.06	68
			500	93.26	0.05	62
			750	94.97	0.08	67
5 (10:00-11:00)	3,310	Inner	250	98.12	0.08	63
			500	95.37	0.06	63
			750	97.81	0.08	64
		Outer	250	96.59	0.07	66
			500	94.83	0.07	61
			750	97.98	0.08	65
6 (11:00-12:00)	2,484	Inner	250	96.89	0.07	62
			500	94.31	0.05	62
			750	97.00	0.06	64
		Outer	250	96.28	0.08	64
			500	93.73	0.06	60
			750	96.69	0.07	59

Note: 1. Distance of incident location is measured from the upstream detecting point.

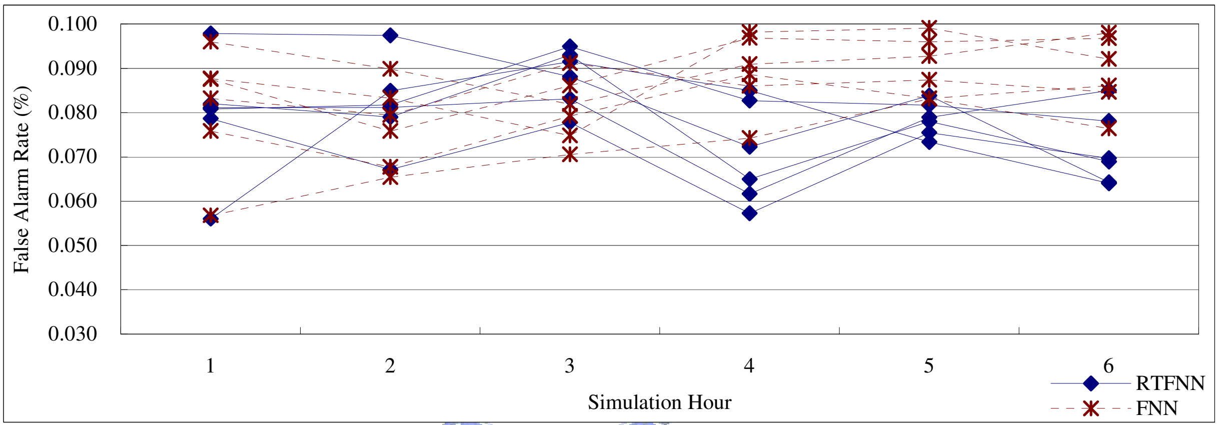
2. Each scenario is simulated for 100 times. The values in this table are the average of 100 simulation runs.

6.2 Comparison with FNN

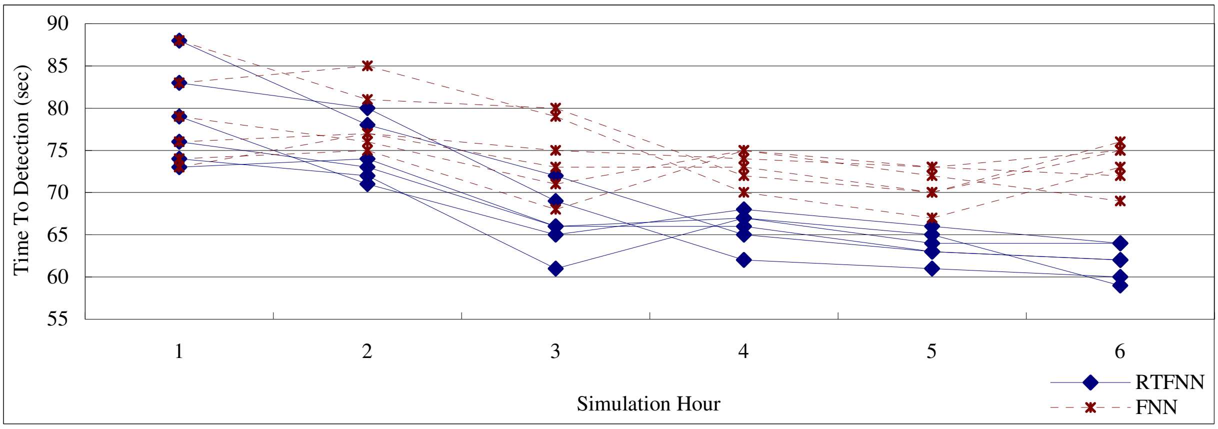
Table 6-2 reports the statistical difference of mean values (t-test) of detection performance between these two approaches -- with rolling-trained (hereafter referred as RTFNN approach) and without rolling-trained (hereafter referred as FNN approach). Initially, both RTFNN and FNN network parameters are based on the same trained results using all six-hour 100 training sets of simulation data, thus they have exactly the same detection performance in the first hour validation. However, after a few hours, RTFNN gradually outperforms over FNN because RTFNN updates the trained parameters in every 60 minutes, but FNN keeps using the initially trained parameters. It is found that the overall DR for RTFNN is 93.95% and for FNN is 91.09%; both are quite high and have statistical difference at 5% significance level. The overall FAR for RTFNN is 0.0754% and for FNN is 0.0803%; both are quite low but have no significant difference. The overall TTD requires only about two time steps, 68.39 seconds for RTFNN and 74.19 seconds for FNN; both are statistically different. The high detection performance suggests that both FNN and RTFNN approaches are all satisfactory in freeway incident detections; but through the rolling-trained, the detection performance can be significantly enhanced. Specifically, as the traffic conditions changed from low to high and then from high to low, the detection performance (DR and TTD) for RTFNN is increased from 90% to about 96%; but the detection performance for FNN remains rather stable between 90% and 92%. As for the FAR, the overall performance shows that there is no significant difference between these two approaches (Table 6-2). Figure 6-1 also demonstrates that the RTFNN approach has outperformed with higher DR, lower FAR and shorter TTD, compared with the FNN approach in various traffic conditions. Note that the six points in the Figure 6-1 represent six different incident locations within the same simulation hours. Figure 6-2 further presents the interaction between DR and FAR for both approaches. In sum, the enhancement of DR (and TTD) without significantly deteriorating the FAR and the superior performance of RTFNN over FNN should be ascribed to the rolling-trained effects of adaptively adjusting the network parameters in response to the traffic variations.



(a) DR



(b) FAR



(c) TTD

Figure 6-1 Comparison of detection performance for each simulation hour between RTFNN and FNN approaches

(rolling horizon = 60 minutes, training sample size = 120)

Table 6-2 Test for the difference of detection performance between RTFNN and FNN approaches (rolling horizon = 60 minutes, training sample size = 120)

Simulation hour (time of day)	Hourly volume (vph)	Detection approaches	DR Average[1]	DR Test result[2]	FAR Average[1]	FAR Test result[2]	TTD Average[1]	TTD Test result[2]
1 (6:00-7:00)	2,403	RTFNN	90.04%	Same	0.0794%	Same	78.83 sec	Same
		FNN	90.04%		0.0794%		78.83 sec	
2 (7:00-8:00)	2,919	RTFNN	92.65%	NSD (0.752)	0.0815%	NSD (0.891)	74.67 sec	SD (0.046)
		FNN	91.15%		0.0760%		78.50 sec	
3 (8:00-9:00)	3,664	RTFNN	93.67%	SD (0.021)	0.0881%	NSD (0.701)	66.50 sec	SD (0.009)
		FNN	91.36%		0.0795%		74.33 sec	
4 (9:00-10:00)	4,514	RTFNN	94.72%	SD (0.003)	0.0658%	SD (0.051)	65.99 sec	SD (0.024)
		FNN	90.27%		0.0801%		73.36 sec	
5 (10:00-11:00)	3,310	RTFNN	96.78%	SD (0.015)	0.0742%	NSD (0.053)	62.62 sec	SD (0.037)
		FNN	91.19%		0.0807%		71.19 sec	
6 (11:00-12:00)	2,484	RTFNN	95.82%	SD (0.011)	0.0634%	SD (0.027)	61.75 sec	SD (0.049)
		FNN	92.55%		0.0862%		73.27 sec	
Overall		RTFNN	93.95%	SD (0.033)	0.0754%	NSD (0.092)	68.39 sec	SD (0.008)
		FNN	91.09%		0.0803%		74.19 sec	

Note: 1. The results for RTFNN and FNN approaches for the first-hour simulation are the same as it is the initial condition. Average represents the mean values of six incident scenarios, each of which undertakes 100 simulation runs.

2. NSD represents no significant difference and SD represents significant difference with P-value in parenthesis (α=0.05). The null hypothesis is that the mean values (DR, FAR, or TTD) between two approaches are the same.

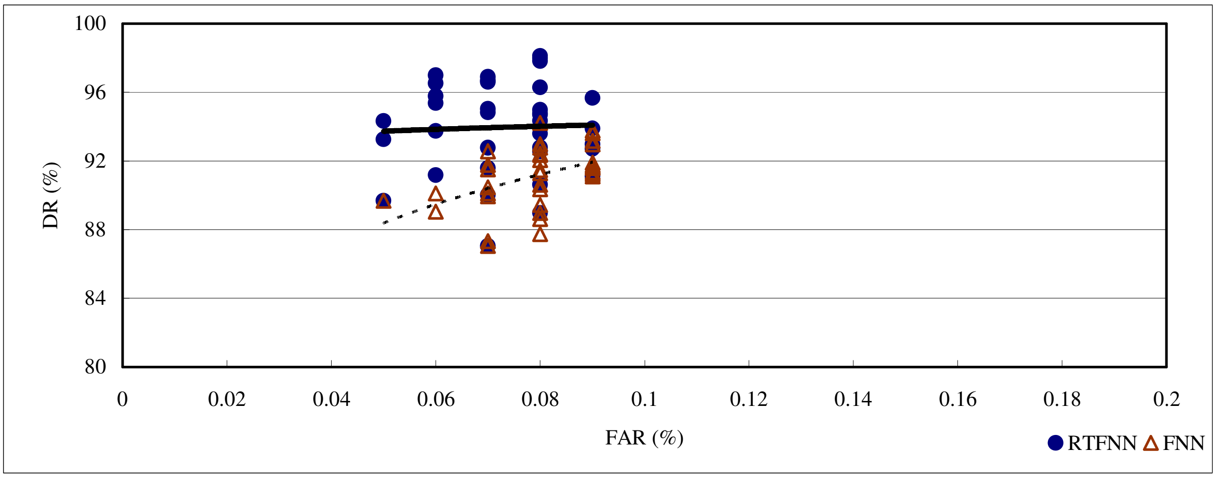


Figure 6-2 Graph of detection rate vs. false alarm rate for 36 incident scenarios

6.3 Sensitivity of Rolling Horizons and Training Sample Sizes

The above-mentioned results conclude that the RTFNN approach, based on the rolling horizon of 60 minutes and the training sample size of 120 samples, can improve the detection performance over the conventional FNN approach. One might wonder if there still exists some room for improvement of detection performance by changing the rolling horizons and/or training sample sizes. Thus, the following sensitivity analyses are further undertaken: case (I) altering the rolling horizons from 15, 20, 30, 45, 90 to 120 minutes, provided that the training sample size is remained as 120; case (II) altering the training sample sizes from 30, 40, 50, 60, 180 to 240, provided that the rolling horizon is remained as 60 minutes; case (III) simultaneously altering both rolling horizons and training sample sizes. Figures 6-3, 6-4 and 6-5 respectively present the change in detection rates for these three cases and Tables 6-3, 6-4 and 6-5 respectively report the details of the change. The sensitivity analyses of these three cases consistently show that the highest average detection rate is at the 45-minute rolling horizon and 90 training sample sizes in this case study.

It is interesting to note that very short or very long rolling horizons can lower the detection rates, compared with the base with rolling horizon of 60 minutes. The main reasons are insufficient updated training samples would be collected if the rolling horizon is too short and less capable of capturing the flow variations for longer rolling horizons. Similarly, small training sample sizes can also lower the detection rates, compared with the base with training sample size of 120. The main reason is the difficulty in reaching the convergence of total error function, should one select a training sample size as small as 30 or 40 samples. The sensitivity analyzes also find that heavier traffic conditions tend to have higher detection rates than lighter ones, regardless of the changes in rolling horizon and/or training sample size.

Table 6-3 Detection rates for Case (I)

(training sample size fixed at 120)

Simulation hours	Hourly flow (veh/hr)	Rolling horizons (minutes)						
		15	20	30	45	60	90	120
1	2,403	91.50	92.13	91.28	90.96	90.04	91.08	91.02
2	2,919	91.68	92.61	92.47	93.24	92.65	92.21	90.93
3	3,664	91.87	93.17	95.61	96.22	93.67	92.59	91.54
4	4,514	92.08	94.37	94.33	97.15	94.72	92.70	90.63
5	3,310	94.02	94.49	94.02	95.29	96.78	93.79	91.26
6	2,484	94.74	95.56	96.25	96.81	95.82	92.84	92.15

Note: shadow indicates the base condition of rolling horizon

Table 6-4 Detection rates for Case (II)

(rolling horizon fixed at 60 minutes)

Simulation hours	Hourly flow (veh/hr)	Training sample sizes							
		30	40	50	60	90	120	180	240
1	2,403	91.03	90.93	91.86	91.02	91.89	90.04	90.12	90.23
2	2,919	91.95	91.64	92.55	93.11	94.17	92.65	92.97	92.10
3	3,664	92.09	92.27	93.07	93.95	95.32	93.67	93.85	93.11
4	4,514	91.81	92.96	93.59	94.48	95.28	94.72	94.07	94.66
5	3,310	92.17	92.94	93.21	94.15	94.39	96.78	95.48	94.70
6	2,484	92.06	92.56	92.61	93.74	94.90	95.82	94.78	93.51

Note: shadow indicates the base condition of training sample size

Table 6-5 Average detection rates for Case (III)

(rolling horizon and training sample size varied)

Training sample size	Rolling horizon (minutes)						
	15	20	30	45	60	90	120
30	91.51	91.72	91.64	91.92	91.85	91.97	91.55
40	91.22	91.60	91.26	91.73	92.22	92.03	91.67
50	93.86	93.49	93.07	92.66	92.82	92.36	92.20
60	93.48	93.93	94.20	93.35	93.41	93.06	92.46
90	95.04	94.67	94.70	95.63	94.33	94.15	93.28
120	92.65	93.72	93.99	94.95	93.95	92.54	91.26
180	95.02	94.63	94.48	93.87	93.54	94.07	92.47
240	93.96	93.98	93.32	93.25	93.05	94.87	93.10

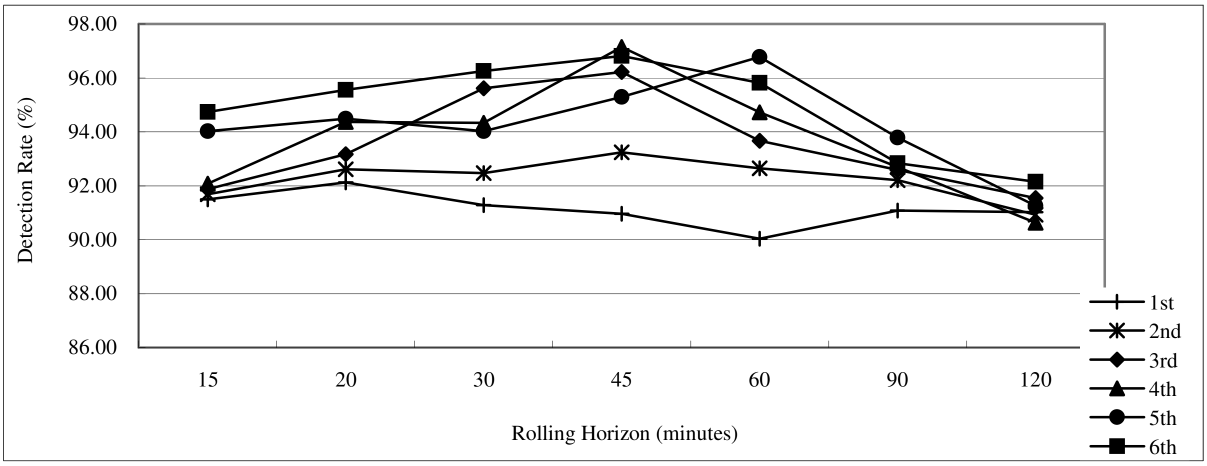


Figure 6-3 Detection rates in each simulation hour for Case (I)
(training sample size fixed at 120)

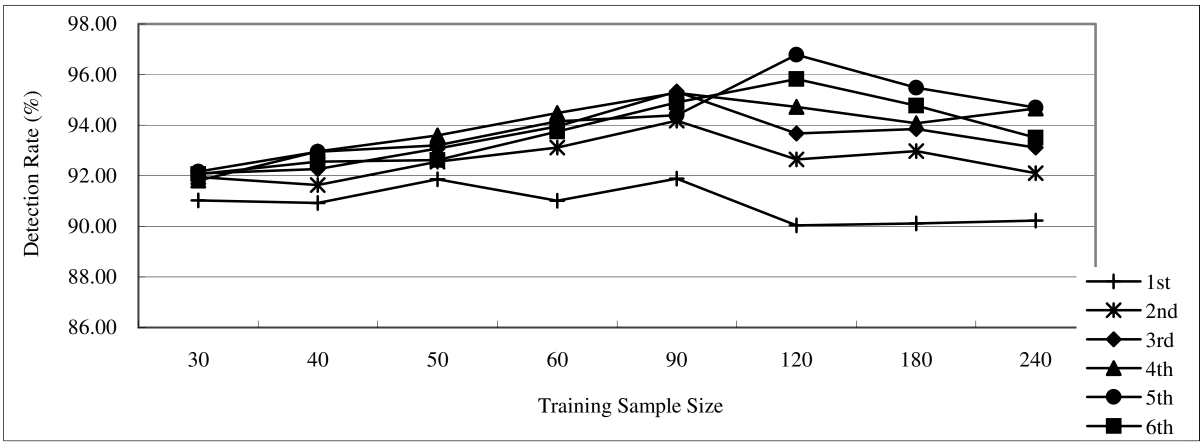


Figure 6-4 Detection rates in each simulation hour for Case (II)
(rolling horizon fixed at 60 minutes)

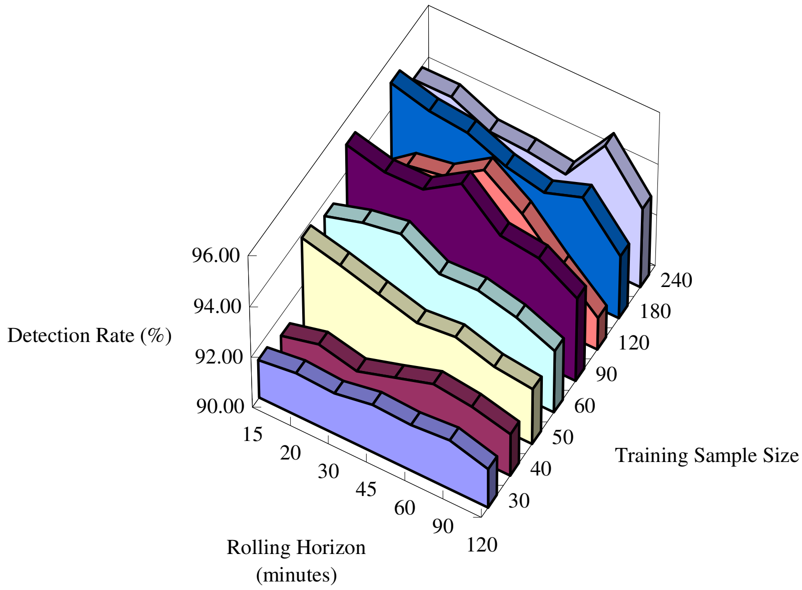


Figure 6-5 Average detection rates of 36 incident scenarios for Case (III)
(rolling horizon and training sample size varied)

6.4 Summary

The main advantage of the proposed RTFNN approach is to adaptively adjust the network parameters using the most up-to-date traffic data in response to the prevailing traffic conditions. The case study has shown that as the traffic volumes vary from low to high and then change from high to low, the detection performance for RTFNN is getting better (but not for the FNN approach), which can be ascribed to the rolling-trained effects of adaptively adjusting the network parameters in response to the traffic variations.

The findings are limited to some thirty-six incident scenarios in the two-lane freeway contexts. One might argue that the lane-specific traffic data used in the input layer of the neural network would limit the transferability potential of the proposed algorithm to other freeway facilities with three or more lanes. A number of studies in the literature (e.g., Ritchie and Cheu, 1993; Lan, *et al.*, 2004) have shown that using the station averages across all lanes rather than lane-specific traffic data does not substantially reduce the accuracy of the incident detection model. Of course, future study can further examine the transferability of the proposed RTFNN approach basing on the station average data.

Paramics is employed in this research for generating speed, flow and density data which are used for training and off-line validations. Future work can attempt other different micro traffic simulators. Additionally, the density is difficult to measure in the field, a surrogate of it, such as percent occupancy that can be readily provided by the field detectors, should be used in the proposed RTFNN approach from practical perspectives.

The robustness of RTFNN approach at different places (e.g., freeway mainline sections with three or more lanes) with different scenarios (e.g., incidents at different locations and affecting more than one lane) can also be examined. Development of new methods to determine the optimal rolling horizon and/or training sample size deserves further exploration.