■ 論 文 ■

Artificial Intelligence Estimation of Network Flows for Seismic Risk Analysis

지진 위험도 분석에서 인공지능모형을 이용한 네트워크 교통량의 예측

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목 차

요 약

지진은 교량과 도로 구조물들에 피해를 입혀서 교통시스템 운행전반과 지역경제에 심각한 피해를 초래하도록 한다. 지진위험도 분석방법은 안전도에 문제가 있는 고속도로 교량들에 대하여 구조물 보강공사를 실시하기 위한 우선순위 결정에 사용되어 진다. 지진위험도 분석방법들은 한 교량의 상대적 중요도를 결정하기 위하여 일일 평균교통량을 사용하고 있다. 본 연구는 도로붕괴시 교통시스템에 추가로 부과되는 시스템비용의 관점에서 수많은 교통량분석을 실행하는데 비용-효과적인 교통망 분석방법을 개발하는데 있다. 본 연구에서 개발된 교통망 분석방법의 핵심은 인공지능분야에서 개발된 연상기억모형의 사용이다. 본 연구에서 개발된 교통망 분석방법을 평가하기 위하여 7개의 교통존으로 구성된 교통망이 구축되었다. 다양한 교통링크 붕괴 시나리오들이 지진으로 붕괴된 교통망에서의 교통량들을 추정하기 위하여 무작위로 선정되었다. 이러한 교통링크 붕괴 시나리오에 대한 교통량의 변화는 여러 연상기억모형들을 이용하여 예측하였고, 그 예측능력을 평가하였다. 다양한 시나리오로부터의 예측결과는 교통량 예측분야에서 연상기억 모형들의 적용 가능성을 보여주고 있다.

I. Introduction

Earthquake is one of the natural disasters that can cause severe damage to urban and transportation systems. The 1994 Northridge earthquake in Southern California and the 1995 Hyogken-Nambu (Kobe) earthquake in Japan show how vulnerable contemporary urban and transportation systems are to major earthquakes. During the past five years, earthquakes have caused nearly 77,000 deaths, over 160,000 injuries, the homelessness of nearly 670,000 people, and property losses of approximately $160 billion, worldwide (EQE International and OES/GIS Group, 1995).

The State of California concerns infrastructure safety for freeway bridges due to frequent occurrence of earthquakes. Earthquakes are neither predictable nor escapable under current technologies of earthquake engineering. However, impacts of earthquakes can be minimized if we develop improved seismic risk mitigation strategies and programs. The California Department of Transportation (Caltrans) has developed bridge retrofit programs that include seismic risk analysis (SRA) procedures for structural re-enforcement projects. Existing SRA procedures use average daily traffic (ADT) volumes to determine the relative importance of a bridge. This is not adequate. The importance of network links should be evaluated in terms of the additional system cost due to failure. Incorporation of an efficient transportation modeling technology in the SRA procedures is essential to determine the relative importance of bridges.

The objective of this research is to develop an efficient transportation network analysis (TNA) procedure for rapidly estimating traffic flows under numerous scenario earthquakes, using a seven-zone transportation network. An important feature of the TNA procedure is the use of an associative memory (AM) approach in traffic flow estimation. The AM approach is a heuristic method derived from the artificial intelligence field.

This paper is organized as follows. Section II reviews the literature on current seismic risk analysis procedures. Section III describes the overall features of transportation network analysis procedure used for system-wide traffic flow analyses. The basic framework and detailed structure of the TNA procedure are presented. The section presents modules including analytical methods for the TNA procedure, relationships between the modules, and required data sets for the modules. Analytical methods employed for the TNA procedure are also described.

Section IV describes the application of the TNA procedure in simple network flow analyses. This section consists of two parts. The first part contains a simple synthetic transportation network and traffic flow simulation. The second part includes the estimation for synthetic network flows in case of seismic risk analysis. A simple synthetic transportation network is developed and used to evaluate the TNA procedure. The synthetic network has seven zones and twenty-four directed links. Network flows are simulated using a static network equilibrium model and synthetic transportation input data. Simple associative memory models, recurrent associative memory models, and multi-criteria associative memory models are applied to estimate simulated network flows. The performance of the AM models is evaluated. Section V summarizes the overall traffic analysis studies and their findings.

II. LITERATURE REVIEW

The increasing interest for the seismic risk analysis (SRA) has stimulated both public and private sectors in developing SRA procedures. Public agencies are major contributors for the development of the SRA procedures. They include: (1) the California Department of Transportation's (Caltrans') SRA procedures (Gilbert, 1993), (2) the Applied Technology Council (ATC) procedure sponsored by the Federal Highway Administration,

(3) the Illinois Department of Transportation (IDOT) procedure, and (4) the Washington State Department of Transportation (WSDOT) procedure (Babaei and Hawkins, 1991).

Earthquake engineers and planners have also developed the SRA procedures. Buckle (1991) introduced a procedure emphasizing bridge importance criteria and soil amplification effects. Kim et al. (1992) and Kim (1993) provided a SRA procedure using geographic information systems (GIS). Other SRA procedures include the procedure considering uncertainties and transportation networks (Cherng and Wen, 1992), the modified versions of Caltrans' multi-attribute procedure (Kiremidjian, 1992), the procedure applied to the Memphis and Shelby County area (Pezeshk *et al.*, 1993), and the general bridge prioritization procedure incorporated with a computer-based GIS system and an expert system named ESCOB (Basoz and Kiremidjian, 1994). Kim *et al.* (1997) introduced a comprehensive SRA procedure for roadway transportation systems.

The importance of transportation systems for SRA procedures has been addressed by Hendrickson et al. (1980), Oppenheim (1981), Oppenheim and Anderson (1981), and Carey and Hendrickson (1984). Yamada *et al.* (1992), Wakabayashi and Kameda (1992), and Basoz and Kiremidjian (1994) provided the procedures incorporated with relevant SRA issues such as the post-earthquake recovery of the transportation network, the change of post-earthquake travel demand, or the importance of accessibility to certain zones. The impacts of the 1989 Loma Prieta earthquake and the 1994 Northridge earthquake have been studied by many researchers. However, the SRA procedures are based on simplified assumptions due to lack of consideration to the system-wide traffic impacts of seismic risks. Consequently, the mainstream SRA procedures apply average daily traffic (ADT) volumes to determine the importance of a bridge.

Ⅲ. TRANSPORTATION NETWORK ANALYSIS PROCEDURE

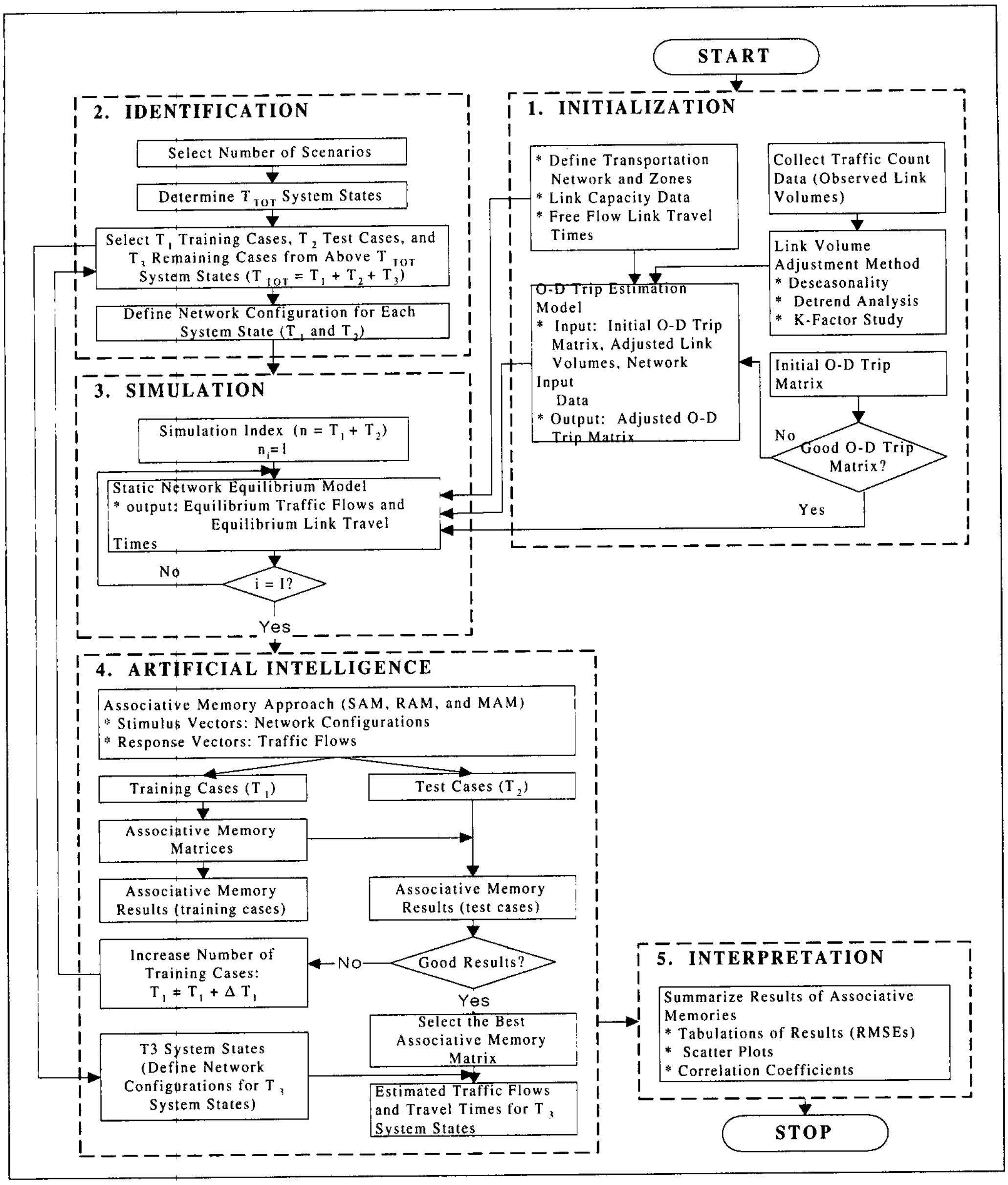
The TNA procedure is developed based on the assumption that both observed post-earthquake link volumes and an accurate O-D trip matrix are not available. The procedure comprises of five modules: (1) initialization of the procedure including data acquisition and modification, (2) identification of system states with respect to scenario earthquakes, (3) simulation of network equilibrium flows with respect to link-failure system states, (4) application of artificial intelligence models for estimating network flows of the remaining link-failure system states, and (5) aggregation and interpretation of results. The framework of the TNA procedure is shown in 〈Figure 1〉.

1. Initialization Module

The initialization module develops reliable transportation system data sets containing free-flow link travel times, link capacities, an origin-destination (O-D) trip matrix, and baseline link volumes. Free-flow link travel times and link capacities are either obtained from MPOs, or computed using link distance and speed information. An O-D trip matrix is established through either transportation models or travel demand surveys. The baseline link volumes are determined by extracting seasonal and/or trend variations from observed link volumes using a link volume adjustment method. An O-D trip estimation method is applied to estimate an O-D trip matrix from the baseline link volumes.

2. Identification Module

The identification module determines an adequate number of post-earthquake system states given scenario earthquakes. This module is carried out



〈Figure 1〉 Transportation Network Analysis Procedure

in four parts. The first part selects the total number of scenarios by either researcher's decisions or seismic hazard models. The second part computes the total number of link-failure system states for each scenario. The third part identifies the number of training and test system states. The states are randomly selected from the total system states. The fourth part defines network configurations for the training and test system states.

3. Simulation Module

The simulation module generates equilibrium traffic flows with respect to the training and test system states. There is an extensive literature on transportation network equilibrium models and solution algorithms. This research employs the static network equilibrium model to simulate traffic flows given network configurations of different link-failure system states. The formulation of the model is:

$$Minimize \sum_a \left[\int_0^{va} ta(w)dw \right] \quad (1)$$

Subject to

$$V_a = \sum_s \nu_a^s \text{ for all links } a \quad (2)$$

$$\sum_{a \text{ in Out}(r)} \nu_a^s - \sum_{a \text{ in In}(r)} \nu_a^s = Demand^{r \to s}$$

for all origin-destination pairs (r,s) (3)

$$V_a^s \geq 0 \text{ for all links } a, \text{ and destinations } s \quad (4)$$

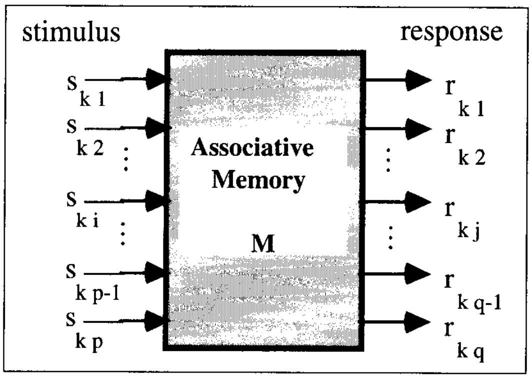
where

w : the variable of integration
v_a : the total flow on link a
$ta(w)$: the link travel cost function for link a
v_a^s : the total flow on link a bound for destination s
$Out(r)$: the set of link flows outbound from node r, and
$In(r)$: the set of link flows inbound to node r.

This is a nonlinear minimization problem with a convex objective function subject to two sets of linear constraints and a set of non-negativity conditions (Eash *et al.*, 1979). The Frank-Wolfe algorithm is applied as the solution algorithm. The BPR link travel cost function is used to describe link travel costs as a function of link flows.

4. Artificial Intelligence Module

The artificial intelligence (AI) module involves the application of AI models to a rapid and inexpensive estimation of post-earthquake network flows for the remaining system states. There are a variety of AI models.[1)] The usefulness of the AI models has been demonstrated by many researchers since 1980s. This research applies the associative memory (AM) models to network flow estimation. The AM models are highly simplified models of human memory derived from the AI field. The AM models are applied in cases in which there seems to be a strong association between a set of vectors (stimulus vectors) and a different set of vectors (response vectors). An ideal AM model is shown in ⟨Figure 2⟩.



⟨Figure 2⟩ An Ideal Associative Memory Model

This research applies eleven heteroassociative memory models to the network flow estimation problem: (1) a simple associative memory (SAM) model; (2) a recurrent associative memory (RAM) model; and (3) nine multicriteria associative memory (MAM) models. They are selected because: (1) they are computationally simple; (2) they provide rapid and reliable estimates of response vectors through the learning process for highly non-linear systems; (3) the usefulness of the models has been demonstrated by many applications; and (4) the AM models are relatively new approaches to transportation. The AM models are used to map the network configurations of link-failure system

1) There are three main paradigms adopted in the field of artificial intelligence: (1) the symbolic paradigm including expert systems and fuzzy systems, (2) the subsymbolic paradigm including neural computing systems, and (3) a mixture of the symbolic and subsymbolic systems (Kasabov, 1996).

states (stimulus vectors) to their associated link traffic flows (response vectors).

The network configurations and flows are divided into two groups: training system states and test system states. Most of the stimulus and response vectors are used as training system states to compute different AM matrices. The remaining pairs are used to evaluate the performance of the AM matrices. The AM matrix providing the closest estimates of test case network flows is applied to predict network flows for the remaining states. The AM models are described by Moore et al. (1993).

5. Result Interpretation Module

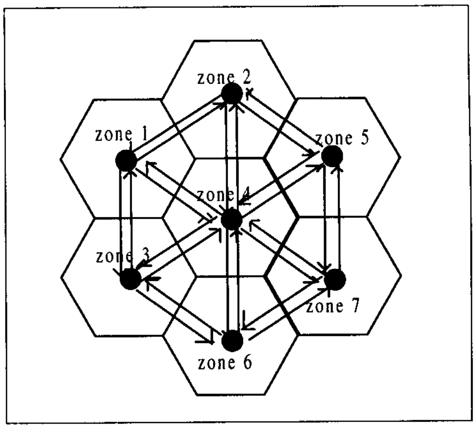
The result interpretation module summarizes the results of different AM models. The performance of the AM models is evaluated by Root Mean Square Errors (RMSEs), scatter plots, and correlation coefficients between traffic flows simulated by the network equilibrium model and flow estimates provided by the AM models.

Ⅳ. ANALYSIS AND RESULTS

1. A Simple Synthetic Network

This section defines a simple synthetic transportation network to examine the applicability of the TNA procedure. The synthetic network includes seven zones and twenty-four directed links. The network is shown in ⟨Figure 3⟩. Three synthetic input data sets of an O-D trip matrix, link capacities, and free-flow link travel times are randomly generated.

A subset of link failure system states is randomly selected to represent all possible link-failure system states. Network configurations of the link failures are represented discretely. Collapsed links are coded as "2," and undamaged links are coded as "1." The static network equilibrium model is applied to simulate link flows. The static model takes less than a second to simulate traffic flows.



⟨Figure 3⟩ Synthetic Network and Zones

The total number of possible link-failure system states can be computed combinatorically. Combinations are defined using the number of subsets of size r that can be constructed from the population of n objects with no concern for the arrangement or order of the r objects. The combinatorial formula is

$$\mathrm{nCr} = \frac{n!}{r!(n-r)!} \tag{5}$$

where n is the total objects and r is the number of subsets to be taken. The total number of possible post-earthquake system states is ${}_{24}C_1 + {}_{24}C_2 + {}_{24}C_3 + {}_{24}C_4 + \cdots + {}_{24}C_{23} + {}_{24}C_{24} = 24+276 + 2{,}024 + 10{,}626 + \cdots + 24 + 1 = 16{,}777{,}215$. This total number includes cases corresponding to one-link, … 24-link closures. This research is conducted to two classes: single and double link failures. The simulation of single link failures has a total of twenty-four system states. The total possible number of double link failures is 276. This number is obtained from the combinatorial formula for selecting any two links out of 24 links:

$$\begin{aligned} {}_{84}C_2 &= \frac{24!}{2!(24-2)!} = \frac{24!}{2! \times 22!} = \frac{24 \times 23 \times 22!}{2 \times 22!} \\ &= \frac{24 \times 23}{2} = 276 \end{aligned} \tag{6}$$

〈Table 1〉 RMSEs of SAM, RAM, and MAM (Single Link Failure)

	MAM(α)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	SAM	RAM
SS	Training	93.32	82.94	72.57	62.2	51.84	41.47	31.1	20.73	10.37	7.95E-13	4.95E-13
1	Test	98.09	98.1	98.1	98.11	98.11	98.11	98.11	98.11	98.11	98.112	98.227
SS	Training	92.86	82.54	72.22	61.9	51.58	41.27	30.95	20.63	10.32	7.23E-13	7.08E-13
2	Test	110	110	110	110.1	110.1	110.1	110.1	110.1	110.1	110.07	110.33
SS	Training	92.88	82.55	72.23	61.91	51.59	41.27	30.95	20.64	10.32	7.76E-13	7.94E-13
3	Test	109.8	109.8	109.8	109.8	109.8	109.8	109.8	109.8	109.8	109.79	109.91
SS	Training	93.19	82.82	72.47	62.12	51.76	41.41	31.06	20.71	10.35	7.46E-13	4.01E-13
4	Test	101.6	101.7	101.7	101.7	101.7	101.7	101.7	101.7	101.7	101.67	101.84
SS	Training	93.45	83.06	72.68	62.29	51.91	41.53	31.15	20.76	10.38	6.25E-13	3.27E-13
5	Test	94.23	94.21	94.21	94.21	94.2	94.2	94.2	94.2	94.2	94.201	94.212
SS	Training	90.84	80.74	70.64	60.55	50.46	40.37	30.28	20.18	10.09	7.50E-13	3.97E-13
6	Test	152.1	152.1	152.1	152.1	152.1	152.1	152.1	152.1	152.1	152.12	152.2
SS	Training	93.19	82.82	72.47	62.12	51.76	41.41	31.06	20.71	10.35	6.19E-13	3.85E-13
7	Test	101.6	101.6	101.6	101.6	101.7	101.7	101.7	101.7	101.7	101.66	101.89
SS	Training	94.56	84.04	73.54	63.03	52.53	42.02	31.52	21.01	10.51	7.52E-13	3.63E-13
8	Test	51.97	51.99	51.99	52	52	52	52.01	52.01	52.01	52.008	52.224
SS	Training	93.57	83.17	72.77	62.37	51.98	41.58	31.19	20.79	10.4	5.47E-13	4.29E-13
9	Test	90.7	90.67	90.66	90.65	90.65	90.65	90.65	90.65	90.65	90.646	90.618
SS	Training	91.98	81.75	71.53	61.31	51.09	40.87	30.66	20.44	10.22	4.82E-13	5.80E-13
10	Test	130.1	130.2	130.2	130.2	130.2	130.2	130.2	130.2	130.2	130.23	130.58
SS	Training	92.17	81.92	71.68	61.44	51.2	40.96	30.72	20.48	10.24	8.63E-13	7.51E-13
11	Test	126.1	126.1	126.1	126.1	126.1	126.1	126.1	126.1	126.1	126.09	126.17
SS	Training	92.91	82.58	72.25	61.93	51.61	41.29	30.97	20.64	10.32	7.66E-13	9.11E-13
12	Test	109	109	109	109	109	109	109	109	109	108.96	109
SS	Training	93.04	82.7	72.36	62.02	51.68	41.35	31.01	20.67	10.34	6.45E-13	5.58E-13
13	Test	105.4	105.4	105.5	105.5	105.5	105.5	105.5	105.5	105.5	105.49	105.77
SS	Training	92.27	82.01	71.76	61.51	51.25	41	30.75	20.5	10.25	6.50E-13	4.93E-13
14	Test	124.2	124.1	124.1	124	124	124	124	124	124	124.01	123.62
SS	Training	94.85	84.3	73.76	63.22	52.69	42.15	31.61	21.07	10.54	5.66E-13	5.21E-13
15	Test	32.9	32.99	33.02	33.04	33.05	33.05	33.06	33.06	33.06	33.067	33.603
SS	Training	94.56	84.04	73.53	63.03	52.52	42.02	31.51	21.01	10.51	6.64E-13	4.36E-13
16	Test	52.14	52.16	52.17	52.18	52.18	52.19	52.19	52.19	52.19	52.192	52.439
SS	Training	94.12	83.65	73.19	62.74	52.28	41.82	31.37	20.91	10.46	7.85E-13	6.67E-13
17	Test	71.69	71.83	71.88	71.9	71.92	71.93	71.94	71.94	71.95	71.95	72.575
SS	Training	93.83	83.4	72.97	62.55	52.12	41.7	31.27	20.85	10.42	5.75E-13	5.92E-13
18	Test	82.41	82.36	82.35	82.34	82.34	82.34	82.33	82.33	82.33	82.33	82.266
SS	Training	93.69	83.27	72.86	62.45	52.04	41.64	31.23	20.82	10.41	6.18E-13	4.15E-13
19	Test	86.82	86.85	86.86	86.86	86.87	86.87	86.87	86.87	86.87	86.872	87.055
SS	Training	90.31	80.27	70.23	60.2	50.17	40.13	30.1	20.07	10.03	6.17E-13	3.75E-13
20	Test	161.1	161.1	161.1	161.1	161.1	161.1	161.1	161.2	161.2	161.15	161.27
SS	Training	93.99	83.53	73.09	62.65	52.21	41.77	31.32	20.88	10.44	8.64E-13	3.82E-13
21	Test	76.96	76.91	76.9	76.89	76.89	76.89	76.89	76.89	76.89	76.885	76.835
SS	Training	91.85	81.63	71.42	61.22	51.02	40.81	31.61	20.41	10.2	6.83E-13	5.89E-13
22	Test	133.2	133.1	133.1	133.1	133.1	133.1	133.1	133.1	133.1	133.08	132.96
SS	Training	92.73	82.42	72.12	61.81	51.51	41.21	30.91	20.6	10.3	1.00E-12	4.96E-13
23	Test	113.6	113.4	113.4	113.4	113.4	113.4	113.4	113.4	113.4	113.35	112.98
SS	Training	90.53	80.46	70.41	60.35	50.29	40.23	30.17	20.12	10.06	6.96E-13	8.83E-13
24	Test	157.5	157.5	157.5	157.5	157.5	157.5	157.5	157.5	157.5	157.45	157.41

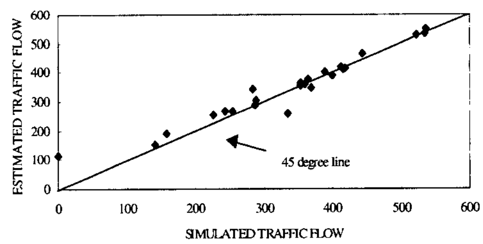
2. Application of Associative Memory Models

The objective is to generate relevant flow estimates without using the static model. Traffic flows are estimated based on the association between the network configurations of link failure system states and simulated link flows. Eleven AM models are computed and used to map the network configurations to the associated link flows. Three AM scenarios are considered based on the flow simulation scenarios: single-link failures, double-link failures, and the mixture of single-link and double-link failures.

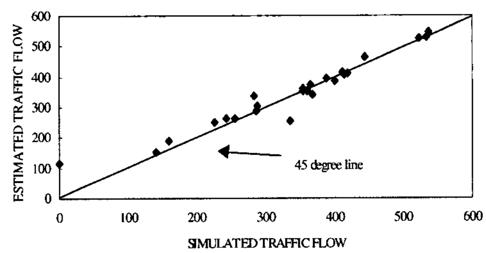
1) Scenario A: Single-Link Failures

The total number of twenty-four system states is randomly ordered. Three AM evaluations are conducted to test the performance of AM models. The MAM models have an additional parameter α. The estimation performance of the MAM procedure is varied due to changing the α parameter. Since the α parameter takes values on the interval [0.1, 0.9], at least nine different MAM procedures can be considered. The first exercise uses each of the twenty-four system states as the test system state in rotation. The other twenty-three system states are used to create different memory matrices. 〈Table 1〉 presents the RMSE results of SAM, RAM, and MAM in estimates in the case of single-link failures. The RMSE results do not significantly vary in the case of test states. The RMSE results show that test state 15 provides the lowest RMSE. Test state 20 provides the highest test case RMSE, representing the worst flow estimate. 〈Figures 4 to 6〉 show the scatter plots and correlation coefficients for test state 15 using SAM, RAM, and MAM (α=0.9). The computation time spent for each estimation is less than a second.

The second evaluation of AM models to the single-link failure system states varies the number of the test system states as well as the training system states. One of the advantageous characteristics of AM techniques is that AM models can estimate a group of test system states simultaneously without significant costs. However, there is a trade-off between the number of simultaneously estimated test system states and the performance of AM models. There is no rule in determining the optimal number of test system states that can be estimated simultaneously without considerably losing the estimation power. This second evaluation investigates that relationship between the number of simultaneous test states and the performance of the AM models. The evaluation begins with the case of test system state 15, providing the lowest test state RMSE. 〈Table 2〉 shows the RMSE results of SAM, RAM, and MAM in estimates in the case of varying test states of single-link failures.

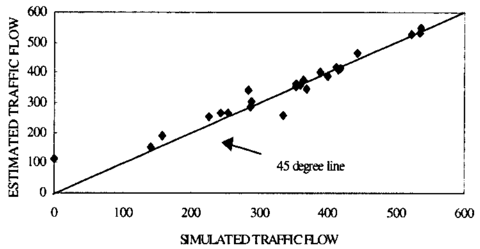


〈Figure 4〉 Estimated vs. Simulated Traffic Flow (SAM, TEST, r=0.9702638, Single Link Failure)



〈Figure 5〉 Estimated vs. Simulated Traffic Flow (RAM, TEST, r=0.9702626, Single Link Failure)

The SAM and RAM models are able to perfectly replicate the training flows, but this is expected. The test results are somewhat disappointing. The AM models do not produce close estimates of test flows in most single-link failures. The results indicate that a training sample consisting of twenty-three system states is not sufficient to train the AM models.



⟨Figure 6⟩ Estimated vs. Simulated Traffic Flow (MAM, TEST, r=0.9702643, Single Link Failure)

2) Scenario B : Double-Link Failures

Fifty system states are used to be representative all the 276 system states of double link failures. The evaluation examines the performance of AM models in the case of varying training and test states. The number of test states increases as the number of training states decreases. The RMSE results of the eleven AM models are shown in ⟨Table 3⟩. RAM scatter plots and correlation coefficients are shown in ⟨Figure 7⟩. The computation time spent for each estimation is less than a second.

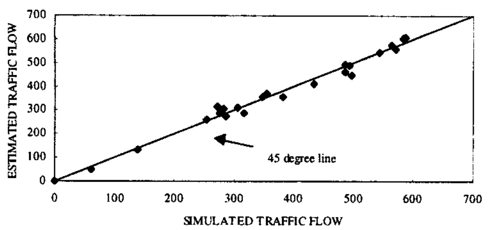
Results demonstrate that the AM models perform reliably with respect to the test states. The best MAM model replicates simulated flows better than SAM and RAM models in most test cases. The best MAM model provides the reliable estimates of traffic flows up to a group of fifteen test states when the remaining system states are used to compute AM matrices. The estimation performance

⟨Table 2⟩ RMSEs of SAM, RAM, and MAM (Single Link Failure:varying test states)

	MAM(α)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	SAM	RAM
CASE	Training:23	94.85	84.3	73.76	63.22	52.69	42.15	31.61	21.07	10.54	5.66E-13	5.21E-13
1	Test: 1	32.9	32.99	33.02	33.04	33.05	33.05	33.06	33.06	33.06	33.067	33.603
CASE	Training:22	94.62	84.1	73.58	63.07	52.56	42.05	31.54	21.02	10.51	6.25E-13	1.01E-13
2	Test: 2	83.49	83.42	83.4	83.38	83.38	83.37	83.37	83.37	83.37	83.365	83.209
CASE	Training:21	93.33	82.95	72.58	62.21	51.84	41.47	31.11	20.74	10.37	4.40E-13	5.70E-13
3	Test: 3	104.2	104.1	104.1	104.1	104.1	104.1	104.1	104.1	104.1	104.05	103.91
CASE	Training:20	94.44	83.94	73.44	62.95	52.46	41.97	31.48	20.98	10.49	5.49E-13	4.11E-13
4	Test: 4	98.11	98.04	98.02	98.01	98	98	97.99	97.99	97.99	97.989	97.862
CASE	Training:19	91.3	81.14	71	60.85	50.71	40.57	30.43	20.28	10.14	4.78E-13	4.36E-13
5	Test: 5	113.5	113.4	113.4	113.4	113.4	113.4	113.4	113.4	113.4	113.41	113.35
CASE	Training:18	91.98	81.75	71.53	61.31	51.09	40.87	30.65	20.44	10.22	6.42E-13	5.62E-13
6	Test: 6	110.2	110.2	110.2	110.2	110.2	110.2	110.2	110.2	110.2	110.15	110.13
CASE	Training:17	92.88	82.55	72.22	61.91	51.59	41.27	30.95	20.64	10.32	5.11E-13	6.05E-13
7	Test: 7	107.7	107.6	107.6	107.6	107.6	107.6	107.6	107.6	107.6	107.59	107.56
CASE	Training:16	94.24	83.75	73.28	62.81	52.34	41.87	31.4	20.94	10.47	4.80E-13	3.58E-13
8	Test: 8	105.1	105.1	105.1	105.1	105.1	105.1	105.1	105.1	105.1	105.09	105.14
CASE	Training:15	96.37	85.65	74.94	64.23	53.53	42.82	32.12	21.41	10.71	4.34E-13	6.27E+13
9	Test: 9	102.1	102	102	102.1	102.1	102.1	102.1	102.1	102.1	102.05	102.13
CASE	Training:14	92.72	82.39	72.09	61.79	51.49	41.19	30.89	20.6	10.3	3.13E-13	5.40E-13
10	Test: 10	109.1	109.1	109.1	109.1	109.1	109.1	109.1	109.1	109.1	109.06	109.12
CASE	Training:13	91.66	81.45	71.26	61.08	50.9	40.72	30.54	20.36	10.18	5.76E-13	2.94E-13
11	Test: 11	110	109.9	109.9	109.9	109.9	109.9	109.9	109.9	109.9	109.9	109.87
CASE	Training:12	91.63	81.41	71.23	61.06	50.88	40.7	30.53	20.35	10.18	3.62E-13	3.68E-13
12	Test: 12	109.9	109.9	109.9	109.9	109.8	109.8	109.8	109.8	109.8	109.84	109.84

〈Table 3〉 RMSEs of SAM, RAM, and MAM in Double Link Failures

	MAM(α)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	SAM	RAM
CASE 1	Training: 49	101.7	76.4	60.3	49.12	41.09	35.31	31.29	28.71	27.32	26.906	4.232
	Test: 1	81.99	61.99	50.59	43.47	38.89	35.98	34.21	33.26	32.88	32.912	20.317
CASE 2	Training: 48	102.1	76.89	60.76	49.53	41.43	35.56	31.45	28.77	27.31	26.867	4.00E-10
	Test: 2	103.1	82.85	69.58	59.84	52.27	46.29	41.71	38.58	37.06	37.381	124.42
CASE 3	Training: 47	102.8	77.58	61.38	50.05	41.83	35.85	31.63	28.87	27.35	26.88	4.08E-12
	Test: 3	101	81.26	67.86	57.87	50.16	44.25	39.99	37.42	36.6	37.599	92.954
CASE 4	Training: 46	103.5	78.16	61.86	50.45	42.15	36.09	31.8	28.97	27.4	26.918	7.32E-13
	Test: 4	100.7	81.73	68.67	58.84	51.14	45.11	40.56	37.54	36.19	36.705	85.085
CASE 5	Training: 45	104.4	78.9	62.45	50.9	42.48	36.3	31.89	28.97	27.34	26.83	9.20E-13
	Test: 5	93.74	76.5	64.58	55.65	48.76	43.53	39.84	37.71	37.24	38.515	87.247
CASE 6	Training: 44	105	79.47	62.97	51.36	42.84	36.54	31.98	28.9	27.15	26.585	6.90E-13
	Test: 6	100.5	83.31	71.11	61.64	54.06	48.14	43.97	41.85	42.11	44.929	89.612
CASE 7	Training: 43	105.8	80.24	63.63	51.9	43.28	36.87	32.22	29.05	27.23	26.638	6.46E-13
	Test: 7	100.3	83.4	71.22	61.7	54.06	48.05	43.79	41.62	41.94	45.061	83.476
CASE 8	Training: 42	106.6	80.99	64.3	52.48	43.74	37.22	32.44	29.15	27.21	26.577	1.61E-11
	Test: 8	101.4	83.83	71.3	61.58	53.8	47.7	43.38	41.19	41.62	45.118	286.71
CASE 9	Training: 41	107.1	81.42	64.71	52.86	44.08	37.46	32.54	29.07	26.96	26.228	5.03E-11
	Test: 9	105.8	90.63	79.43	70.28	62.49	55.89	50.8	47.97	48.61	54.054	1154.6
CASE 10	Training: 40	108	82.2	65.38	53.41	44.51	37.76	32.69	29.07	26.84	26.068	1.34E-09
	Test: 10	105.2	90.44	79.48	70.48	62.84	56.47	51.74	49.39	50.5	56.123	18000
CASE 11	Training: 39	108.7	83.12	66.24	54.15	45.09	38.19	32.98	29.23	26.91	26.094	4.37E-11
	Test: 11	106.4	90.55	78.95	69.61	61.81	55.41	50.69	48.39	49.6	55.531	1001.4
CASE 12	Training: 38	109.7	84.03	67.01	54.76	45.56	38.52	33.19	29.34	26.94	26.098	4.98E-13
	Test: 12	105.2	89.37	77.78	68.49	60.76	54.42	49.73	47.37	48.39	53.928	79.422
CASE 13	Training: 37	110	84.53	67.62	55.42	46.2	39.09	33.64	29.64	27.1	26.185	6.40E-13
	Test: 13	110.2	94.77	83.07	73.3	64.82	57.51	51.73	48.35	48.75	54.465	79.525
CASE 14	Training: 36	111.2	85.53	68.46	56.11	46.75	39.5	33.9	29.74	27.06	26.075	9.13E-13
	Test: 14	109	93.67	82.11	72.5	64.16	56.97	51.28	47.96	48.43	54.308	81.604
CASE 15	Training: 35	111.6	86.48	69.56	57.16	47.64	40.15	34.27	29.85	26.96	25.897	4.50E-13
	Test: 15	112.6	96.28	83.82	73.46	64.54	56.92	50.95	47.5	47.93	53.751	79.293
CASE 16	Training: 34	112.1	87.32	70.48	58	48.31	40.59	34.42	29.68	26.46	25.219	3.76E-13
	Test: 16	115.2	98.26	85.3	74.59	65.5	57.92	52.18	49.14	50.09	56.509	81.635
CASE 17	Training: 33	112.5	87.7	70.71	58.05	48.14	40.17	33.73	28.68	25.19	23.807	3.71E-13
	Test: 17	116.6	100.2	87.54	77.04	68.11	60.62	54.9	51.7	52.29	58.326	87.411
CASE 18	Training: 32	113.5	88.45	71.26	58.42	48.37	40.29	33.75	28.6	24.96	23.444	4.17E-13
	Test: 18	116.1	99.96	87.57	77.35	68.68	61.42	55.79	52.49	52.92	60.216	83.835
CASE 19	Training: 31	114.6	89.45	72.1	59.13	48.97	40.8	34.19	28.99	25.34	161.4	3346.8
	Test: 19	116.2	100.5	88.53	78.77	70.47	63.38	57.61	53.67	52.81	2.83E+16	2.96E+17
CASE 20	Training: 30	113.8	89.49	72.72	60.11	50.09	41.86	35.02	29.45	25.38	144.34	147.46
	Test: 20	123	107.3	94.52	83.54	73.82	65.26	58.15	53.29	52.28	6.82E+16	3.94E+15
CASE 21	Training: 29	114.7	90.5	73.67	60.89	50.64	42.12	34.94	29	24.56	411.31	5.66E-13
	Test: 21	122.8	107.1	94.42	83.51	73.88	65.49	58.63	54.1	53.49	1.69E+17	141.78
CASE 22	Training: 28	115.4	91.18	74.41	61.69	51.46	42.87	35.48	29.13	24.06	21.618	4.01E-13
	Test: 22	123.8	109	96.86	86.17	76.51	67.85	60.61	55.89	55.98	65.848	90.163
CASE 23	Training: 27	113	88.72	71.95	59.4	49.49	41.35	34.49	28.72	24.19	22.014	3.53E-13
	Test: 23	132	120.1	110.9	103.4	96.85	91.23	86.6	83.37	82.73	88.196	103.18
CASE 24	Training: 26	112.7	88.34	71.46	58.83	48.87	40.71	33.85	27.98	23.11	628.86	4.83E-13
	Test: 24	133.2	121.5	112.6	105.2	98.84	93.17	88.15	84.03	82.02	9.02E+16	149.87
CASE 25	Training: 25	114.1	89.63	72.62	59.83	49.68	41.32	34.18	27.93	22.4	544.14	3.42E-13
	Test: 25	133.5	122	113.1	105.6	98.98	93.06	87.81	83.67	82.64	4.21E+16	170.91



〈Figure 7〉 Estimated vs. Simulated Traffic Flow (RAM, TEST, r=0.9934711, Double Link Failure)

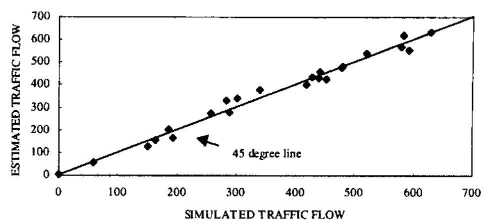
of AM models is not sensitive to the order of training or test system states.

Fifty system states seem to be sufficient for the learning process of AM models. The RMSE results from the two double-link failures are usually lower than those of single-link failures. This may be because more system states are trained in the case of the double-link failure evaluations. Further, each link has a higher chance of being selected as link failures. The RMSE results of test states tend to decrease when the alpha of MAM increases.

3) Scenario C : The Mixture of Single-Link and Double-Link Failures

This scenario examines the performance of AM models from mixed system states of single-link and double-link failures. This scenario includes seventy-four system states. The seventy-four data sets are combined and re-arranged. The RMSE results of the eleven AM models in estimates in the case of the combined link failures are shown in 〈Table 4〉. SAM scatter plots and correlation coefficients between simulated and estimated traffic flows in test cases are shown in 〈Figure 8〉.

This mixed link failure evaluation provides the lowest RMSE results among the three link failure scenarios. This may be due to the increased number of system states available for training. The estimation performance of SAM, RAM, and MAM (α=0.9) is very close. The RMSE results do not vary significantly as the number of training system states decreases.



〈Figure 8〉 Estimated vs. Simulated Traffic Flow (SAM, TEST, r=0.992686, Single & Double Link Failure)

V. Conclusions

The AM approach is based on the heuristic architecture, producing heuristic solutions to the network equilibrium models. The major point of this exercise is not to predict link flows on an individual link, but for the entire system. The objective is to generate a cheap, credible prediction of system-wide traffic flow changes with respect to given alternative network configurations related to earthquake scenarios. The seven-zone synthetic network is simple, but captures several elements of a highway system. Empirical link volumes are not available in the synthetic network. Thus, this exercise measures the performance of AM models by comparing flow estimates provided by the AM approach with noise-free numerical solutions to the network equilibrium model.

In most cases, the procedure performs very well in evaluation. Outputs from AM models provide good estimates of individual link flows. The results from different link failure scenarios demonstrate the applicability of AM models to seismic risk analysis. The SAM, RAM, and MAM models provide good overall estimates of traffic flows, if the number of training system states is sufficient (greater than fifty). There is not much difference of the performance among eleven AM models. The MAM models demonstrate an advantage with respect to the test flows due to MAM's built-in penalty function for overfitting, containing the less sensitivity to error terms than SAM and RAM models. Results

〈Table 4〉 RMSEs of SAM, RAM, and MAM (Single and Double Link Failure)

	MAM(α)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	SAM	RAM
CASE 1	Training: 73	87.94	64.56	50.56	41.45	35.38	31.38	28.84	27.37	26.65	26.445	15.031
	Test: 1	118.5	90.52	70.48	55.43	43.92	35.21	28.92	24.89	22.95	22.761	23.842
CASE 2	Training: 72	88.34	65.03	50.98	41.78	35.61	31.5	28.89	27.36	26.61	26.403	13.994
	Test: 2	108.2	81.49	62.68	49.08	39.43	33.1	29.68	28.65	29.33	31.043	27.59
CASE 3	Training: 71	88.5	65.34	51.28	42.03	35.77	31.6	28.92	27.35	26.57	26.358	12.147
	Test: 3	114.8	87.77	69.06	55.6	45.93	39.26	35.07	32.91	32.31	32.804	38.922
CASE 4	Training: 70	88.92	65.71	51.59	42.28	35.98	31.75	29.04	27.44	26.65	26.426	12.021
	Test: 4	106	81.58	64.64	52.43	43.62	37.49	33.56	31.45	30.74	31.043	36.668
CASE 5	Training: 69	89.38	66.12	51.95	42.56	36.19	31.9	29.14	27.5	26.69	26.464	11.829
	Test: 5	101.5	78.92	62.92	51.28	42.83	36.95	33.22	31.27	30.72	31.156	36.024
CASE 6	Training: 68	89.56	66.43	52.27	42.82	36.35	31.94	29.07	27.35	26.49	26.246	12.825
	Test: 6	105.2	82.91	67.01	55.31	46.81	40.98	37.45	35.86	35.77	36.748	35.936
CASE 7	Training: 67	89.98	66.89	52.68	43.16	36.6	32.11	29.16	27.39	26.49	26.242	13.029
	Test: 7	104.2	81.81	65.96	54.31	45.85	40.06	36.59	35.09	35.11	36.214	34.299
CASE 8	Training: 66	90.57	67.4	53.06	43.42	36.75	32.16	29.14	27.32	26.39	26.131	12.763
	Test: 8	100.9	78.76	63.38	52.27	44.38	39.17	36.24	35.2	35.56	36.892	35.83
CASE 9	Training: 65	91.07	67.8	53.4	43.7	36.97	32.33	29.26	27.39	26.45	26.174	12.457
	Test: 9	97.59	76.6	61.97	51.34	43.73	38.62	35.67	34.53	34.81	36.085	34.518
CASE 10	Training: 64	91.64	68.28	53.76	43.95	37.12	32.4	29.26	27.35	26.37	26.096	12.027
	Test: 10	96.03	75.23	60.96	50.74	43.54	38.79	36.13	35.18	35.53	36.784	36.576
CASE 11	Training: 63	92.19	68.8	54.19	44.28	37.37	32.57	29.37	27.41	26.41	26.128	11.882
	Test: 11	95.33	74.46	60.17	49.95	42.75	38.01	35.38	34.46	34.85	36.148	35.311
CASE 12	Training: 62	92.31	69.14	54.59	44.65	37.64	32.72	29.4	27.34	26.28	25.969	12.318
	Test: 12	98.39	77.08	62.33	51.65	44	38.87	35.94	34.87	35.25	36.677	35.83
CASE 13	Training: 61	92.58	69.49	54.89	44.85	37.71	32.65	29.2	27.05	25.93	25.601	12.691
	Test: 13	100.3	78.83	64.04	53.33	45.65	40.5	37.54	36.44	36.8	38.216	179.57
CASE 14	Training: 60	93.14	69.95	55.23	45.07	37.83	32.69	29.17	26.96	25.8	25.469	12.378
	Test: 14	98.99	77.96	63.53	53.15	45.74	40.81	37.99	36.96	37.32	38.679	45.558
CASE 15	Training: 59	93.71	70.46	55.67	45.42	38.04	32.72	29.02	26.66	25.4	25.028	10.683
	Test: 15	97.59	77.25	63.12	52.84	45.54	40.83	38.47	38.14	39.41	41.793	50.486
CASE 16	Training: 58	94.05	70.84	56.05	45.75	38.31	32.92	29.13	26.68	25.36	24.966	152.42
	Test: 16	98.54	78.52	64.46	54.1	46.59	41.6	38.97	38.46	39.71	42.269	169.02
CASE 17	Training: 57	94.49	71.29	56.46	46.11	38.61	33.15	29.3	26.8	25.45	25.045	306.02
	Test: 17	98.53	78.8	64.84	54.48	46.88	41.74	38.91	38.2	39.26	41.665	319
CASE 18	Training: 56	94.76	71.66	56.8	46.36	38.75	33.19	29.25	26.68	25.28	24.856	43.409
	Test: 18	100.6	80.72	66.62	56.11	48.34	42.96	39.82	38.76	39.46	41.555	67.544
CASE 19	Training: 55	94.87	71.84	57.01	46.59	38.97	33.38	29.39	26.77	25.33	24.889	7.1233
	Test: 19	102.5	83.39	69.75	59.37	51.43	45.58	41.69	39.74	39.61	41.144	2.85E+08
CASE 20	Training: 54	95.07	72.18	57.41	47	39.34	33.68	29.61	26.9	25.4	24.943	28.618
	Test: 20	103.7	84.95	71.27	60.7	52.46	46.26	42.04	39.8	39.49	40.944	7.21E+15

from the MAM models indicate that the best value of α is in the neighborhood of 0.9.

The "good" estimates of AM models demonstrate that the post-earthquake system states derived from different link failure scenarios can be combined and used to train AM models. The performance of AM models mostly depends on the number of training system states as well as the number of test system states. The addition of more training states in the learning process tends to increase the performance of AM models. The comparison between the static network equilibrium model and AM models does not show the substantial evidence of benefits using AM models in terms of computation time savings. This is because we use the simple synthetic transportation network with only seven zones and twenty-four directed links. Equilibrium traffic flows are computed within a second. However, the static network equilibrium model may require enormous computation times if we apply the model to an empirical transportation network with many zones and links.

Further, the static model requires linearly increasing computation times in case of a large number of traffic flow simulation. Suppose that we want to obtain traffic flows for 1,000 post-earthquake system states. Suppose that the best static model takes one minute to simulate traffic flows for each system state. This results in 1,000 minutes for all post-earthquake system states. However, AM models require only sufficient training information to understand the pair association between network configurations and their traffic flows. Suppose that the network configurations and traffic flows for the first 100 system states are used to train eleven AM matrices (SAM, RAM, and nine MAMs). Each training episode requires at most one minute to compute an AM matrix. The best performing AM matrix is used to estimate traffic flows of the remaining 900 system states.

AM models can estimate traffic flows for a group of system states simultaneously. Thus, the 900 system states are divided into nine groups. Each group of 100 system states can be estimated simultaneously. This estimation takes around one minute. As a result, the AM models require 100 minutes for the first 100 applications of the conventional network equilibrium model, 11 minutes for determining the best AM from among the eleven candidates, and 9 minutes for the remaining 900 system states to be estimated. The total computation time for the AM approach is 120 minutes. This is an enormous time saving.

The results of AM models with varying training and testing system states indicate that the AM models are able to estimate a group of test system states simultaneously without significant loss of the estimation power, if the number of training system states is sufficiently large. Conventional transportation network models may require huge computational times to generate exact solutions for a large-scale transportation. The cheap, heuristic solutions of the AM models can be used as good starting points for the conventional models. This is conducted in two steps. AM solutions are adjusted to feasible solutions, satisfying all the network flow constraints. After a feasible solution is obtained, the conventional network equilibrium models are applied to improve the feasible solution to the exact solution.

In an empirical context, this is second best. Both sets of flows are predictions. The static network equilibrium model is an incomplete representation of the process that simulates link volumes. Empirical studies indicate that there are significant differences between the traffic flows simulated by conventional network equilibrium models and observed link volumes. Further studies are suggested by using a large-scale transportation network and empirical link volumes.

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