Use of Supervisory Control and Data Acquisition for Damage Location of Water Delivery Systems

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Abstract: Urban water delivery systems can be damaged by earthquakes or severely cold weather. In either case, the damage cannot easily be detected and located, especially immediately after the event. In recent years, real-time damage estimation and diagnosis of buried pipelines attracted much attention of researchers focusing on establishing the relationship between damage ratio (breaks per unit length of pipe) and ground motion, taking the soil condition into consideration. Due to the uncertainty and complexity of the parameters that affect the pipe damage mechanism, it is not easy to estimate the degree of physical damage only with a few numbers of parameters. As an alternative, this paper develops a methodology to detect and locate the damage in a water delivery system by monitoring water pressure on-line at some selected positions in the water delivery systems. For the purpose of on-line monitoring, emerging supervisory control and data acquisition technology can be well used. A neural network-based inverse analysis method is constructed for detecting the extent and location of damage based on the variation of water pressure. The neural network is trained by using analytically simulated data from the water delivery system with one location of damage, and validated by using a set of data that have never been used in the training. It is found that the method provides a quick, effective, and practical way in which the damage sustained by a water delivery system can be detected and located.

DOI: 10.1061/(ASCE)0733-9399(2005)131:3(225)

CE Database subject headings: Damage; Water distribution; Water pipelines; Buried pipes; Urban areas; Data collection.

Introduction

Urban water delivery systems can be damaged by earthquakes or severely cold weather. In the former situation, usually multiple pipelines are damaged together, but damaging earthquakes occur infrequently; while in the latter case, one or several pipes may be simultaneously damaged seasonally or under usually traffic loads. In either case, the location and severity of breaks cannot easily be identified, especially immediately after the event.

An ASCE (1984) guideline summarized the experience for identification of potential damage and pointed out that earthquake damage to buried pipelines is most often associated with some type of permanent ground movement, and the identification of permanent ground movement along pipelines following an earthquake can help indicate the damage location. The guideline also suggested instrumentation for measuring ground motion since it is difficult to evaluate how much strain or damage pipelines experienced with little knowledge of ground motion.

In recent years, real-time damage estimation and diagnosis of buried pipelines attracted much attention of researchers. Eguchi et al. (1994) proposed a methodology for early postearthquake damage detection of water distribution systems, in which a prior prediction of pipeline damage based on early data (earthquake magnitude and location) was estimated and then a parameter estimation technique was used to gradually update the a priori prediction of pipeline damage through hydraulic analysis with incoming postearthquake field data on system performance (outages reported by customers, hydrant pressure losses reported by the fire department, sporadic pressure or flowrate readings, reports of pipe leakage, etc.). Unfortunately, the method is only limited to assessments within a large service area, i.e., as the authors said, it is not possible to provide indications of which pipes have been damaged, which may be due to the following reasons. The primary damage prediction is based on earthquake magnitude and location and attenuation of ground motion, and the results are in the form of damage ratio (break number per unit length of pipe), so the damage position is somewhat arbitrary. Also, collecting postearthquake field performance data requires time and it is usually uneven, so the convergence of updating process is very difficult, which may need too much time compared with the postearthquake emergency response and recovery.

A real-time earthquake monitoring and early warning system of a large-scale city gas network for the Tokyo metropolitan area, called SIGNAL (Seismic Information Gathering and Network Alert), was established by the Tokyo Gas Company in 1994 (Yamazaki et al. 1994). The monitoring system consists of 331 spectrum intensity (SI) sensor, 5 accelerometers, and 20 liquefaction sensors. Once an earthquake occurs, monitored values by these sensors are sent to the network control center by radio, and damage estimation of gas networks in each microzone is carried out by SI value combining with peak ground acceleration (PGA),

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Note. Associate Editor: George Deodatis. Discussion open until August 1, 2005. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on May 22, 2001; approved on August 23, 2001. This paper is part of the ***Journal of Engineering Mechanics***, Vol. 131, No. 3, March 1, 2005. ©ASCE, ISSN 0733-9399/2005/3-225–230/$25.00.

then the emergency shutoff of gas networks can be decided based on the damage estimation. The service area is divided into a microzone with mesh size of $250\ \mathrm{m} \times 175\ \mathrm{m}$, and the damage ratios in each microzone are calculated based on empirical relationships from historical damage data. It should be noted that the output of the damage estimation is the damage ratio (break number per unit length of pipe), and not specific damage locations.

Takada and Ogawa (1995) presented a methodology for real-time damage estimation of lifeline systems based on seismic monitoring of ground motion, taking liquefaction into consideration. This monitoring system consists of 37 seismometers operated by Osaka Gas Company. After the occurrence of an earthquake, ground motion data monitored by seismometers are collected, and PGA and peak ground velocity in each microzone with size of $300\ \mathrm{m} \times 400\ \mathrm{m}$ are calculated by interpolation of ground motion at monitored stations, then damage estimation is carried out by liquefaction potential index in each microzone.

Nishio (1994) proposed a relationship between damage ratios of buried gas pipelines and ground motion, deformability of pipelines and nonuniformity of ground, based on seismic observations and field experiments.

The methodologies (Nishio 1994; Takada and Ogawa. 1995; Yoshikawa et al. 1995) all try to establish the relationship between damage ratio (breaks per unit length of pipe) and ground motion, taking the soil condition into consideration. On the one hand, due to the uncertainty and complexity of the parameters that affect the pipe damage mechanism, it is not easy to estimate the degree of physical damage with only a few numbers of parameters; and on the another hand, the methodologies may only be appropriate for gas networks since the strategy of postearthquake emergency operation of gas systems is to shutoff the gas supply once the damage ratio exceeds a certain value in that block. However, for postearthquake operation of water distribution systems, the damage ratio is not enough, since we expect to find out damage locations and so isolate the damage portions in order to maintain the water supply to important facilities. Therefore, these methodologies are not appropriate for water distribution systems, at least they are not the best strategies.

As an alternative, this paper develops a method to identify the location and severity of damage in a water delivery system by monitoring water pressures on-line at some selected positions in the water delivery system. For this purpose, a neural network-based inverse analysis method is used to carry out the identification based on water pressure variation before and after pipe breaks. As will be shown, this method provides a quick, effective, and practical tool to identify the damage location and severity.

In the city of Tianjin, China, a real-time water pressure monitoring system (Liang 1996) was installed, in which the water pressure signals are transmitted to headquarters at a certain time interval automatically. The pipe break data due to severely cold weather have been collected for several years, and they are used to construct an inverse analysis model to identify the possible locations and severity of damage.

This study explores the inverse analysis method to identify the location and extent of damage in the hope that the supervisory control and data acquisition (SCADA) technology will be able to provide pressure and possibly flow measurement data on-line and in real-time for actual water delivery systems. SCADA systems have recently been installed in water delivery networks to transmit, by means of wireless communication, water pressure/flow rate, water quality, and other relevant data collected at remote sensor units to a control center for the purpose of surveillance and control of system function. Taking advantage of an existing SCADA system for estimating the location and extent of damage is expected to make much more sense than using the ground motion information, since the water pressure and flow-rate data are more sensitive to damage of the water delivery network, as long as the location and the number of the sensors are chosen optimally or at least adequately. The proposed method, however, presents a significant technical challenge due primarily to the limited number of SCADA sensor units placed in a spatially extensive and functional complex water delivery network. In this respect, use of inverse analysis combined with neural network techniques as demonstrated in the present study appears to be promising to alleviate this technical difficulty.

Database Development

To establish a relationship between water pressure variation at monitoring stations and the damage location and severity in a water delivery system, a substantial input-output database is required. For a given water delivery system, there are basically two ways in which such a database can be developed; One is to collect the data actually monitored, and the other is to analytically simulate the data. Primarily for the purpose of demonstrating the efficiency of the proposed inverse analysis method, the simulation method is used in this study dealing with a system having only one location of damage and three monitoring stations. The multiple-damage case will be a cumbersome but straightforward extension of single-damage case, which will be the subject of another study.

In the following, the severity of the damage is defined in such a way that the major damage represents a pipe rupture equivalent to the pipe cross-sectional area, through which the water leaks, and the minor damage is equivalent to one hundredth $(1/100)$ of the cross-sectional area. Other degrees of damage severity can be described by varying the equivalent rupture area. Damage can be located by the distance from the breakpoint to the three monitoring stations. In fact, at least three monitoring stations are needed for this method of identification. For simplicity, the break is assumed to be located at the middle of a link between two directly connected nodes in the water delivery system.

The computer program developed by Tanaka et al. (1993) is used for the specific system considered in this paper in order to perform hydraulic analysis of a water delivery system to generate the data needed for the forward analysis.

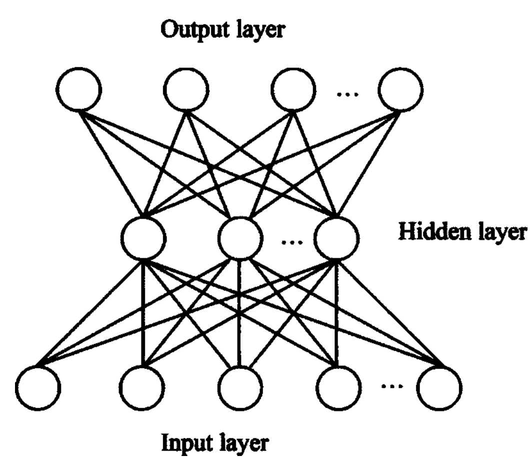

Fig. 1. Neural network model

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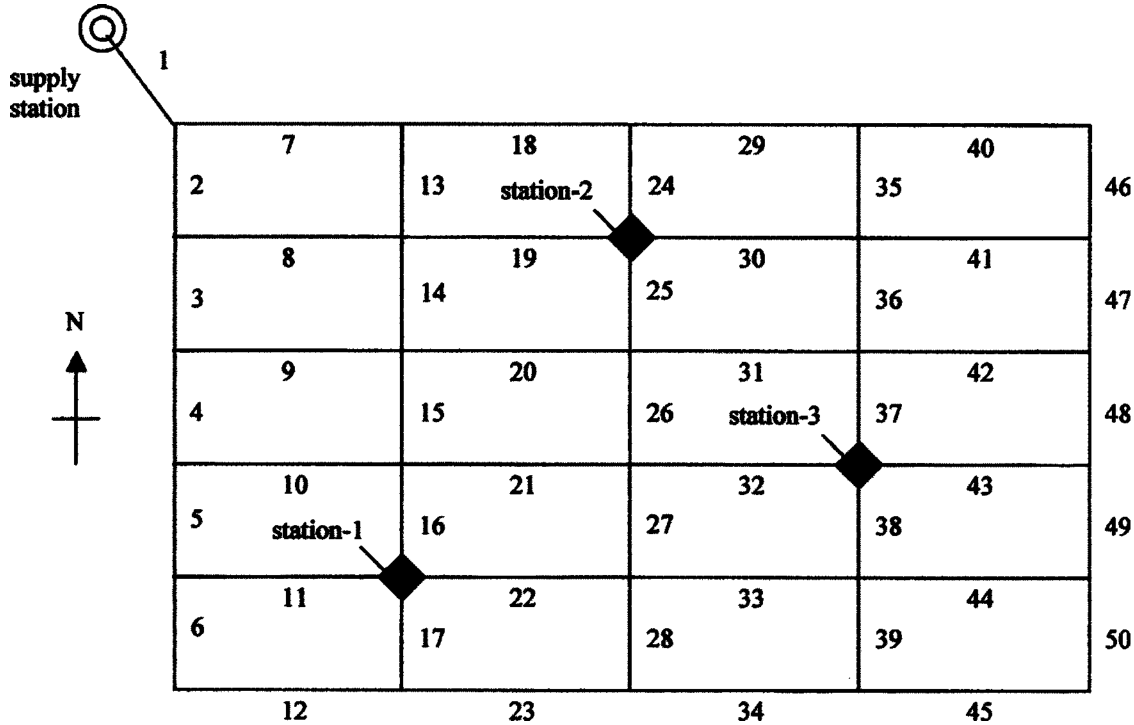

Fig. 2. Water delivery system

Neural Network Model

A back-propagation neural network is used to train the data obtained above. The neural network consists of three layers: Input, hidden, and output layer (Fig. 1). After input data are fed into the neural network at the input layer, they are propagated through the hidden layer until output data are generated. The output data are then compared with the target output, and an error signal is computed for each output node. Then the error signals are transmitted backward from the output layer to each node in the intermediate and input layers that contributes directly to the output. This process is repeated until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error thus evaluated, connection weights are updated at all nodes forcing the network to converge to an acceptable state of performance measured in terms of the root-mean-square (RMS) error defined as

$$E_{\mathrm{RMS}} = SQRT\left[\frac{1}{M}\frac{1}{N}\sum_{i=1}^{M}\sum_{j=1}^{N}(\mathrm{out}_{ij}^{t} - \mathrm{out}_{ij}^{a})^2\right] \qquad (1)$$

where out_{ij}^{t} and out_{ij}^{a}=target and actual output, respectively; M=number of data sets for training; and N=number of nodes in the output layer.

We train the neural network in this way: Pressure variation at three monitoring stations as input, and location of break and damage index as output. In order to normalize the influence of input with different nodes and to prevent the saturation of the transfer

Table 1. Parameter of the Water Delivery System

Link No.	Diameter (m)	Length	Link No.	Diameter (m)	Length (m)	Link No.	Diameter (m)	Length (m)	Link No.	Diameter (m)	Length (m)
1	0.80	50	14	0.50	1,000	27	0.40	1,000	40	0.50	2,000
2	0.60	1,000	15	0.50	1,000	28	0.35	1,000	41	0.40	2,000
3	0.60	1,000	16	0.40	1,000	29	0.50	2,000	42	0.40	2,000
4	0.50	1,000	17	0.40	1,000	30	0.50	2,000	43	0.35	2,000
5	0.50	1,000	18	0.60	2,000	31	0.40	2,000	44	0.35	2,000
6	0.40	1,000	19	0.50	2,000	32	0.40	2,000	45	0.30	2,000
7	0.60	2,000	20	0.50	2,000	33	0.35	2,000	46	0.40	1,000
8	0.60	2,000	21	0.40	2,000	34	0.35	2,000	47	0.40	1,000
9	0.50	2,000	22	0.40	2,000	35	0.50	1,000	48	0.35	1,000
10	0.50	2,000	23	0.35	2,000	36	0.40	1,000	49	0.35	1,000
11	0.40	2,000	24	0.50	1,000	37	0.40	1,000	50	0.30	1,000
12	0.40	2,000	25	0.50	1,000	38	0.35	1,000			
13	0.60	1,000	26	0.40	1,000	39	0.35	1,000			

Table 2. Normalized Distances to Three Stations

Link No.	Distance to Station 1	Distance to Station 2	Distance to Station 3	Link No.	Distance to Station 1	Distance to Station 2	Distance to Station 3
1	0.5709	0.5396	0.7802	26	0.3862	0.2931	0.3453
2	0.5287	0.5287	0.7585	27	0.3453	0.3862	0.3453
3	0.4515	0.5287	0.7291	28	0.3453	0.4792	0.3862
4	0.3862	0.5511	0.7139	29	0.6189	0.2851	0.4478
5	0.3453	0.5925	0.7139	30	0.5484	0.2465	0.3616
6	0.3453	0.6482	0.7291	31	0.4891	0.2851	0.2851
7	0.5372	0.4478	0.6962	32	0.4478	0.3616	0.2465
8	0.4478	0.4327	0.4547	33	0.4327	0.4478	0.2851
9	0.3616	0.4484	0.6281	34	0.4478	0.5372	0.3616
10	0.2851	0.4891	0.6189	35	0.6482	0.3453	0.3862
11	0.2465	0.5484	0.6281	36	0.5925	0.3453	0.2931
12	0.2851	0.6189	0.6547	37	0.5511	0.3862	0.2000
13	0.4792	0.3453	0.5925	38	0.5287	0.4515	0.2000
14	0.3862	0.3453	0.5511	39	0.5287	0.5287	0.2931
15	0.2931	0.3862	0.5287	40	0.7494	0.4478	0.4478
16	0.2000	0.4515	0.5287	41	0.6962	0.4327	0.3616
17	0.2000	0.5287	0.5511	42	0.6547	0.4478	0.2851
18	0.5372	0.2851	0.5484	43	0.6281	0.4891	0.2465
19	0.4478	0.2465	0.4891	44	0.6189	0.5484	0.2851
20	0.3616	0.2851	0.4478	45	0.6281	0.6189	0.3616
21	0.2851	0.3616	0.4327	46	0.8000	0.5287	0.4515
22	0.2465	0.4478	0.4478	47	0.7585	0.5287	0.3862
23	0.2851	0.5372	0.4891	48	0.7291	0.5511	0.3453
24	0.5287	0.2000	0.4515	49	0.7139	0.5925	0.3453
25	0.4515	0.2000	0.3862	50	0.7139	0.6482	0.3862

function, the input and output are scaled based on the minimum and maximum values of the training data. Scaled values are (−1.0, 1.0) for input and (0.2, 0.8) for output.

Results and Discussions

Fig. 2 shows an example water delivery system with one supply station, consisting of 31 nodes and 50 pipe links. Table 1 shows the diameter and length of each pipe link. The roughness coefficient is 140 for all links, and the demand is assumed to be uniform throughout the water delivery system equal to 0.05 m^3/s at each node. The water pressure at the source node is fixed at 52.0 m. Three nodes (Fig. 2) were selected as locations of water pressure monitoring and referred to as Station 1, Station 2, and Station 3, respectively, and Table 2 shows the normalized distances to the three stations.

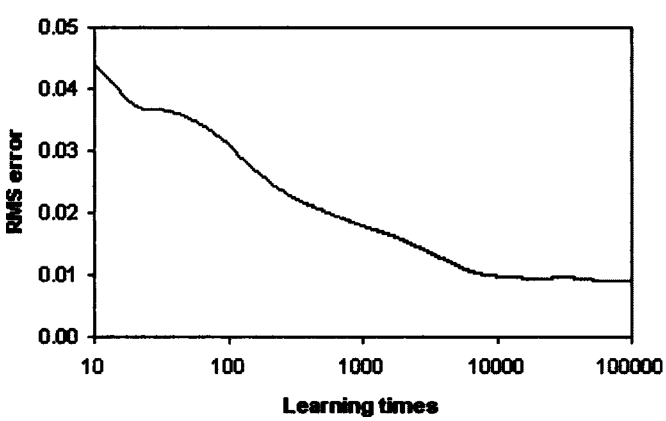

Fig. 3. Neural network training

We generate 350 pairs of input-output data for 7 states of damage with respective break area 0.01, 0.02, 0.05, 0.1, 0.2, 0.5, and 1.0 times cross-sectional area of the pipe. In the neural network training, therefore, the parameters M and N in Eq. (1) are equal to 350 and 4, respectively. Fig. 3 shows the training curve expressing the relationship between RMS error and learning time. The training ends after 100,000 time units with the last RMS error being 0.00879.

The following analysis is performed to examine whether the neural network trained above can provide the results expected. The data used for training were fed to the neural network as the input to obtain the location and severity of the damage. Pipe link Nos. 9, 20, 31, 42, 24, 25, 26, 27, and 28 are examined in Table 3. The numbers (except those in round brackets) in Columns 2 to 5 show the normalized distances to the three monitoring stations and the normalized severity index of the damage. (The normalized length for each pipe link is 0.247 in the north-south direction and 0.340 in the east-west direction based on the minimum and maximum values (500.0 and 6,946.2) of the training data.) The numbers in round brackets indicate the relative error to the data that was used for training, and the minimum relative error is 0.42% and the maximum relative error is 20.5%. Looking at link No. 9, the normalized distances from the damage location to the three monitoring stations are 0.371, 0.427, and 0.636, respectively, and the severity index is 0.545 (see Fig. 4). The pipe links (any points in the links) at distance 0.371 to Station 1 are link Nos. 4, 9, 14, 20, 26, 32, 33, and 34. The links at distance 0.427

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Table 3. Damage Output for Data Used for Training

Link No.	Distance to Station 1	Distance to Station 2	Distance to Station 3	Severity index
9	0.371	0.427	0.636	0.545
	(2.65%)	(4.86%)	(1.32%)	(9.08%)
20	0.363	0.268	0.428	0.480
	(2.77%)	(6.00%)	(4.47%)	(3.96%)
24	0.534	0.239	0.467	0.765
	(1.08%)	(19.4%)	(3.52%)	(7.83%)
25	0.433	0.228	0.373	0.713
	(4.01%)	(14.1%)	(3.42%)	(1.52%)
26	0.373	0.299	0.358	0.631
	(3.44%)	(2.05%)	(3.53%)	(11.1%)
27	0.359	0.367	0.355	0.690
	(4.03%)	(4.87%)	(2.81%)	(2.85%)
28	0.355	0.456	0.367	0.656
	(2.84%)	(4.84%)	(5.05%)	(7.64%)
31	0.565	0.343	0.324	0.274
	(15.6%)	(20.5%)	(13.6%)	(5.65%)
42	0.669	0.446	0.245	0.320
	(21.8%)	(0.42%)	(14.2%)	(10.2%)

to Station 2 are the link Nos. 7, 8, 9, 10, 16, 27, 38, 43, 42, 41, and 40, and the links at distance 0.636 to Station 3 are link Nos. 7, 8, 9, 10, 11, and 12. Only link No. 9 satisfies the three conditions and, therefore, link No. 9 is judged to be the damaged link, as expected. Other links, Nos. 20, 24, 25, 26, 27, 28, 31, and 42, can be checked in the same way. Table 3 shows that the neural network trained above is sufficiently effective for the purpose of identification.

The same neural network trained above is now examined if it can identify the location and severity of damage well for the data never used for training. The results are shown in Table 4 also for link Nos. 9, 20, 24, 25, 26, 27, 28, 31, and 42, with the minimum and maximum relative errors being, respectively, 0.09%, and 25.8%, which are larger than the corresponding errors in Table 3 as expected. Table 4 shows that again only link No. 9 is the damaged link, as also expected.

The following observations are made with respect to link No. 31 which has the largest relative error. The links at distance 0.560 to Station 1 are link Nos. 2, 7, 18, 24, 30, 31, 37, 43, 44, and 45, at distance 0.332 to Station 2 are link Nos. 18, 19, 20, 26, 29, 30, and 31, and at distance 0.359 to Station 3 are link Nos. 21, 30, 31, 33, 34, 35, 41, 42, 44, and 45. In this way, link Nos. 30 and 31 are

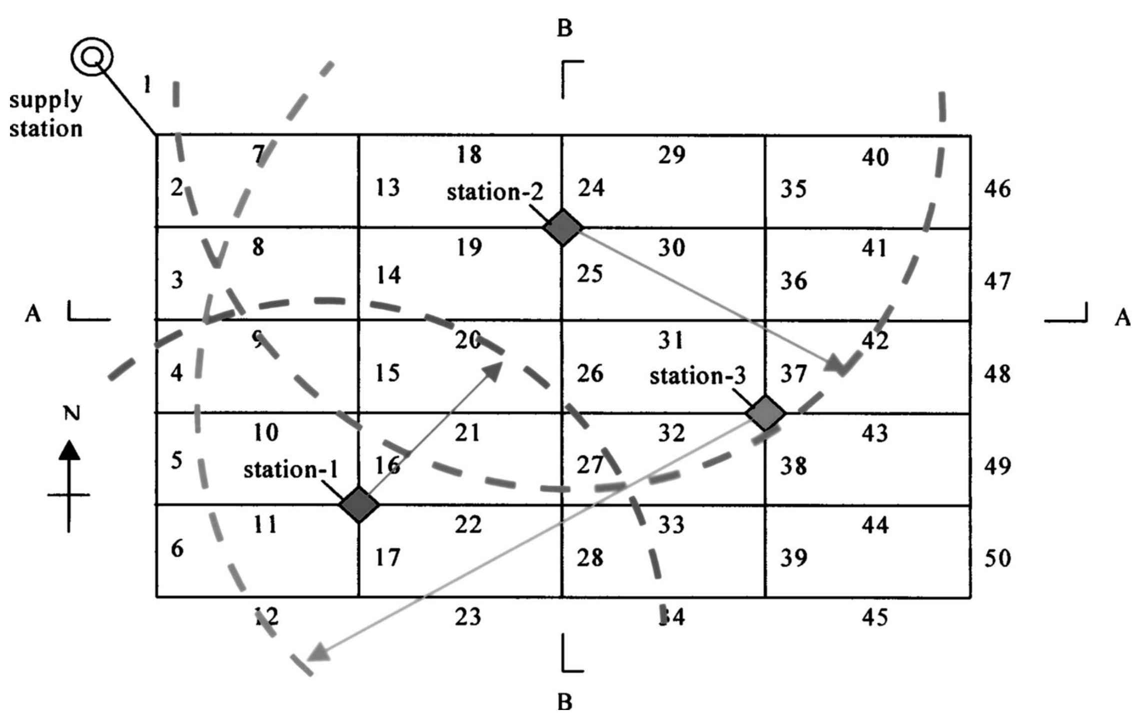

Fig. 4. Damage location

Table 4. Damage Output for Data Not Used for Training

Link No.	Distance to Station 1	Distance to Station 2	Distance to Station 3	Severity index
9	0.413	0.471	0.676	0.467
	(14.1%)	(4.95%)	(7.69%)	(8.92%)
20	0.395	0.318	0.487	0.482
	(9.32%)	(11.4%)	(8.82%)	(5.93%)
24	0.562	0.239	0.480	0.797
	(6.33%)	(19.5%)	(6.36%)	(10.3%)
25	0.470	0.241	0.406	0.678
	(4.08%)	(20.4%)	(5.02%)	(6.05%)
26	0.361	0.293	0.359	0.645
	(6.60%)	(1.02%)	(4.03%)	(10.8%)
27	0.345	0.348	0.357	0.8143
	(0.09%)	(9.84%)	(3.30%)	(12.8%)
28	0.365	0.486	0.410	0.703
	(5.73%)	(14.2%)	(6.08%)	(2.60%)
31	0.560	0.332	0.359	0.369
	(14.4%)	(16.3%)	(25.8%)	(21.8%)
42	0.666	0.461	0.324	0.280
	(1.74%)	(2.95%)	(13.7%)	(7.63%)

judged to be potential candidates to be the damaged links. However, actually only link No. 31 is the damaged link, and therefore link No. 30 was mistakenly identified as a damaged link in addition to link No. 31, though link No. 31 is more consistent with what the data suggest. Actually, if the distance to Station 2 is greater than 0.340 with a relative error of 14.2%, then link No. 30 could be excluded from the candidate group of damaged links, which means that the relative error (16.3%) presently for the distance to Station 2 is still not acceptable. The reason is that the RMS error in the back-propagation neural network is an average error for all data used for training in accordance with the learning rule, and not for each set of data or for each node in the output layer. This problem can be resolved by additional training effort or reselecting the three monitoring stations, which will be studied further.

Conclusions

The purpose of this study is to develop a method to identify location and severity of damage in a water delivery system by monitoring water pressure on-line (SCADA) at some selected positions in the water delivery system. The method can also be applied in principle to other networks such as electric power systems.

A neural network-based inverse analysis method is developed for the stated purpose. The method is based on on-line water pressure variation before and after pipe breaks, and provides a quick, effective, and practical analysis tool to serve the purpose. The results also show that the number of monitoring stations can be less than one-tenth of the number of nodes in a water delivery system.

Acknowledgments

This work was supported partially by U.S. National Science Foundation under Grant No. INT-9604614, the Multidisciplinary Center for Earthquake Engineering Research under Grant No. R92249-A, and the National Natural Science Foundation of China under Grant No. 59878032, which are gratefully acknowledged.

References

ASCE. (1984). *Guidelines for the seismic design of oil and gas pipeline systems*, ASCE, New York, 424–427.

Eguchi, R. T., Chrostowski, J. D., and Till, C. W. (1994). "Early postearthquake damage detection for lifeline system." *EQE Research Rep. Prepared for National Science Foundation*.

Liang, J. (1996). *A comprehensive framework for postearthquake rehabilitation plan of lifeline networks*, ASME, New York, Vol. 340, 283–289.

Nishio, N. (1994). "Damage ratio prediction for buried pipelines based on the deformability of pipelines and the nonuniformity of ground." *J. Pressure Vessel Technol.*, 116, 459–466.

Tanaka, S., Shinozuka, M., and Hwang, H. H. M. (1993). "LIFELINE-W(2) user's guide: A program for connectivity and flow analysis of a water delivery system under intact and seismically damaged Conditions." *Technical Rep.*, Princeton Univ., NJ.

Takada, S., and Ogawa, Y. (1995) "Seismic monitoring and real time damage estimation for lifelines." *Proc., 4th U.S. Conf. on Lifeline Earthquake Engineering, ASCE*, New York, 224–231.

Yamazaki, F., Katayama, T., and Yoshikawa, Y. (1994). "On-line damage assessment of city gas networks based on dense earthquake monitoring." *Proc., 5th U.S. Conf. on Earthquake Engineering, EERI*, El Cerrito, Calif. 4, 829–837.

Yoshikawa et al. (1995).