Estimate of pipe deterioration and optimal scheduling of rehabilitation

E.S. Kim*, C.W. Baek and J.H. Kim****

*Dept. of Civil Engr., Sunmoon University, Asan-si, Chungnam, South Korea 336-708
(E-mail: *hydrokes@sunmoon.ac.kr*)

**Dept. of Civil and Envir. Engr., Korea University, Seoul, South Korea 136-701
(E-mail: *chunoobaek@hanmail.net; jaykim@korea.ac.kr*)

Abstract This study proposes an optimal scheduling model for rehabilitation based on the deterioration prediction of existing pipes by using the deterioration survey method for a water distribution system. The deterioration prediction model divides the deterioration degree of each pipe into 5 degrees by using the Probabilistic Neural Networks (PNN). Furthermore, the maximum residual service time is estimated by the calculated deterioration degree for each pipe and pipe diameter. The optimal rehabilitation model by integer programming (IP), based on the shortest path, can calculate the time and cost of maintenance, rehabilitation, and replacement. Consequently, the model proposed by the study can be utilized as a quantitative method for the management of a water distribution system.

Keywords Optimal rehabilitation; probabilistic neural networks; maximum residual service time

Introduction

The primary goal of all water distribution systems is the delivery of water to meet demands on quality, quantity and pressure. Unfortunately, as a system ages, its ability to transport water diminishes and the demands placed upon it typically increase. Older systems have reduced carrying capacity due to corrosion and tuberculation which require time and money to repair. Thus, the rehabilitation, replacement, and/or expansion of an existing system to meet current and future demands of flow rate and pressure head has always been a topic of interest to engineers. A breakage in pipe network systems can disrupt the drinking water service to a wide area of the community. In order to reduce the break ratio of a pipe system, it is required that the pipes in the system be replaced and/or rehabilitated depending upon the condition of the system components, mostly pipes.

Shamir and Howard (1979) developed a procedure to schedule pipe replacement based on the forecasted number of breaks of existing and new pipes, the cost of repairing a break, the cost of replacing the existing pipe, and the discount rate. Walski (1982) developed a new criterion to replace pipes that stated that if the current break rate of a pipe is greater than some critical break rate, the pipe should be replaced. Walski (1982, 1985) considered the economic analysis of the rehabilitation of water mains. The criteria developed can be used to determine if it is economical to clean and reline a pipe, for two cases: flow is not significantly changed by rehabilitation of the pipe, or the system is looped so that the change in carrying capacity significantly changes flow. The decision criterion is to rehabilitate if the cost for rehabilitation is less than the extra cost for pumping energy and the additional equipment required to force water through the mains with a low Hazan-Williams C-Factor. Kim and Mays (1994) presented a methodology that can select the pipes to be rehabilitated and/or replaced in an existing water-distribution system and determine the increase in pumping capacities so that water demands and pressure requirements at all demand nodes are satisfied while the total rehabilitation and energy costs are minimized. KOWACO (1995) developed a numerical weighting model which

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proportionally scores the effect of each factor on the deterioration rate depending upon the condition of the various factors in the pipe. Dandy and Engelhardt (2001) presented the use of the genetic algorithm technique to find a near optimal schedule for the replacement of the water supply pipes. The goal was to minimize the present value of capital, repair, and damage costs. Loganathan *et al.* (2002) proposed an economically sustainable threshold break. Relations of equivalence are established between the threshold break rate and both the rate of failure and the hazard rate functions. These statistical functions are used to predict the break rates for a system. All the models described up to this point involve no pipe deterioration research methods. In fact, most of the decision processes were based only on the actual field data and some general guidelines.

However, since most pipe networks for drinking water are underground, it is very difficult, if not impossible, to evaluate the deterioration state of the pipes. Therefore, it is necessary to develop a model for the deterioration evaluation of water supply pipes. The method in this study, which is more efficient than the existing methods, proposes an optimal rehabilitation model based on the deterioration prediction of the inground pipe by using the deterioration survey method of the water distribution system. This study proposes a new approach for deterioration evaluation of water supply pipes using Probabilistic Neural Networks (PNN). Specht (1990) formulated a PNN that can compute nonlinear decision boundaries by replacing the sigmoid activation function often used in neural networks with an exponential function. The optimal rehabilitation model by integer programming (IP) based on the shortest path can calculate the time and cost of maintenance, rehabilitation, and replacement.

Probabilistic neural networks (PNN)

Specht (1990) discovered that the Bayes-Parzen classifier could be cast in the form of a neural network. He showed how the algorithm could be split up into a large number of simple processes, each of which has its own dedicated procedure, and most of which can run in parallel. The implication of this discovery is that extremely fast hardware implementations of the algorithm are possible. The structure of Specht's PNN is composed of four layers, shown in Figure 1, as opposed to the three layers, input, hidden, and output, of an ordinary neural network.

The network in Figure 1 has two inputs, two classes, and two training cases in each class. The pattern layer contains one neuron for each training case. The summation layer has one neuron for each class. Execution starts by simultaneously presenting the input vector to all pattern-layer neurons. Each pattern neuron computes a distance measure between the input and the training case represented by that neuron. It then subjects that distance measure to the neuron activation function. Each summation neuron in the following layer is dedicated to a single class. It simply sums the pattern layer neurons corresponding to members of that summation neuron class. The output neuron decides which

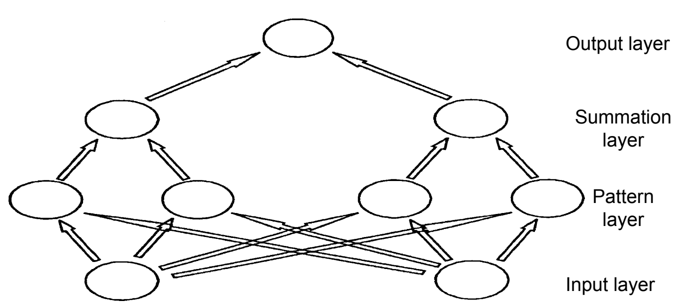

Figure 1 Specht's PNN architecture

of its inputs from the summation units is the maximum. The PNN architecture is elegantly simple, yet capable of extremely high-speed operation if the pattern units can be operated in parallel.

Model development

PNN model

The model developed in this study uses the same deterioration factors used in the KOWACO report (1995). Table 1 shows the weight distribution of each deterioration factor used in the KOWACO model. The weight for each factor in Table 1 is divided into several points depending upon the condition of the pipe in the system.

The points for each factor (category) are added up to yield the total points. The PNN model uses condition values: 1 for the condition which causes severe deterioration of the pipe, 0 for the condition which causes few problems, and 0.5 for an intermediate condition. The value 1 can be considered as the center point for a Gaussian distribution and the value 0 can be considered as the tail of the distribution. These condition values can be adjusted case by case depending on the field data obtained in the region of practical interest. Since the fourteen factors don't have the same impact on the deterioration of pipes, a weighting scheme is applied to those factors in this study. These weighting factors are allocated between input layer and pattern layer, so that the weighting factors can be multiplied to the input data before the neuron is trained with the data. Table 2 shows two cases of different weighting factors for the two groups of fourteen and nine deterioration factors considered in this study.

The deterioration weighting factors are divided into 14 factors with digging and experiment and into 9 factors without digging and experiment, and the deterioration degree is calculated. The model developed in this study is composed of four layers: input, pattern, summation, and output, as are most PNN models. The condition value (1, 0.75, 0.5, 0.25, 0) based on the condition of each sample pipe is input to each neuron in the input layer. The pattern layer is composed of five big neurons, each of which handles its own boundary condition value, i.e., 1, 0.75, 0.5, 0.25 and 0, respectively. Figure 2 shows the structure of the PNN model developed in this study.

Each big neuron in the pattern layer also includes fourteen small neurons because fourteen deterioration factors are considered in this study. The pattern layer carries out a core role that classifies the characteristics of input data by including the measured distance between input data and pattern neurons into an active function. Gaussian function is used as the active function in this study. There is only one summation neuron in the summation layer. This summation neuron executes a simple summation of trained data from the pattern layer. The output layer has five neurons that have a function of simple classification, in which the five neurons denote five classes of deterioration. Each of the five neurons in the output layer has a probabilistic value, and these values for all three neurons add up to 1. The value is a probability for a pipe in a pipe network system to be classified into one of the five classes of deterioration. The five probabilistic values are named Class 1, Class 2, Class 3, Class 4, and Class 5, in this study. It is possible to say that the condition of a pipe is in Class 1 if Class 1 is the biggest among the five Class values. However, it may be better to evaluate the deterioration condition of the pipe with all five probability values, which denote the probability to be classified into each of the five classes.

Optimal rehabilitation model

The optimal rehabilitation model by IP based on the shortest path can calculate the time and cost of repair, rehabilitation, and replacement. Two assumptions are applied for

Table 1 Weight distribution for each factor (KOWACO, 1995)

Deterioration factor	Condition	Class	Deterioration factor	Condition	Class
1. Maximum pressure (kg/cm^2)	Above 7	1.00	8. Pipe outside corrosion (sulfide/chloride)	Sulfide above 500 mg/kg,	1.00
	6	0.75		Chloride above 250	
	5	0.50		Sulfide 200–500	0.50
	4	0.25		Chloride 100–250	
	Below 3	0.00		Sulfide below 200	0.00
				Chloride below 100	
2. Installed district	Industrial area	1.00	9. Inside corrosion (coefficient of C)	Below 75	1.00
	Load area	0.75		76–90	0.75
	Metropolitan area	0.50		91–105	0.50
	Apartment area	0.25		106–119	0.25
	Side street area	0.00		Above 120	0.00
3. Road wide	Highway, Industrial road	1.00	10. Foundation	Bottom foundation	1.00
	A four-lane load	0.75		Sand foundation	0.50
	A two-lane load	0.50		Conc. or Pile foundation	0.00
	Etc	0.25			
	Footpath	0.00			
4. Pipe type	ST	1.00	11. Refilled soil	Not good drainage	1.00
	CI, CP	0.75		Silt/loam	0.50
	CIP, DT	0.50		Good drainage	0.00
	PFP, EP	0.25			
	DTC, STC	0.00			
5. Elapsed time from installation	Above 21 years	1.00	12. Diameter of pipe	Below 80 mm	1.00
	16–20 years	0.75		81～100 mm	0.75
	10–15 years	0.50		100～150 mm	0.50
	5–9 years	0.25		151～250 mm	0.25
	Below 4 years	0.00		Above 300 mm	0.00
6. Record of leakage and breakage	4 times per 5 years	1.00	13. Valve, divergence, coupling pipe	Plenty	1.00
	3 times per 5 years	0.75		Average	0.50
	2 times per 5 years	0.50		None	0.00
	1 times per 5 years	0.25			
	0 per 5 years	0.00			
7. Pipe outside corrosion (pH)	Below 5	1.00	14. Type of joint	electric welding	1.00
	5 ～7	0.50		rubber gaskets	0.50
	Above 8	0.00		mechanical couplings	0.00

Table 2 Weighting factors applied to deterioration factors

	Deterioration factors													
Weighting group	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
14	1.1	1.1	0.9	1.8	1.0	1.6	0.5	0.5	1.4	0.8	1.1	0.8	0.7	0.7
9	–	0.7	0.3	2.0	0.8	1.2	–	–	–	1.7	1.0	0.9	–	0.4

model construction. The first assumption is residual service life: after assuming the maximum service life of a pipe as 25 years and 35 years, the residual service life is assumed according to the pipe class result. Table 3 shows the results of that assumption.

The second assumption is the residual service life increase by rehabilitation: considering the realistic situation and the assumed increase of residual service life by rehabilitation. Table 4 shows the results of that assumption. These two assumptions were assumed with the survey research results from the Pusan waterworks that are the model for all application areas.

The objective of the model is to minimize the sum of the pipe replacement, pipe rehabilitation and pipe repair costs. The minimization problem is subject to the rehabilitation time that occurs before replacement time and rehabilitation are possible once. If the residual service life is estimated from the deterioration prediction model, the repair can be performed during the maximum service life period R. This time, the residual service life is reduced if repair is undertaken one. Also, residual service life increases when residual service life period is k if the rehabilitation is performed. Figure 3 shows the structure of the optimal rehabilitation model.

Application

The developed PNN and optimal rehabilitation models were applied to real data from 85 pipes of 14 waterworks in Pusan. The results were analysed for the purpose of applying the model. Pusan is a city of 3.8 million people on the south coast of Korea. The investigated data consisted pipe type is CIP and DCIP, pipe diameter is 80–300 mm, laying-years were 1966–1995, laying location and environment consists of 85 pipes with varying condition and so on.

According to Figure 4, the results of PNN, most of the pipes were deterioration class 2–4, and 75 pipes had the same deterioration classes except 10 pipes (5, 8, 28, 37, 38, 49, 54, 56, 69, 72). According to Figures 4, 5 pipes of class 2 needed urgent replacement. The application results of the PNN model showed that a difference of the deterioration

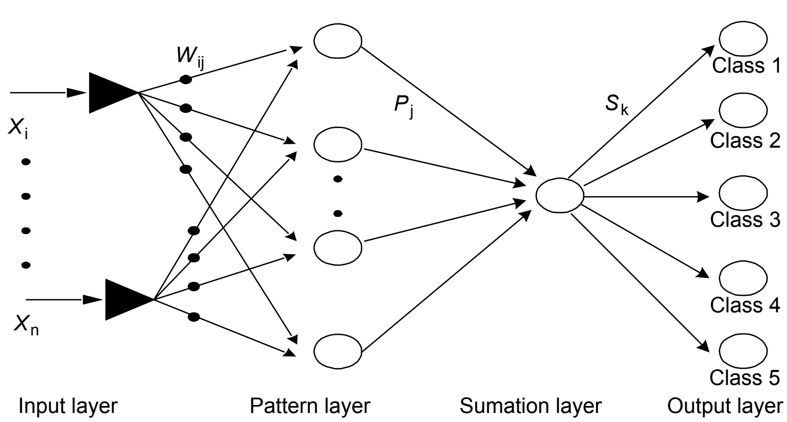

Figure 2 Boundary condition values used in the PNN model

Table 3 Residual service life value by Class and Diameter

	Pipe diameter (mm)									
	Below 100		150		200		250		Above 300	
Maximum residual service (year)	**25**	**35**	**25**	**35**	**25**	**35**	**25**	**35**	**25**	**35**
Class 1	1	3	2	4	3	5	4	6	5	7
Class 2	6	10	7	11	8	12	9	13	10	14
Class 3	11	17	12	18	13	19	14	20	15	21
Class 4	16	24	17	25	18	26	19	27	20	28
Class 5	21	31	22	32	23	33	24	34	25	35

Table 4 Residual service life increase by rehabilitation

	Pipe diameter (mm)				
Maximum residual service life (year)	**Below 100**	**150**	**200**	**250**	**Above 300**
25	6	7	7	8	8
35	10	11	11	12	12

class according to factor numbers was within 11.77%. Also, the PNN model could evaluate the deterioration degree of each pipe with only 9 factors, which means digging and extensive experiment are not required.

The optimal rehabilitation model estimated the optimal cost and time using the PNN model results and the residual service time which was estimated by pipe diameter. Figure 5 shows the results from the optimal rehabilitation model using the 9 and 14 factors.

In case of a maximum residual service time of 25 years, for each of the 9 and 14 factors, rehabilitation and replacement happened at the same time, except no. 2, 5, 36, 49 and 54 pipes. Table 5 shows the min/max time of each rehabilitation and replacement using the maximum residual service time and factors.

Table 6 shows the results of rehabilitation and replacement cost for the whole 85 pipes. The 25 years of maximum residual service time (pipe) indicated the increase of 11,236 won when it is evaluated with 14 check factors rather than with 9 factors, while the 35 years of maximum residual service time (pipe) showed the decrease of 815,808 won in the same situation. The results, in fact, suggest that replacement would bring more efficient economic benefit than rehabilitation, because the older the optimal residual service time is, the higher the value of the pipe. Comparing the total rehabilitation cost of the 85 pipes with that suggested by Shamir and Howard (1979), the 9 factors showed a cost saving effect of rehabilitation in the estimation from 17,754,082 won to 23,083,342

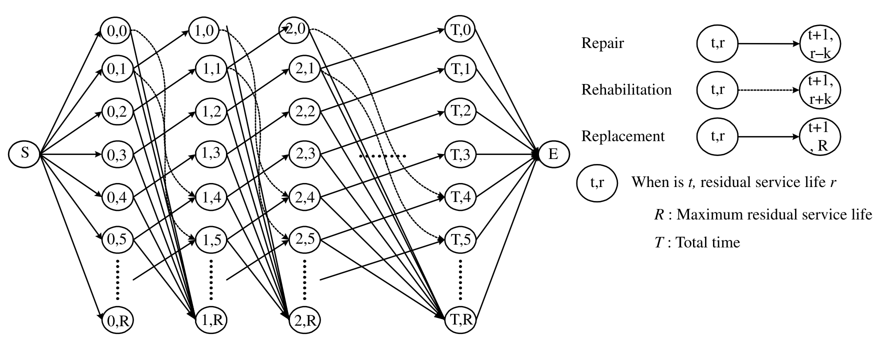

Figure 3 Flowchart of optimal rehabilitation model

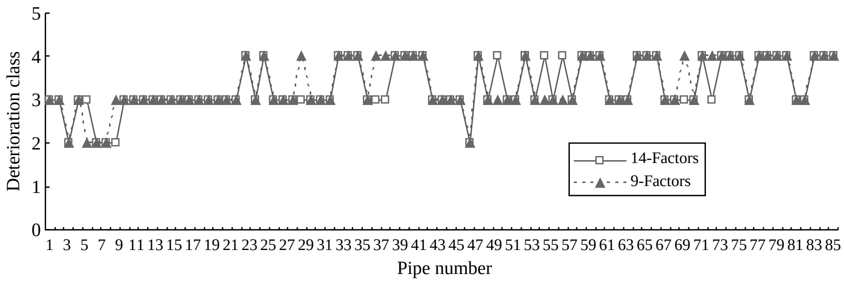

Figure 4 Results of PNN (deterioration class of each pipe)

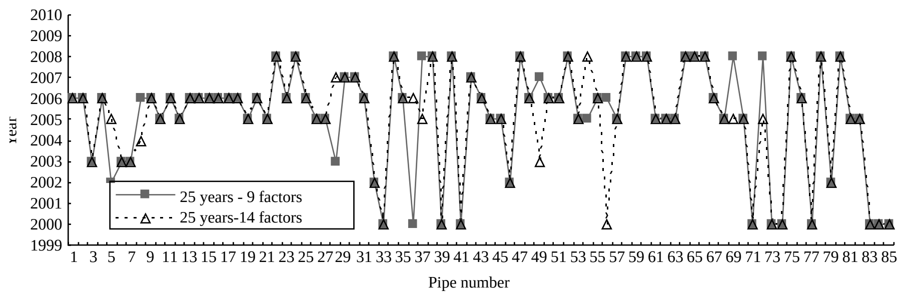

Figure 5 Nine and 14 factors: The optimal rehabilitation and replacement time

Table 5 Min or Max time of each rehabilitation and replacement

	Maximum residual service time 25 years				Maximum residual service time 35 years			
	Rehabilitation		Replacement		Rehabilitation		Replacement	
	9 factors	14 factors	9 factors	14 factors	9 factors	14 factors	9 factors	14 factors
Min(year)	5	5	13	13	5	9	17	9
Max(year)	20	20	45	45	18	30	48	48
Max-Min	15	15	32	32	13	21	31	39

won and the 14 factors also indicated a decrease from 18,569,889 won to 23,072,106 won. The model developed in this study results in 35 to 45 percent savings compared to the Shamir and Howard (1979) model. It is considered that the uneconomic cost by Shamir and Howard (1979) model is due mainly to its high dependency on the pipe ages, while the model developed in this study considers various deterioration factors other than the pipe ages. It is also noteworthy that the difference in the results obtained by both cases with 9 and 14 deterioration factors is minimal as shown in Table 6.

Table 6 Comparison of rehabilitation and replacement cost for 85 pipes

	Maximum residual service time	
	25 years	35 years
9 factors	27,532,749 (won)	32,862,010 (won)
14 factors	27,543,985 (won)	32,046,202 (won)
Difference	11,236 (won)	815,808 (won)

∗ 1 Euro ≈ 1,400 won

Conclusions

This research estimated the deterioration of installed pipes in an analysis of 85 existing pipes in Pusan city in Korea and suggested the optimal rehabilitation model considering the residual service time. The level of pipe-deterioration was decided based on Probabilistic Neural Networks (PNN). The application of the model shows that the deterioration class resulting from the estimate with 14 deterioration factors is similar to that from the estimate with 9 factors, which indicates that an intensive field examination can be avoided without compromise of the model accuracy. This finding demonstrates that this research could provide solid ground for the practical application of pipe-deterioration estimates.

The research estimates the optimal rehabilitation time and efficient cost level based on mixed-integer programming (MIP), which resulted from the shortest path flow. The research result presented in this study demonstrates more efficient cost savings in comparison with those of previous study of Shamir and Howard (1979). The optimal rehabilitation model of this study determines the optimal replacement and rehabilitation times based on the deterioration estimate which considers various pipe deterioration factors, while the previous study considers the pipe break rate only, which in turn a function of the pipe age. If similar research is further developed with an in-depth study of residual service time and the lifetime increase of the rehabilitated pipes, it is expected that such research will provide the most optimal model.

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