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Development of the corrosion depth prediction model of water pipe using fuzzy theory

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ABSTRACT

To use the fuzzy theory for considering the corrosion-influencing factors, this study developed the corrosion depth prediction model for steel pipe. An analysis result of individual factors affecting corrosion shown that it was reasonable to apply the method to simultaneously consider the various corrosion influence factors using fuzzy theory. To make corrosion depth prediction models, a modified two-phase model that combines the fuzzy score was adopted. The developed models can express different corrosion characteristics according to the various environmental conditions, and the models had higher correlation than previous models. Especially, the proposed model that considers corrosion influence factors provided higher explanatory and prediction power than the models that simply consider only the pipe age. In conclusion, it is expected that the proposed corrosion depth prediction model will make it possible to predict the service life of water pipes more accurately as a basic model that can be utilized for predicting the physical residual life of water pipes.

Keywords: Corrosion influence factors; Fuzzy theory; Pipe corrosion depth prediction

1. Introduction

The deterioration of water pipes lowers the safety and reliability of water supply in various ways. In the case of metal pipes, corrosion is the major cause of water pipe deterioration [1]. The causes of corrosion in metal pipes such as a steel pipe (SP) and ductile cast iron pipe (DCIP) can be summarized as follows. The iron component included in metal pipes acts as an anode where oxidation occurs, and it can also become an electrical conductor that connects the anode with the cathode. As water pipes are buried underground and oxygen and moisture in soil, as well as water flowing in pipes, become the cathode, buried water pipes are naturally exposed to corrosion.

Owing to the damages caused by the failure or malfunction of deteriorated water pipes, the need for replacing old water pipes with new ones is well understood, but it is always difficult to determine the most appropriate replacement timing. Deb et al. [2] proposed a method of assessing the physical condition of a water pipe through the safety factor between the stress acting on the pipe and the residual strength. The extension of this concept has been frequently used as a method of determining the replacement timing of water pipes from a physical perspective.

Bae et al. [3] proposed a regression equation capable of deriving the residual strength of water pipes through the corrosion rate. If the corrosion depth of a water pipe can be predicted by year, it is possible to predict the residual strength of the pipe by year. Furthermore, it is possible to derive the safety factor of the pipe by year under the assumption that the burial environment of the pipe does not significantly change [4]. These processes can be utilized to predict the physical residual life of a water pipe.

Romanoff's [5] model and Rossum's [6] model using the power model are the representative early studies on predicting the corrosion depth and corrosion rate of a water pipe.

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Afterward, Sheikh et al. [7] proposed the linear model as a corrosion depth model, and Rajani and Makar [8] proposed the two-phase model by combining the linear model and power model. Lee [9] derived the coefficients of the model equation with the highest correlation with the collected data using the power model, linear model, and exponential model (two-phase model). The model equation was created to predict the external corrosion depth and internal corrosion depth of each pipe type. K-water [10,11] also created a model to predict the external and internal corrosion depth for the three models, as with Lee [9].

As can be inferred from the model equations of the power model, linear model, and two-phase model, previous studies on the corrosion depth and corrosion rate of water pipes have limitations in that the corrosion depth and corrosion rate can be expressed only as functions of the pipe age. However, research results have suggested that there are various factors that affect the corrosion of water pipes other than the pipe age [12]. Rajani and Makar [8] found that the water contents, soil pH, soil resistivity, and sulfur-oxidizing bacteria affect the external corrosion of water pipes, and Chung et al. [13] revealed that the soil pH, as well as the chloride ion and sulfate ion concentrations, is highly correlated with external corrosion. Katano et al. [14] pointed out that the redox potential, soil resistivity, and sulfate ion in soil are major factors that accelerate corrosion, and Sarin et al. [15] pointed out that the mineral iron and soil permeability are factors that influence corrosion rates. Arai et al. [16] found that the sulfide concentrations are the factor that most significantly affects the external corrosion of water pipes, and Peterson and Melchers [17] presented that moisture properties are the major factors of external corrosion. Kim et al. [18,19] suggested that major corrosion influence factors are the pipe–soil potential difference and water contents for SP and the soil resistivity and sulfide concentrations for DCIP through the discriminant analysis of factors affecting the corrosion of water pipes. In addition, Chung et al. [13] obtained a research result that internal corrosion is affected by the water pH, dissolved oxygen, electrical conductivity, residual chlorine, alkalinity, and microorganisms inside water pipes.

As can be seen, there are various factors that affect the corrosion of water pipes other than the pipe age. Bae et al. [3] proposed an external corrosion rate model in the form of a nonlinear regression equation considering corrosion influence factors, and De Masi et al. [20] proposed a model of predicting internal corrosion through an artificial neural network model for various influence factors. However, these models have limitations in that they cannot secure a large number of specimens and that their usability is somewhat low in specifically identifying the replacement timing of water pipes.

Therefore, this study aimed to develop a corrosion depth prediction model for SP, which is mostly utilized as a large-diameter water pipe, considering various corrosion environments through a large number of investigations on specimens. To consider various corrosion environments, fuzzy theory was utilized in this study. The purpose of this study is to propose a model that can express the corrosion tendency of water pipes better than the existing models. Also, the purpose of this study is to propose a quantitative model that can be utilized as a basic model for calculating the specific replacement timing of water pipes by developing a modified two-phase model that combines the fuzzy score for comprehensively expressing various corrosion environments with the two-phase model proposed by Rajani and Makar [8].

2. Methods

The corrosion depth prediction model was developed using the flow shown in Fig. 1. Fuzzy theory was applied to consider various factors affecting corrosion, and the weight for each fuzzy item was determined using a genetic algorithm. This study aimed to propose a modified two-phase model that reflects the fuzzy scores of factors affecting corrosion based on the two-phase model, which has been frequently used in previous studies. The coefficients of the modified two-phase model were obtained using the curve fitting method so that the differences between them and the measured values could be as small as possible.

2.1. Data investigation

South Korean law designates multiregional water supply systems as important facilities. Accordingly, such water supply systems are subject to safety diagnosis every 5 years. For development of a corrosion depth prediction model, this study utilized the results of 43 precision safety diagnoses for 23 multiregional water supply systems from 1988 to 2013, that is, the results of corrosion depth measurements and corrosion influence factor investigations.

The external and internal corrosion of water pipes have different corrosion influence factors. Therefore, it was deemed appropriate to develop the model by distinguishing external and internal corrosion. External corrosion is mostly affected by the soil outside water pipes, while internal corrosion is affected by the quality of the water flowing in water pipes.

The investigated external corrosion items were the pipe–soil potential difference, soil resistivity, soil pH, water contents, chloride (Cl^-) concentrations, and sulfide (SO_4^{2-}) concentrations, while the investigated internal corrosion items were the water pH, Langelier saturation index (LI) utilized as the water quality corrosion index, and alkalinity. Table 1 shows the number of investigated data for the development of the corrosion depth prediction model.

The investigated data may have outliers. After examining whether each of the investigated items formed a normal distribution, if an open form that can be determined as a normal distribution appeared, the data that exceeded the 95% confidence level were determined as outliers, and such data were excluded from the analysis.

2.2. Application of fuzzy theory

The fuzzy theory proposed by Zadeh [21] can handle the inaccuracy of variables through the many-valued logic for a qualitative state or unclear or ambiguous state instead of applying the binary concept of "Yes" or "No." In other words, it is a theory that expresses inaccuracy by creating rules that use approximate or subjective values [22].

Fuzzy theory means that a target is not expressed with a single value but with infinite values between 0 and 1.

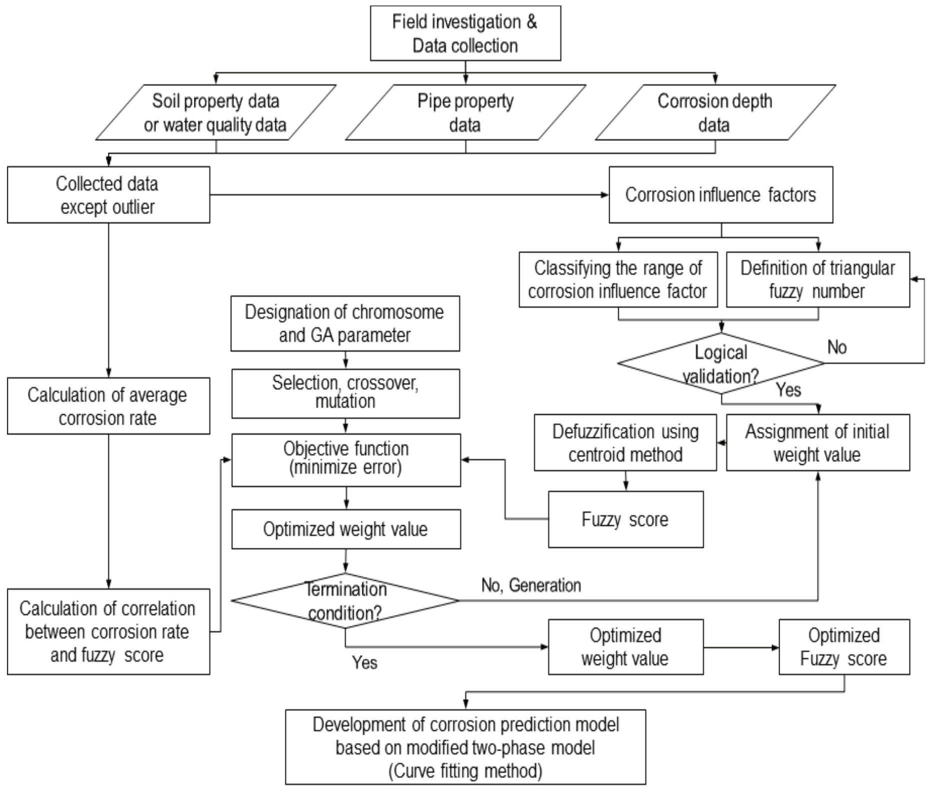

Fig. 1. Development flow for corrosion depth prediction model.

Table 1
Number of data for developing corrosion depth prediction model

Case	Total number of samples	Corrosion influence factors
SP external	223	Pipe–soil potential difference, soil resistivity, soil pH, water contents, Cl^- concentrations, and SO_4^{2-} concentrations
SP internal	192	Water pH, LI index, and alkalinity

Therefore, fuzzy theory can be highly applicable to systems in which subjective thinking can be involved or systems in which uncertain human judgments are involved. It can be used as a methodology for objectifying subjective and uncertain systems.

In this study, triangular fuzzy numbers were applied as fuzzy numbers, and a function with a triangular form was applied considering that the fuzzy membership function uses triangular fuzzy numbers. The triangular fuzzy numbers that represent the seven grades used in this study (Excellent, Good, Adequate, Normal, Poor, Bad, and Fail) are shown in Fig. 2.

Tables 2 and 3 show the grades applied to fuzzify the factors affecting external and internal corrosion, respectively.

The process of converting the fuzzy-inferenced value calculated using a fuzzy set into a definite scalar value is referred to as defuzzification. In this study, the center-of-gravity method was used among various defuzzification methods. The fuzzy membership value calculated by multiplying the weight value of each influence factor, as shown in Eq. (1), was used to derive the center of gravity. As for the weight values, the values with the highest correlations with the corrosion rate (mm/y) were applied using a genetic algorithm.

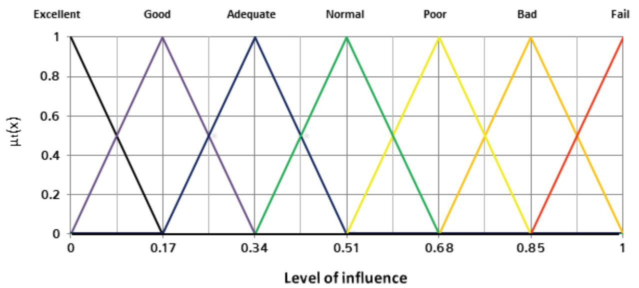

Fig. 2. Transformation of fuzzy number of membership function.

$$C_\mu = (W_1, W_2, \cdots, W_n) \times \begin{pmatrix} H_1 \\ H_2 \\ \vdots \\ H_n \end{pmatrix} \tag{1}$$

where C_μ is the value of μ fuzzy membership, W_n is the weight value of influence factor, and H_n is the grade of influence factor.

Table 2
Grade classification of influence factor for SP external corrosion

Factor	Classification	Grade
Installation year	After 2010	Excellent
	2000–2010	Good
	1990–2000	Normal
	1980–1990	Bad
	Before 1980	Fail
Soil resistivity	Above 20,000 Ω cm	Good
	10,000–20,000 Ω cm	Adequate
	5,000–10,000 Ω cm	Normal
	1,000–5,000 Ω cm	Poor
	Below 1,000 Ω cm	Bad
Soil pH	6.5–7.5	Excellent
	7.5–8.5	Adequate
	4.5–6.5	Normal
	Above 8.5	Poor
	Below 4.5	Bad
Water contents	Below 20%	Adequate
	Above 20%	Normal
Chloride (Cl^-) concentrations	Below 5 mg/L	Excellent
	5–30 mg/L	Good
	30–100 mg/L	Normal
	100–500 mg/L	Bad
	Above 500 mg/L	Fail
Sulfide (SO_4^{2-}) concentrations	Below 5 mg/L	Excellent
	5–30 mg/L	Good
	30–100 mg/L	Normal
	100–500 mg/L	Bad
	Above 500 mg/L	Fail
Pipe–soil potential difference	Below –2,000 mV	Excellent
	–1,500 to –2,000 mV	Good
	–1,000 to –1,500 mV	Normal
	–500 to –1,000 mV	Bad
	Above –500 mV	Fail

2.3. *Genetic algorithm to finding the weight value of influence factor*

The weight values of fuzzy items, that is, the weight values for each corrosion influence factor, were determined using a genetic algorithm. The objective function of the genetic algorithm was set using the weight value that maximizes the correlation coefficient between the fuzzy score derived through the center-of-gravity method and the corrosion rate, as shown in Eq. (2).

Table 3
Grade classification of influence factor for SP internal corrosion

Factor	Classification	Grade
Installation year	After 2010	Excellent
	2000–2010	Good
	1990–2000	Normal
	1980–1990	Bad
	Before 1980	Fail
Type of water	Raw water	Bad
	Purified water	Normal
Internal coating material	Epoxy	Good
	Enamel	Adequate
LI index	Above 0.0	Excellent
	–0.5 to 0.0	Good
	–1.0 to –0.5	Normal
	–2.0 to –1.0	Bad
	Below –2.0	Fail
Water pH	6.5–7.5	Excellent
	7.5–8.5	Adequate
	4.5–6.5	Normal
	Above 8.5	Poor
	Below 4.5	Bad
Alkalinity	Below 30 mg/L as $CaCO_3$	Bad
	Above 30 mg/L as $CaCO_3$	Normal

$$\text{Max } r = \text{Max}\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\left(\sum_{i=1}^{n}(x_i-\bar{x})^2\right)\left(\sum_{i=1}^{n}(y_i-\bar{y})^2\right)}} \quad (2)$$

where r is the correlation coefficient between corrosion rate and fuzzy score, x_i is the corrosion rate of specimen i (mm/y), $\bar{x}$ is the average corrosion rate (mm/y), y_i is the fuzzy score of specimen i (–), $\bar{y}$ is the average fuzzy score (–), i is a specimen, and n is the total number of specimen.

The chromosome of the genetic algorithm was constructed with the weight values for each influence factor, and the weight values were set between 0.000 and 1.000. The population, generation, crossover rate, and mutation rate, which are the genetic parameters of the genetic algorithm, were set to 50, 2,000, 0.8, and 0.2. The genetic operation was set to be terminated upon completion of calculation for the set generation. The genetic algorithm used the EVOLVER software that runs in Microsoft Excel.

2.4. *Development of model*

As mentioned, this study aimed to develop a corrosion depth prediction model for SP using the fuzzy score derived through factors affecting the corrosion of water pipes. As shown in Eq. (3), the modified two-phase model, which applies the fuzzy score as a direct variable, was developed by transforming the two-phase model, which predicts the corrosion depth according to the pipe age. Because the model equation is a function that represents a nonlinear form, coefficients that minimize the difference between the investigated corrosion depth and the predicted corrosion depth were derived using the curve fitting method and applied to the model equation.

$$d_{i,t} = a_i FT + \left(b_i F + C_i\right)\left(1 - e^{-f_i T}\right) \quad (3)$$

where $d_{i,t}$ is the corrosion depth at T age (mm), T is the exposure time which can be said pipe age (year), F is the fuzzy score (–), a_i, b_i, c_i, and f_i are the constant, i refers to the internal corrosion or external corrosion.

2.5. Evaluation of model

The developed model was evaluated through a comparison with the models proposed in previous studies. Model A, the first comparison target, was proposed by K-water [10]. It is a corrosion depth prediction model based on the two-phase model developed for large-diameter water pipes in South Korea. It considered only the pipe age without considering corrosion influence factors. Model B, the second comparison target, was proposed by Kim et al. [19]. It is a two-phase model developed for large-diameter water pipes in South Korea, but it added a regression equation after deriving corrosion influence factors through discriminant analysis. Model C, the third comparison target, is a two-phase model developed considering only the pipe age for the specimens investigated in this study, and it does not consider corrosion influence factors.

The model evaluation was performed through the comparison of the determination coefficient (r^2) and the root mean square error (RMSE).

3. Results and discussion

3.1. Analysis of investigated data

Table 4 shows the minimum, average, and maximum values of the investigated data as well as the skewness and kurtosis values for examining whether the investigated data exhibit a normal distribution. In general, when the absolute value of skewness is less than 2 and that of kurtosis is less than 4, such a case can be judged as a normal distribution. Among the investigated data, all of the influence factors, except for the qualitative factor and installation year, exhibited a normal distribution. Because the investigated data exhibited a normal distribution, the data that exceeded the 95% confidence level were determined as outliers and excluded from the model development. Finally, 21 data for SP external corrosion and 6 data for SP internal corrosion were removed as outliers.

After removing outliers from the investigated data, the results of plotting each corrosion depth influence factor for the corrosion depth are shown in Figs. 3 and 4.

Figs. 3 and 4 show that even the specimens with the same pipe age exhibit significantly different corrosion depths when only the pipe age is considered. For example, in Fig. 3(a), the pipes installed in 1988 show external corrosion depths ranging from 0.05 to 2.60 mm, indicating significant differences.

Meanwhile, when only one influence factor was considered, some factors were found to exhibit tendencies that are different from those already known. The chloride and sulfide concentrations may accelerate external corrosion as they increase. However, the tendency between the corrosion rate and influence factors was different. This is because high soil resistivity may have triggered the factors inhibiting corrosion, even if the chloride and sulfide concentrations were high. As another example, even if low water pH may act as a factor that accelerates corrosion, high alkalinity may inhibit corrosion.

These lead to the conclusion that simply considering only one influence factor is not reasonable. Therefore, in this study, it was deemed appropriate to apply fuzzy theory, a method capable of comprehensively considering various influences.

3.2. Results of weight value of influencing factors using genetic algorithm

Figs. 5(a) and (c) show the relationship between the fuzzy score and the corrosion rate derived after applying the same weight value to each fuzzy item for SP external corrosion and internal corrosion, respectively. Figs. 5(b) and (d) show the relationship between the fuzzy score and the corrosion rate after applying the weight values that exhibit the highest correlation between the fuzzy score and the corrosion rate using the genetic algorithm.

Table 4
Analysis results of investigated data

Case	Factor	Minimum	Average	Maximum	Skewness	Kurtosis	Remark
SP external	Soil resistivity (Ω cm)	1,246.00	14,270.00	85,000.00	1.58	2.71	Normal distribution
	Soil pH (–)	4.00	6.40	12.40	0.45	0.37	Normal distribution
	Water contents (%)	4.70	18.52	50.70	0.41	–0.11	Normal distribution
	Chloride concentrations (mg/L)	0.90	18.05	453.10	1.45	3.62	Normal distribution
	Sulfide concentrations (mg/L)	0.00	48.53	1,069.15	1.76	3.87	Normal distribution
	Pipe–soil potential difference (mV)	–6,974.00	–1,050.00	–89.00	–0.99	1.09	Normal distribution
SP internal	LI index (–)	–2.93	–1.65	–0.33	0.16	–1.30	Normal distribution
	Water pH (–)	6.66	7.92	8.99	–0.06	0.35	Normal distribution
	Alkalinity (mg/L as $CaCO_3$)	16.01	35.38	61.53	0.19	–0.78	Normal distribution

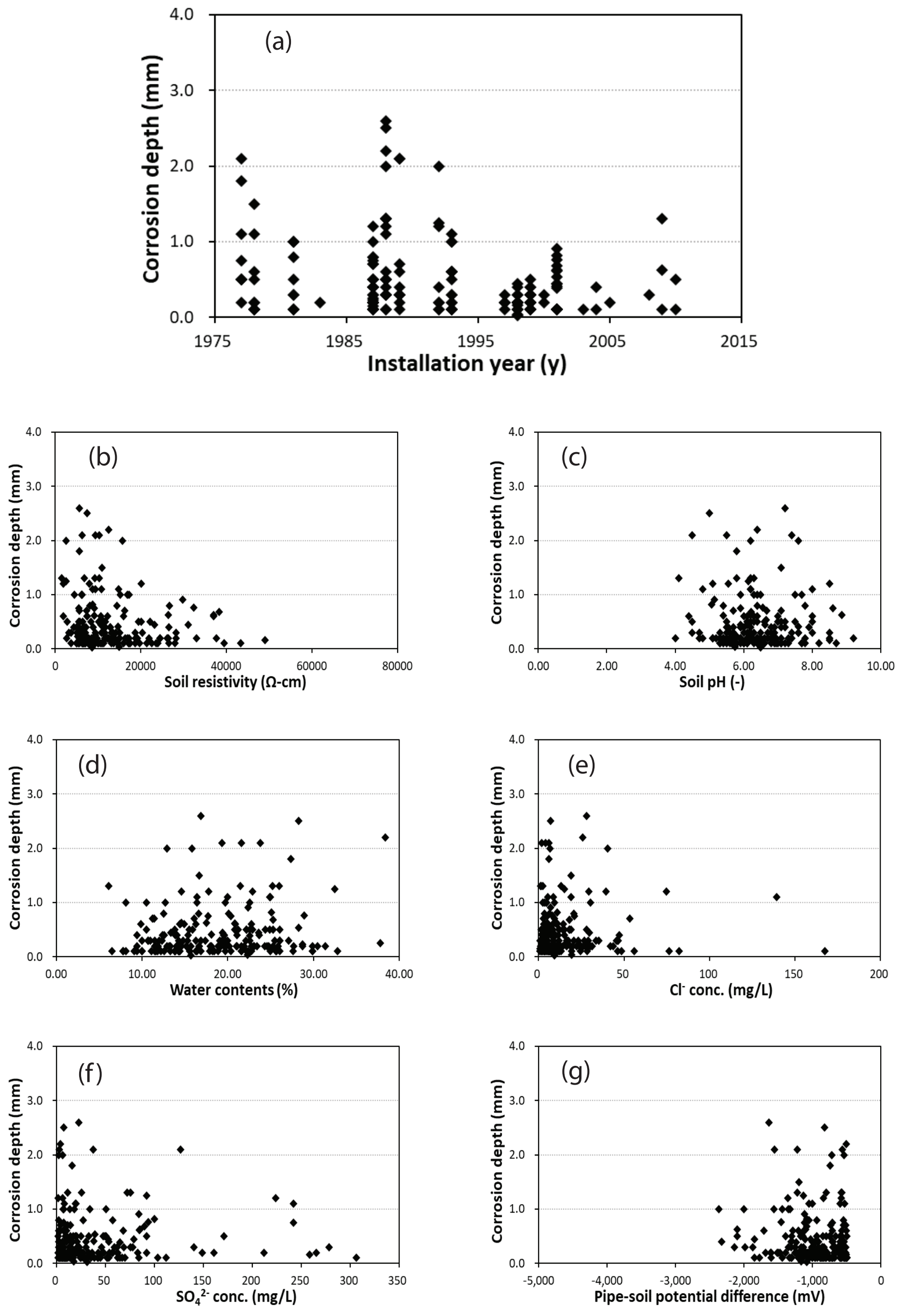

Fig. 3. Investigated external corrosion depth data by influence factors: (a) by installation year, (b) by soil resistivity, (c) by soil pH, (d) by water contents, (e) by chloride concentrations, (f) by sulfide concentrations, and (g) by pipe–soil potential difference.

The results show that, when the same weight value was applied, the determination coefficient (r^2) between the fuzzy score and the corrosion rate was as low as 0.1532 for external corrosion rate and 0.1023 for internal corrosion rate. When the optimized weight values were applied, however, the determination coefficient (r^2) was 0.3689 for external corrosion rate and 0.3011 for internal corrosion rate, which was improved compared with the previous value, and the corrosion rate showed a tendency to increase as the fuzzy score increased.

Tables 5 and 6 show the results of applying the optimized weight values to the fuzzy items affecting external and internal corrosion, respectively. The weight values that increase the correlation between the fuzzy score and the corrosion rate can be construed as representing the importance of corrosion influence factors.

Among the factors affecting the external corrosion of SP, the soil resistivity exhibited the highest weight value of 0.295, followed by the sulfide concentrations (0.253) and installation year (0.201). This tendency is similar to

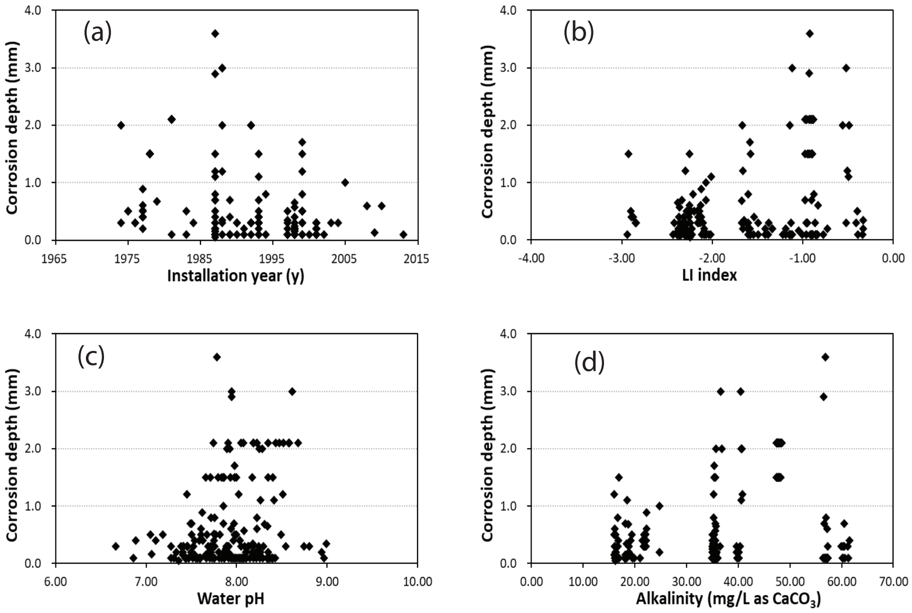

Fig. 4. Investigated internal corrosion depth data by influence factors: (a) by installation year, (b) by LI index, (c) by water pH, and (d) by alkalinity.

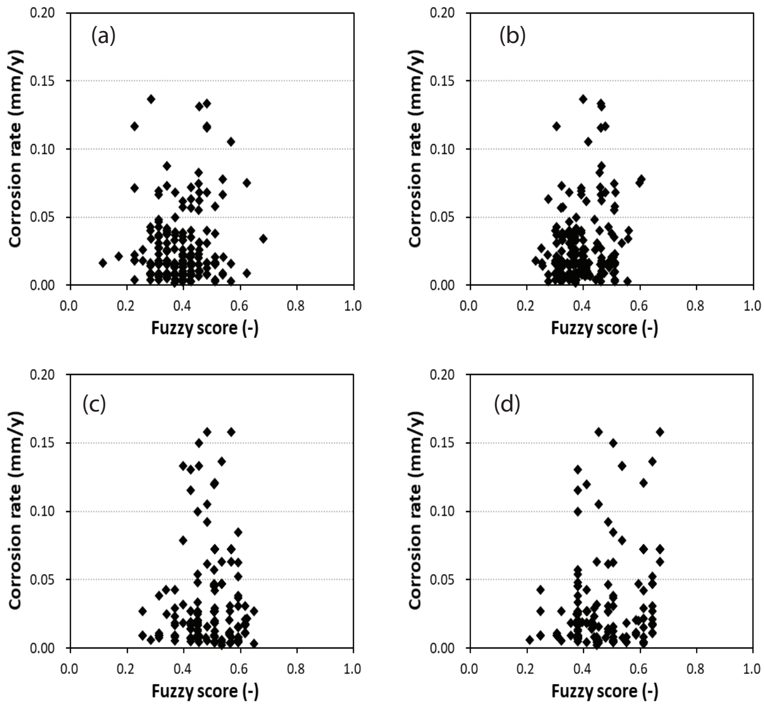

Fig. 5. Fuzzy score and corrosion rate by weight value: (a) in case of same weight value for external corrosion, (b) in case of optimized weight value for external corrosion, (c) in case of same weight value for internal corrosion, and (d) in case of optimized weight value for internal corrosion.

those presented as the results obtained by Arai et al. [16] and Peterson and Melchers [17]. Meanwhile, the pipe–soil potential difference was found to have the lowest influence on external corrosion. In South Korea, it is recommended to install water pipes in areas with a pipe–soil potential difference of less than –500 mV to prevent corrosion. Owing to this recommendation, water pipes are installed in areas that can minimize corrosion in terms of the pipe–soil potential difference, and the investigated specimens also exhibited the same tendency. It appears that the pipe–soil potential difference received the lowest weight value for this reason.

Table 5
Weight value of external corrosion influence factors of SP

Influence factors							Sum
Installation year	Soil resistivity	Soil pH	Water contents	Chloride concentration	Sulfide concentration	Pipe–soil potential difference	
0.201	0.295	0.035	0.026	0.097	0.253	0.087	1.000

Table 6
Weight value of internal corrosion influence factors of SP

Influence factors						Sum
Installation year	Type of water	Internal coating	LI index	Water pH	Alkalinity	
0.314	0.026	0.597	0.038	0.003	0.021	1.000

As for the internal corrosion of SP, the water quality influence factors, such as the LI index, water pH, and alkalinity, exhibited the lowest influence on internal corrosion. However, internal coating materials exhibited the highest influence. The water quality data used in this study were investigated at a specific time point and, thus, cannot reflect all the water quality characteristics that change every moment. For this reason, the influence of the water quality factors was low. In the case of internal coating materials, the use of epoxy as a coating material was found to be better than the use of enamel in terms of preventing internal corrosion. However, this result appears to be because of the characteristics of the investigated specimens. The specimens that used epoxy coating material accounted for 67% of all the specimens, and their average pipe age was 21.4 years, while the specimens that used enamel coating material represented 33% and their average pipe age was 26.9 years. Lee [9] investigated large-diameter water pipes in South Korea and suggested that the peeling of the internal coating of SP is accelerated 25 years after the installation of SP. Therefore, the results derived in this study can be constructed as results reflecting the influence of the characteristics of the specimens. For this reason, it is reasonable to analyze the influence of internal coating on corrosion after securing more specimens from a long-term perspective.

3.3. Developed fuzzy-based corrosion depth prediction model

Eqs. (4) and (5) represent the models developed for the external and internal corrosions of SP, respectively, and Fig. 6 shows the results of predicting the corrosion depth according to the pipe age and fuzzy score using the developed model. The coefficient of determination between the investigated corrosion depth and the predicted corrosion depth through the model was also found to be higher than 0.6, indicating that the developed model accurately represents the investigated value.

$$d_{\text{external},t} = 0.046FT + (1.212F - 0.233)(1 - e^{-0.352T})(r^2 - 0.612) \quad (4)$$

$$d_{\text{internal},t} = 0.043FT + (1.579F - 0.139)(1 - e^{-0.654T})(r^2 - 0.626) \quad (5)$$

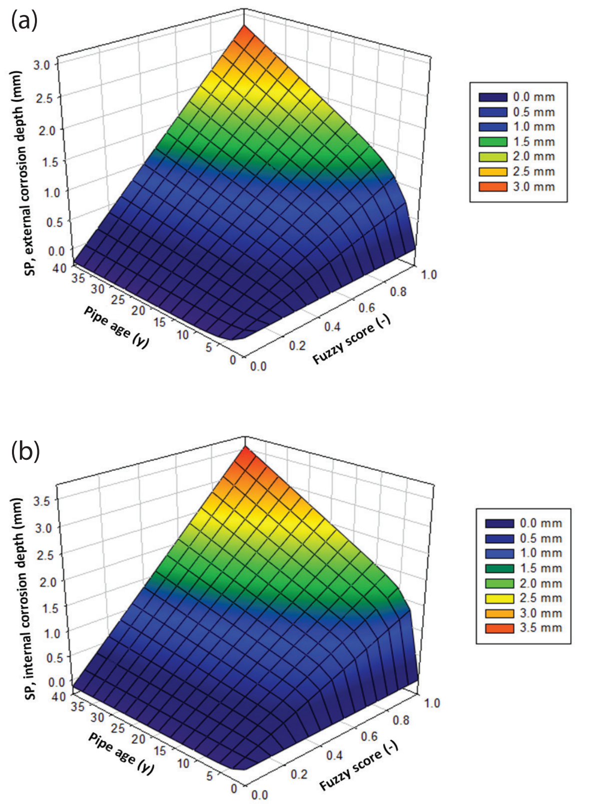

Fig. 6. Corrosion depth according to pipe age and fuzzy score: (a) by external corrosion depth prediction model and (b) by internal corrosion depth prediction model.

where $d_{\text{external},t}$ is the external corrosion depth of SP at T age (mm), $d_{\text{internal},t}$ is the internal corrosion depth of SP at T age (mm), T is the exposure time which can be said pipe age (y), and F is the fuzzy score (–).

If the fuzzy score in Eq. (4) is less than 0.192 and the pipe age is close to 0.0 year, the corrosion depth may be negative. However, the external corrosion depths did not appear to be negative for investigated specimens, because the minimum fuzzy score of investigated specimens was 0.232. Likewise, in Eq. (5), there was no case where the corrosion depth was negative for investigated specimens.

Table 7
Evaluation results of developed model

Model	External corrosion depth		Internal corrosion depth	
	r^2	RMSE	r^2	RMSE
Model A [10]	0.218	1.153	0.437	1.193
Model B [19]	0.308	0.816	0.397	0.734
Model C (two-phase model only considering pipe age)	0.377	0.502	0.444	0.662
Developed model (fuzzy-based two-phase model considering corrosion influence factors)	0.612	0.458	0.626	0.524

As shown in Fig. 2, when corrosion is accelerated, in other words, the fuzzy membership is Fail, the fuzzy score was defined as 1.0 in this study. As can be seen from the model equation, the initial and overall corrosion rates appear to be high as the score (fuzzy score) of the factor accelerating corrosion increases. It was confirmed that this tendency was applied to the developed model equation without logical errors.

3.4. Evaluation results of developed model

Table 7 shows the coefficients of determination and error indices of Model A, Model B, and Model C, which are comparison targets, as well as the developed model. Compared with the previously proposed models, the correlation of the developed model was higher, and its difference from the investigated values was smaller. In other words, the developed model exhibited higher explanatory power and more-accurate prediction results compared with the models proposed in previous studies.

There are factors that could not be considered in this study. The oxidation–reduction potential is known to affect external corrosion, while the flow velocity and microorganisms inside pipes are known to affect internal corrosion. These factors, however, could not be considered, because it was not possible to investigate significant data. If additional factors affecting the corrosion of water pipes are considered, it is expected that a model closer to the actual corrosion tendency will be developed using the same methodology.

4. Conclusion

In this study, fuzzy theory was applied to the factors affecting the corrosion of SP, which is frequently utilized as a large-diameter water pipe, and then a modified two-phase model was developed by reflecting the derived fuzzy score.

As a result of analyzing the factors affecting corrosion, it was deemed reasonable to apply the fuzzy theory capable of comprehensively analyzing various factors. When the fuzzy theory was applied in this study, weight values for each influencing factor that exhibited the highest correlation with the corrosion rate were applied using a genetic algorithm to derive reasonable results. The soil resistivity and sulfide concentrations were found to have the highest influence on external corrosion. This indicates that it is reasonable to select the areas with high soil resistivity and low sulfide concentrations for the installation of new water pipes in the future. For internal corrosion, the type of internal coating material was found to have the highest influence. However, because this result appears to be caused by the characteristics of the specimens investigated in this study, further research is required.

The proposed corrosion depth prediction model that considers corrosion influence factors provided higher explanatory and prediction power than the models that simply consider only the pipe age. In addition, the developed model also exhibited higher explanatory and prediction power for specimens similar to those investigated in this study. Therefore, it is expected that the proposed corrosion depth prediction model will make it possible to predict the service life of water pipes more accurately as a basic model that can be utilized for predicting the physical residual life of water pipes.

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