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Original Article

Pipe thinning model development for direct current potential drop data with machine learning approach

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ABSTRACT

The accelerated corrosion by Flow Accelerated Corrosion (FAC) has caused unexpected rupture of piping, hindering the safety of nuclear power plants (NPPs) and sometimes causing personal injury. For the safety, it may be necessary to select some pipes in terms of condition monitoring and to measure the change in thickness of pipes in real time. Direct current potential drop (DCPD) method has advantages in on-line monitoring of pipe wall thinning. However, it has a disadvantage in that it is difficult to quantify thinning due to various thinning shapes and thus there is a limitation in application. The machine learning approach has advantages in that it can be easily applied because the machine can learn the signals of various thinning shapes and can identify the thinning using these. In this paper, finite element analysis (FEA) was performed by applying direct current to a carbon steel pipe and measuring the potential drop. The fundamental machine learning was carried out and the piping thinning model was developed. In this process, the features of DCPD to thinning were proposed.

1. Introduction

Flow Accelerated Corrosion (FAC) is a phenomenon that results in metal loss from piping, vessels, and equipment made of carbon steel. FAC occurs under the certain conditions of flow, chemistry, geometry, and materials. Unfortunately, these conditions are common conditions in nuclear power plants (NPPs) or fossil-fueled power plants. FAC can cause ruptures of pipe; it has become a major issue particularly for NPPs [1]. Although major failures are rare, the consequences can be severe. The "break before leak" caused four people to die in the Surry NPP in United States in 1986, and four people were died and six were injured in the Mihama NPP in Japan in 2004 [2]. In addition to concerns about personnel safety, FAC failures can pose challenges to plant safety. Also, FAC failure can force a plant to shutdown and purchase replacement power at a price approaching a million dollars per day depending upon the MWe size of a plant [1]. Programs to diagnose and manage the pipe thickness to manage the FAC has been developed [3], and the development of water chemistry of the NPPs to reduce the occurrence of FAC has been progressed [4], and the research such as the development of carbon steel materials resistant to the FAC has been carried out [5].

Ultrasonic Testing (UT) is mainly used for measurement of pipe thinning, and Eddy Current Testing (ECT) is sometimes used. Research on thickness measurement using vibration sensor [6] and technique for screening degree of thinning using Direct Current Potential Drop (DCPD) [7,8] have been studied. In particular, DCPD is excellent for high temperature application, thus it is advantageous for online application [9], and it is suitable for online thickness measurement because it can detect precise thickness change with good signal to noise ratio [10]. However, it is technically difficult to quantify the rate of thinning from various DCPD signals caused by various thinning shape [11].

It is expected that the machine learning approach can be a solution. Various shapes of thinning or cracks produce different DCPD signals. It is intuitively difficult to derive the shape of a thinning or crack based on a signal of the potential drop type. Also, since the development of the model is almost impossible without prior information on the position and shape of the thinning or defect, a machine learning approach can be useful. It would be useful if we could extract features of the position and shape of thinning in DCPD signal. In this paper, the features of DCPD signals for various thinning shape is suggested as shape factor and relative potential drop, and the fundamental machine learning approach is applied to

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derive piping thinning model.

2. Analysis model

Since the thinned shape by FAC is caused by the reduction of diffusion boundary layers by flow change, the thinned shape is not angled, and in most cases, it has an elliptical shape. Therefore, the thinning shape can be modeled as shown in Fig. 1. In this case, the shape of the thinning can be described by the depth ratio (a/t), the length ratio (b/L), and the angle ratio ($\theta/2\pi$). The depth ratio is a normalized value of the thickness of the initial thickness of the pipe (t) to the thickness of the reduced thickness due to the thinning (a), the length ratio is a normalized value of the thinning portion (b) in the measuring range (L), and the angle ratio is a normalized value of the thinning in the circumferential direction (θ). The piping without the thinning was modeled as a reference case, and the four maximum depth ratios were modeled for each of the four maximum angular ratios. Table 1 summarizes these.

For the model development, four maximum angle ratios (A to D) and maximum depth ratios (1–4) were modeled (A1 to D4). The potential drop was analyzed at 64 points of circumferential direction at 0.5 cm from the end of the thinning. Since each potential difference value is assumed to have information of the depth and width of the thinning at the position, a total of 1024 DCPD values were used for model development. The DCPD data for the angle ratio of 1/2 was not used for model development; they were used to confirm the model after the model development was completed (T1 to T4).

A total current of 10 A was applied to the piping surface at a position 10 cm away from the measurement point. The applying position and amount of DC do not affect the potential drop. However, if the current is applied too close to the measurement position, the current may not distribute uniformly in the pipe, which may cause an error in the model. It can be generally considered that current is uniformly distributed when a current is applied at a distance of about 1.5 times the pipe diameter. The amount of current is normalized by the potential drop, so it does not affect the model. In actual cases, the amount of current to be applied should be determined considering the specifications of the measuring system and the size of the piping. The repeatability and reproducibility error of switching DCPD (S-DCPD) in 2.5-inch pipe is about 0.06% GR&R (analysis of variance (ANOVA) gauge repeatability & reproducibility (GR&R)) when the current is 5 A, and about 0.02% error of GR&R when the current is 10 A [10]. In this paper, the pipe used in the analysis is a 2.5-inch carbon steel pipe. Since the shape of the thinning is normalized, there is no model variation with respect to the size of the pipe.

The resistivity of the material does not affect the model because the DCPD is normalized by the potential difference. To confirm this, the verification data (T1~T4) was modeled using stainless steel material. In actual cases, there may be a change in the resistivity due to the temperature difference for each measurement time. This effect can be offset by correcting the resistivity change using reference coupon [9].

Table 1
Modeled thinning shape.

Case	$\theta_{max}/2\pi$ (degree)	a_{max}/t	Material
R	0	0	Carbon steel
A1	1/8 (45)	1/6	
A2		1/3	
A3		1/2	
A4		2/3	
B1	1/4 (90)	1/6	
B2		1/3	
B3		1/2	
B4		2/3	
C1	3/8 (135)	1/6	
C2		1/3	
C3		1/2	
C4		2/3	
T1	1/2 (180)	1/6	Stainless steel
T2		1/3	
T3		1/2	
T4		2/3	
D1	5/8 (225)	1/6	Carbon steel
D2		1/3	
D3		1/2	
D4		2/3	

3. Analysis results and derived piping thinning model

Fig. 2 and Fig. 3 show the potential drop generated by applying DC current to the thinning shape of Table 1. In these figures, the potential drop is shown in terms of the ratio of the depth and the length at each point. It is not easy to quantify the shape of the thinning based on the potential drop data. This is because the potential drop data is affected by both the depth of the thinning and the length of the thinning.

It was assumed that the DCPD has information on the depth and width of the thinning in the current flow direction at the measuring point. In this assumption, it is reasonable that the DCPD value of the measurement position where there is no thinning in the current flow direction is zero. However, in Figs. 2 and 3, it can be seen that the DCPD at the position without thinning is not zero. The increase in overall resistance caused by the thinning increases the potential even at locations where no thinning occurs. Fig. 4 shows the effect of the potential drop due to this overall resistance increase. In order to apply the assumption that the DCPD has information on the depth and width of the thinning in the current flow direction at the

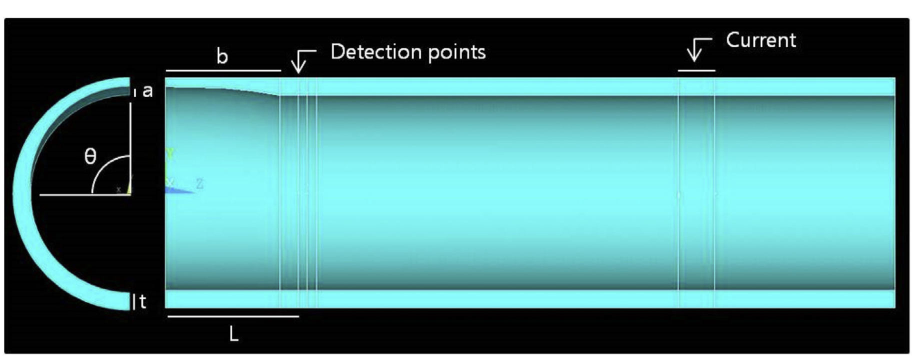

Fig. 1. Modeled thinning shape, 1/4 model.

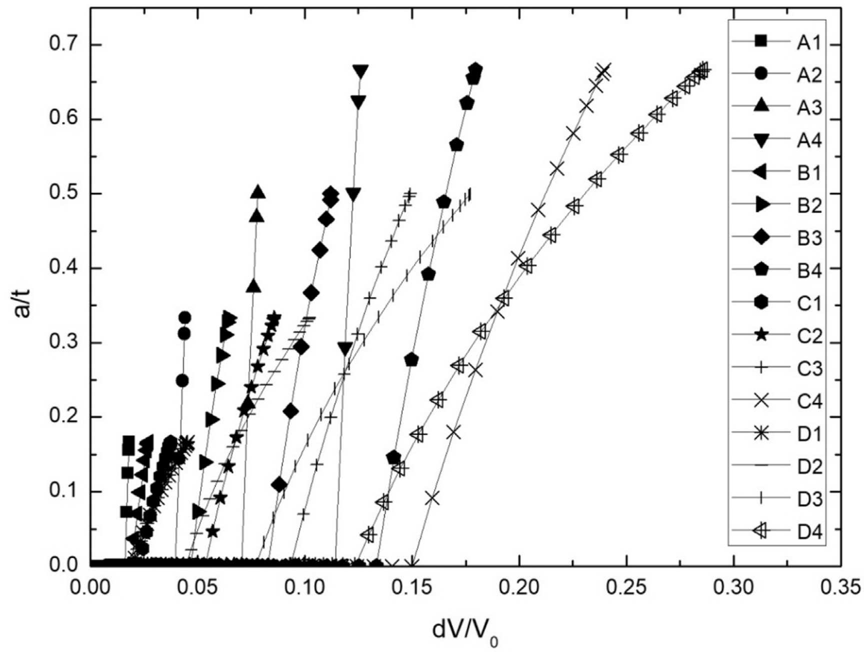

Fig. 2. Potential drops to the each depth ratio of thinning.

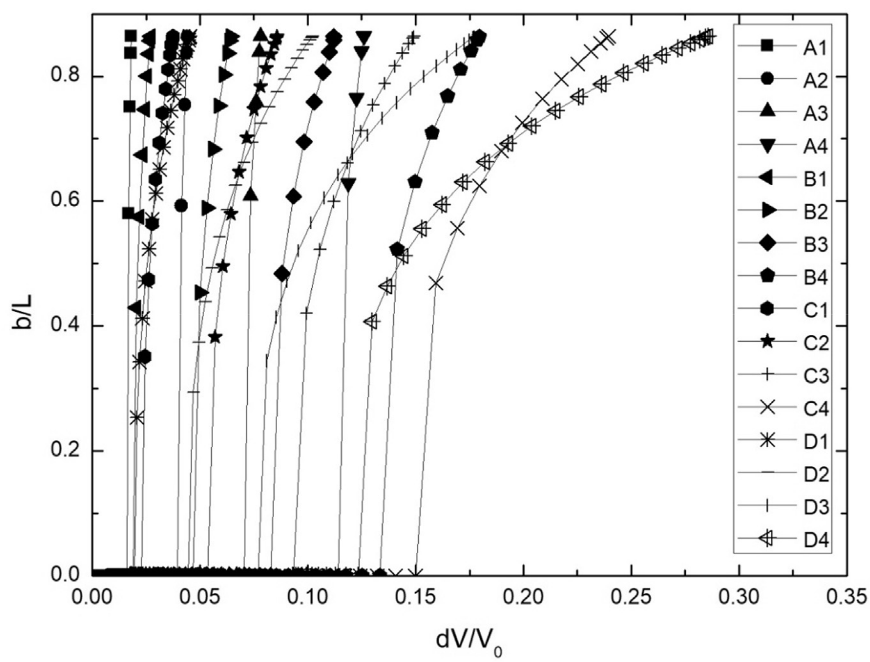

Fig. 3. Potential drops to the each length ratio of thinning.

measuring point, it is needed to adjust the potential drop to zero at the 90° position without thinning. The concept used for this purpose is the relative potential drop. Generally, by setting the potential drop of the end portion of the defect to zero and adding the potential drop of the symmetric position with respect to the defect, the entire resistance effect can be eliminated effectively. In this paper, the relative potential drop is simply defined as Equation (1).

$$\frac{dV}{V_0} \equiv \frac{dV}{V_0}\bigg|_{\mathrm{rel}} = \frac{dV}{V_0} - \frac{dV}{V_0}\bigg|_{\text{end of thinned point}} \tag{1}$$

where dV is the difference between the obtained potential and the potential without thinning (case R), V_0.

Even if the concept of relative potential drop is introduced, the relation between DCPD and thinning shape is not shown which the relation is defined as the feature of DCPD. Since the potential drop is related both the depth and the width of the thinning, it is necessary to define the feature in three dimensions, but it is not easy to intuitively define the feature. In future work, the deep learning technology can be used for cases where feature extraction is not clear, but in this paper, dimension reduction is performed to extract features. For this purpose, it is assumed that the obtained DCPD

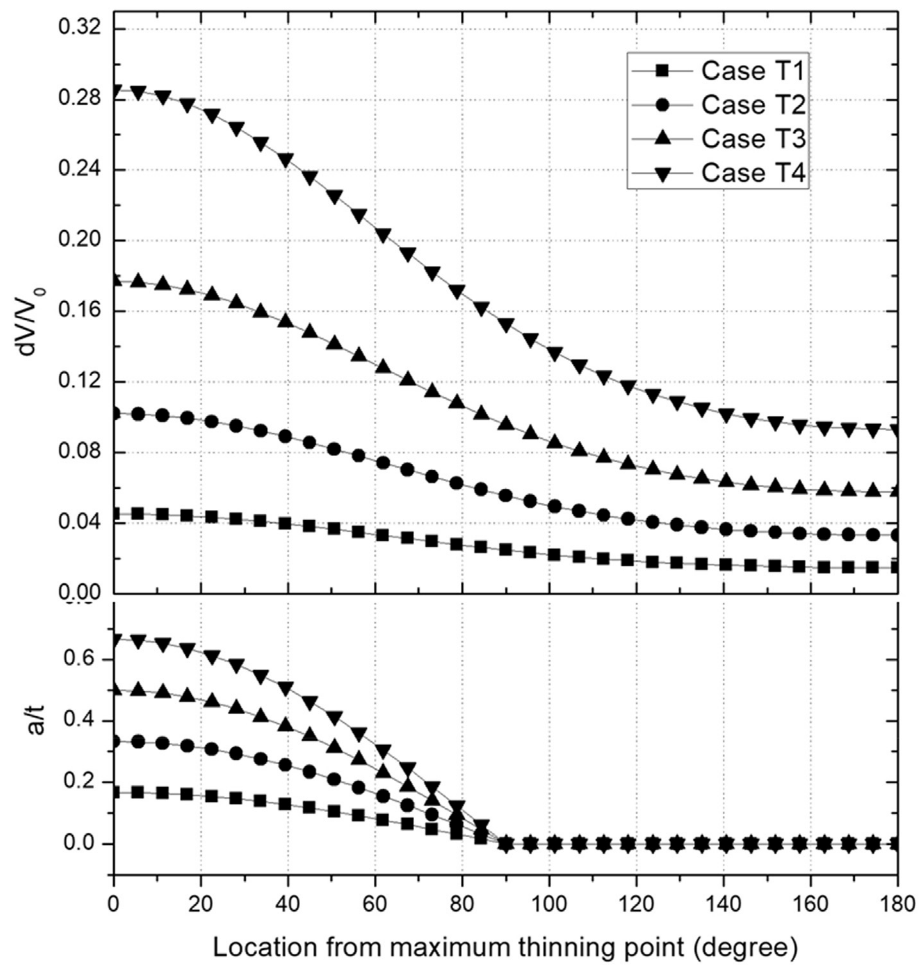

Fig. 4. DCPD vs. depth ratio of thinning.

only indicates the resistance change due to the thinning in the current direction, and the feature of the DCPD can be extracted through the resistance change. This assumption, of course, is different from reality. The potential drop is affected not only by a change in resistance but also by a current that changes due to the resistance. However, when relative potential drop is used, these assumptions may well describe the obtained values. The resistance change due to the thinning can be expressed as shown in Equation (2), taking into account the simple assumption of thinned shape as triangle in two dimensions. The equation is derived from the definition of resistance that is proportional to length and resistivity, and inversely proportional to area. The value is defined as a shape factor, Y, and used as a thinning feature for DCPD.

$$Y=\frac{b}{L}\cdot\left[\frac{t}{a}\cdot\ln\left(\frac{1}{1-a/t}\right)-1\right] \tag{2}$$

In this paper, the concept of shape factor and relative DCPD is defined and presented as features of correlation between DCPD and thinning. It is briefly explained why we tried to find these features in this paper. It is difficult to derive the correlation between DCPD and thinning shape. For one case in Fig. 5 (T1 case), the empirical equation can be derived from the 3D fitting, but the empirical equation derived in this way is not applicable to different cases, such as A1 to D4, because the slop and curvature are different. In this paper, we have tried to derive a thinning model which can be commonly applied to various thinning shapes by FAC (elliptical thickness reduction). For this purpose, the machine learning approach was used in DCPD signal analysis. It was important to select a clear feature of DCPD for the thinning shape as the first step in learning the machine. This paper is about this first phase of the study and can contribute to future research in this area by suggesting key features between DCPD and thinning shapes. In order to use the fundamental machine learning approach, the relative

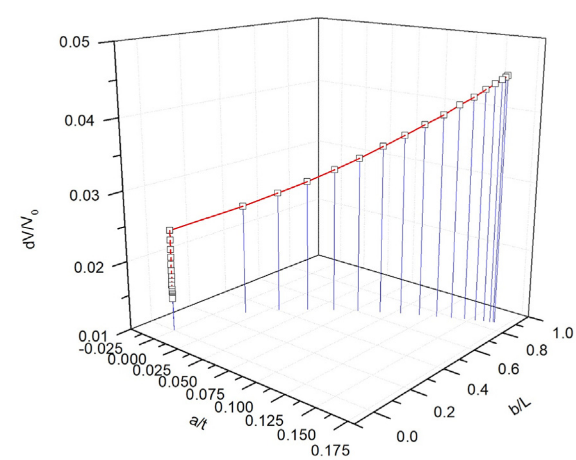

Fig. 5. DCPD vs. depth and width ratio of thinning: Case T1.

DCPD and shape factor are suggested. If there are more data, and if the machine is learned not by the expert but by the machine itself; thus the machine finds the features of DCPD by itself, then what results can be obtained is the main topic of future work. The relative DCPD according to the shape factor for the T1 case is shown in Fig. 6. Compared to Fig. 5, the dimension was reduced to 2 dimensions and the potential drop value was simplified to almost linear shape.

The main features are proposed as shape function and relative DCPD, and these values are used in the learning. The relative DCPD with respect to the shape factor is assumed to be linear, and this hypothesis is expressed as simple form by Equation (3). The cost function in this hypothesis is given in equation (4) and weight factor to minimize the cost function was calculated.

$$Y = H(x) = W \cdot x \tag{3}$$

where x is the relative DCPD, and W is weight factor for the DCPD to shape factor, Y.

$$\mathrm{cost}(W) = \frac{1}{m}\sum_{i=1}^{m}\left(Wx^{(i)} - Y^{(i)}\right)^2 \tag{4}$$

where m is number of DCPD data.

When weight factors are obtained that minimize the cost function, a correlation model between relative DCPD and thinning shape factor can be obtained.

From case A1 to case D4, 64 measurement data for each case, a total of 1024 DCPD data were used for the learning data. The machine learning process was conducted using Google's tensor flow, open source software. The learning was performed 100,000 times for each thinning shape to find the minimum weight values. The weight values for each thinning shape derived from this process are summarized in Table 2.

The weight factors summarized in Table 2 are shown in Fig. 7. In this process, reciprocals were taken to the thinning angle ratio and square roots were taken to the weight factors. The reason for taking the inverse and square root is to find the relation of the weight value in each thinning shape.

In Fig. 7, the inverse of the angle ratio of thinning and the square root of the weight factor have a linear relationship. From this, the equation for the weight factor for various thinning shapes can be obtained as in equation (6). This equation was derived from the linear fit of Fig. 7, where the R^2 value of the linear fitting was 0.9967. Finally, the piping thinning model of DCPD is presented in Equations (5) and (6).

$$Y = W \cdot \left(\frac{dV}{V_0}\right) \tag{5}$$

$$W = \left(\frac{0.7351}{\theta_{max}/2\pi} + 0.4559\right)^2 \tag{6}$$

4. Confirmation of developed piping thinning model

The pipe thinning model was developed based on 16 thinning shapes (case A1 to D4) and presented in equations (5) and (6). Additional finite element analysis was performed to confirm that the model can be applied to various thinning shapes as well as to 16 thinning shapes. The additional FEA was performed for cases T1 to T4 which are summarized in Table 1. The analysis was performed on 316 stainless steel rather than carbon steel, and it was confirmed whether the developed model could be applied regardless of the

Table 2
wt factor in each case.

$\theta_{max}/2\pi$	Weight, W
1/8	40.9723
1/4	10.5804
3/8	5.50739
5/8	3.12721

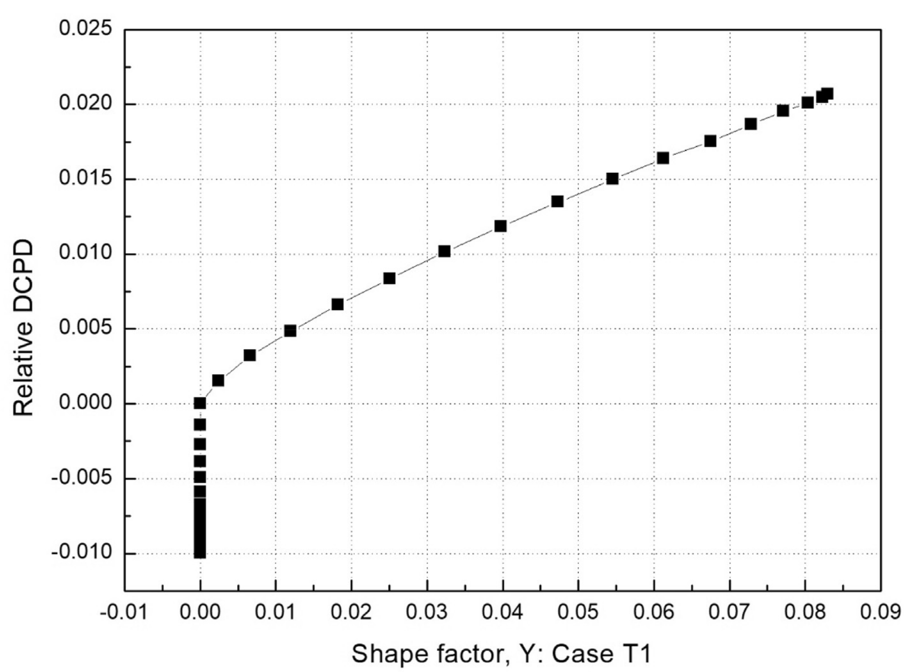

Fig. 6. Relative DCPD vs. Shape factor: Case T1.

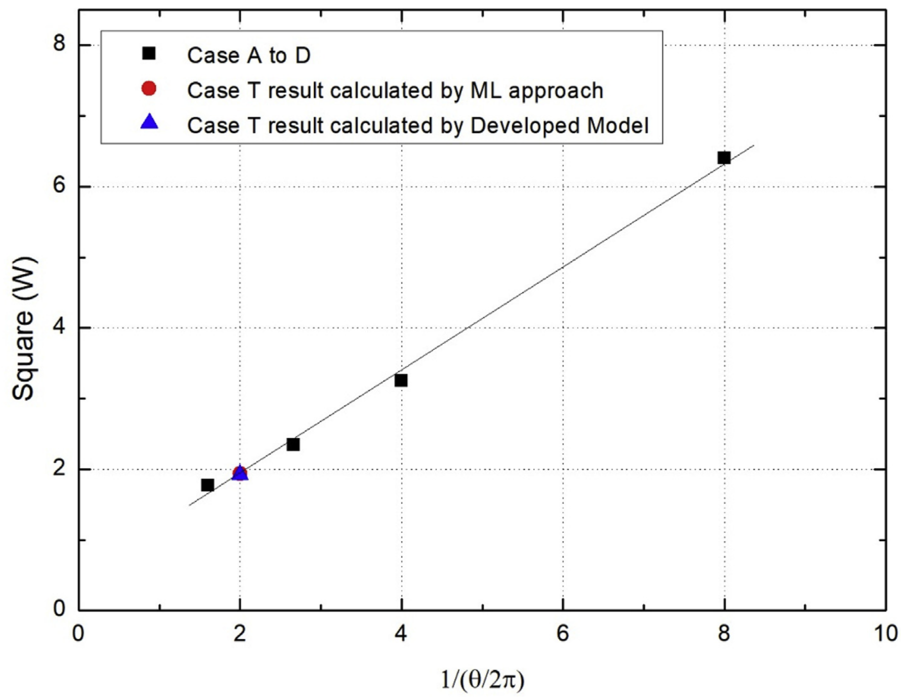

Fig. 7. wt factors for each thinning shape.

type of material. The electrical resistivity used in the analysis was 0.0000174 Ω-cm for carbon steel and 0.0000740 Ω-cm for 316 stainless steel.

A total of 256 DCPD values were further calculated with 64 DCPD in the circumferential direction for 4 thinning shape (case T1 to T4). This obtained DCPD values were calculated using the same assumptions and learning methods as those used to derive weight factor in Table 2. The calculated weight factor is shown in Table 3. Table 3 also shows the weight factor obtained from equation (6). The difference between the two values is 0.06413, which shows an error of about 1.71%. This shows that although the model is developed from four thinning shapes, but the model can be applied to various thinning shapes commonly without further machine learning, not limited to thinning shapes. The two weight factors in Table 3 are additionally shown in Fig. 6.

5. Discussion

In this paper, pipe thinning model of DCPD was developed by machine learning approach. It was confirmed that the developed model can be applied commonly to various thinning shapes.

The model developed through this paper has several limitations as follows.

1) A reference potential (V_0) where no thinning has occurred is required.
2) Since the value derived by the model is a shape factor (Y), it is needed that prior information or accurate prediction of the thinning shape to calculate the thickness reduction.
3) This is similar to the second limitation, it is necessary that prior information or precise prediction on how far the thinning is distributed in the circumferential direction.

In fact, these limitations are inherent limitations of DCPD technique. When even diagnosing cracks by DCPD, you similarly need to know the reference potential and prior information of the shape and the location of the crack. The first limitation of DCPD is very fundamental and cannot escape the limitation in any way. This is because DCPD does not use the potential but uses the potential drop. In diagnosing FAC, the second limitations of DCPD can be solved using reasonable assumptions. It is assumed that the shape of the thickness reduction due to FAC is a semi-elliptical shape. The pipe thinning by FAC is caused by the reduction of the thickness of the diffusion boundary layer caused by the change of the flow, the thinning shape is not angled, and in most cases, it has an elliptical shape. When analyzing the shapes of various thickness reductions that occurred at the commercial NPPs, it does not deviated from semi-elliptical shape [9]. Therefore, if only the location information at which thinning has occurred is accurate, the degree of thinning can be calculated from the shape factor. That is, if the third limitation is solved, it can be great help in diagnosing defects using DCPD technique.

However, the third limitation does not have a suitable solution. Of course, we can make assumption that thinning occurs in the extrados part of an elbow. Even in the case of a tee, it will be possible to have preliminary information on how thinning occurs from any place along the fluid flow. However, it is difficult to know in advance the location information that is sufficient to compensate for the increase in overall resistance caused by thinning. This seems

Table 3
wt factor in each case.

$\theta_{max}/2\pi$	Weight factor calculated by the developed thinning model	Weight factor calculated by ML approach
1/2	3.69024	3.75437

almost impossible with traditional signal processing methods, as it solves the inverse problem. That is the reason for using the machine learning approach in this paper. I believe that the location information of thinning can be provided from the overlapped potential drop signal through data driven signal processing that has been dramatically improved recently. Of course, so many potential drop signals are needed for the purpose. In this paper, as a first step for the purpose, supervised learning method was used to make the machine learn the potential drop signals and the pipe thinning model was derived. In order to make use of the supervised learning method, it is required to understand the features between the potential drop and the thinning. The two features suggested by this paper, the relative potential drop and the shape factor, can be used and contributed in various ways in the field of data driven signal processing of DCPD.

Future work seems to be required the development of a model that describes the overall resistance increase and verification or improvement the model in various pipe shapes such as elbow, tee, etc. It may be needed to build big data of DCPD and develop model using artificial intelligence (AI) algorithm. If signal processing algorithms that do not require prior knowledge of thinning shapes and positions are developed through AI, it will be greatly increased the use of DCPD technique.

6. Summary and conclusion

Much research is being conducted to monitor the thinning of pipes and the resulting breakage by FAC online. DCPD technology is suitable for online monitoring because of its high applicability and high signal-to-noise ratio in high temperature and radiation environments. However, it is difficult to quantify the degree of thinning in the DCPD signal. The machine learning approach is thought to have an advantage in quantifying thinning with DCPD signals. As a first step in this paper, we conducted a study to develop the features of DCPD to thinning and developed thinning model to quantify thinning through a basic machine learning approach.

To this end, various thinning shapes were modeled and FEA was performed. Thinning by FAC is not angled and has a rounded shape because it is affected by the reduction of the diffusion layer by the flow. Thus, various thinning shapes can be represented by the length, width and angle of thinning. In this paper, we modeled four maximum thinning angles and four maximum thinning depths at each maximum thinning angle. DCPD was acquired by setting 64 measuring points in the circumferential direction. Each measuring point can then be thought of as simulating different lengths and widths of thinning. Thus, DCPD with a total of 1024 measuring points and each thinning shapes were used for model development.

Assuming DCPD at each measuring point as a function of the depth and length of thinning, the empirical equation can be derived by 3D fitting, however, the empirical equation derived in this way in not applicable to different cases. In this paper, we tried to develop a thinning model that can be applied to various thinning shapes in common. It is important to develop key features between DCPD and thinning shapes. Relative potential drop and shape factor are presented as features of the DCPD to thinning shape. The concept of relative potential drop could be used for measurements in piping in circumferential direction. The shape factor is the theoretical value of the change in resistance, which can be meaningful if used with a relative potential drop that can offset the change in current. These features allowed us to develop a thinning model with a basic machine learning approach. It is validated that the developed thinning model can be applied regardless of the thinning shape and material properties.

Many studies still take a knowledge-based approach to quantifying DCPD. However, DCPD signals are still difficult to quantify because current and resistance change simultaneously. Two of the features developed in this paper could be used to develop knowledge-based models. However, in the long term, DCPD signal interpretation makes sense to follow a data-based approach. I hope this paper can be the first step in such research.

Declaration of competing interest

This research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

[1] Electric Power Research Institute, Flow-Accelerated Corrosion in Power Plants: Technical Report (TR-106611), EPRI, 1996.
[2] Organization for Economic Cooperation and Development, Flow Accelerated Corrosion (FAC) of Carbon Steel & Low Alloy Steel Piping in Commercial Nuclear Power Plants: Topical Report (NEA/CSNI/R(2014)6), OECD-NEA, 2015.
[3] S.H. Lee, Y.S. Lee, S.K. Park, J.G. Lee, Corros. Sci. Technol. 14 (2015) 1.
[4] H.J. Gwon, H.K. Ahn, C.H. Song, B.G. Park, J. Korea Acad. Ind. Coop. Soc. 12 (2011) 6.
[5] KAERI, *Development of Carbon Steel with Superior Resistance to Wall Thinning and Fracture for Nuclear Piping System:* Final Report (RR-3181), Korea Atomic Energy Research Institute, 2009.
[6] S.W. Han, J.S. Seo, J.H. Park, J. Korean Inst. Gas 21 (2017) 1.
[7] K.H. Ryu, I.S. Hwang, N.Y. Lee, Y.J. Oh, J.H. Kim, J.H. Park, C.H. Sohn, Nucl. Eng. Des. 238 (2008).
[8] K.H. Ryu, I.S. Hwang, J.H. Kim, Nucl. Eng. Des. (2013) 265.
[9] K.H. Ryu, T.H. Lee, J.H. Kim, I.S. Hwang, N.Y. Lee, J.H. Kim, J.H. Park, C.H. Sohn, Nucl. Eng. Des. (2010) 240.
[10] K.H. Ryu, I.S. Hwang, J.H. Kim, J. Korean Soc. Nondestruct. Test. 28 (2008) 2.
[11] K.H. Ryu, Development of Piping Wall Thinning Screening Technique Based on Equipotential Switching Direct Current Potential Drop Method, Ph.D. Thesis, Seoul National University, 2010.