공학석사학위논문

베이지안 S-파라미터 모델을 이용한 시간영역반사계 기반 파이프 다중누수 감지 시스템 개발

Time-Domain Reflectometry based Multiple Leak Detection System using Bayesian S-parameters Model for Pipelines

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이 논문을 공학석사 학위논문으로 제출함

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우시형의 공학석사 학위논문을 인준함

2016 년 2 월

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Abstract

Time-Domain Reflectometry based Multiple Leak Detection System using Bayesian S-parameters Model for Pipelines

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Leaks in water distribution systems cause economic, environmental, and social problems. In order to detect leaks in pipelines, techniques have been developed based on time-domain reflectometry (TDR) combined with Bayesian inference. However, these techniques are not practical for applications involving long-distance pipelines due to the large size and significant time required to build the training sample data set required for Bayesian inference in these settings. To solve these challenges, this study proposes two approaches: (a) an S-parameter based forward model to reduce the size of sample data, and (b) an algorithm to estimate the time required to build an training sample data set. Unlike existing methods that model the voltage from both the TDR instrument and the sensing cable, the proposed S-parameter based model has only to estimate the voltage measured at only the input port of TDR instrument without considering the sensing cable. Thus, the voltage of the sensing cable is not required for modeling the TDR signal in this proposed detection system. In terms of the amount of training data required by each method, therefore, the S-parameter based model is much more efficient than existing models from a computational point of view. In addition, the algorithm proposed here to predict the time required to build the sample data allows the user to determine the feasibility of the TDR-based leak detection technique for a particular setting. To validate the proposed method, lab experiments were conducted using a pipeline, leak detectors, sensing cable, and TDR instrument. Through the experiments, the applicability of the suggested S-parameter based model in a long-distance pipeline was validated.

Keywords: Leak Detection System

Water Distribution System

S-parameters

Long Distance Pipeline

Time-Domain Reflectometry

Bayesian Inference

Forward Model

Inverse Model

Student Number: 2014-20662

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Nomenclatures

α	direction of footstep
R	resistance
L	inductance
C	capacitance
G	conductance
Z_0	characteristic impedance
Z_L	changed impedance
Z_S	source impedance of TDR instrument
Γ	reflection coefficient
V	voltage
L_f	location of fault
v_p	velocity of propagation
t	time
S	scattering (S)-parameter
Pr	probability
y	measured TDR signal
θ	random variable related to leaks

v_M	modeled voltage signal in the time domain
V_M	modeled voltage signal in the frequency domain
V_S	modeled transmitted signal in the frequency domain
H	transfer function
G	gain factor of TDR instrument
t_M	internal time delay in the TDR instrument
ω	continuous frequency
$\mathrm{N_i}$	normal segment
$\mathrm{L_i}$	leakage segment
Γ_{FW}	forward reflection coefficient of segment
Γ_{BW}	backward reflection coefficient of segment
γ	propagation constant
l_k	length of segment
μ	permeability of dielectric
σ_{c}	conductivity of conductor
σ_{d}	conductivity of dielectric
ε	permittivity of dielectric
a	radius of conductor
d	distance between conductors
μ_{c}	permeability of conductor

f	input bandwidth
l_L	length of leakage segment
t_d	travel time of pulse
T_{tot}	total time required to build sample data set
$N_{training\ data}$	total number of training data
t_{sample}	time required to model one instance of trained data
$N_{detector}$	number of detectors
K	number of maximum detectable leaks
C	combination operator
V	voltage
σ_M	standard deviation of noise

Chapter 1. Introduction

1.1 Motivation

In the water distribution system, water is supplied from its source to users through a pipeline. During water transfer, often a large amount of water is not supplied to the end user but instead leaks from the pipeline along the pipeline route. According to the International Water Supply Association (IWSA), 20-30 percent of total produced water is not supplied to users [1-4] as a result of several causes including leaks. For example, 250 billion liters of water annually leak from pipelines in the Great Lakes states; this quantity of water could serve the needs of 1.9 million Americans for a year [5]. Unaddressed leaks not only waste resources and money but also cause environmental and social problems, such as sinkholes. Thus, it is very important to quickly and accurately detect leaks to avoid these problems. However, this is not an easy task because most pipelines are buried underground or – in the case of long-distance pipelines – installed in remote regions.

Many methods have been proposed for accurately detecting pipeline leaks. For example, methods include acoustic emission, leak noise correlators (LNC) [6], ground penetrating radar (GPR) [7-9] and pig-mounted acoustic (PMA) sensing [10]. These methods are not suitable for detection of leaks over a wide area or in long-distance pipelines; rather, they are only suitable for inspecting a specific area where leaks are suspected based on prior information, such as a civil complaint. In addition, in cases of these prior methods, surveyors must also be dispatched to the suspected leak area, resulting in significant personnel costs and inspection time.

(a)

(b)

Fig. 1 Existing leak detection system for local area: (a) acoustic emission method, (b) ground penetrating radar method

Other researchers have proposed techniques for monitoring leaks in pipelines over wider areas. Some researchers suggest that analyzing the pressure change of a transient wave can detect the location of a leak [11-14]. However, this method contains uncertainties that are caused by disparities of pipe connectors, foreign substances like rust in the pipe, bending of the pipeline, etc. These uncertainties reduce detection accuracy. To increase the accuracy, detailed information can be added to the numerical algorithm used in the method; however, these additions cause other problems, including increasing the computational load in the numerical model. The added information must also be continually updated as the uncertainties change over time. To overcome these limitations, the time-domain reflectometry (TDR) based leak detection method has been researched.

1.2 Overview of existed TDR Leak Detection System

The suggested methods in this research use time-domain reflectometry (TDR) [15-17], which has fewer uncertainties caused by the configuration conditions of a pipeline than are found in the former method. The TDR technique can inform observers about the state of a transmission line or its periphery through the measurement of a reflected signal on the line. Thus, researchers utilize this method in various situations, such as for monitoring the health state of electronic devices [18, 19], monitoring bridge scour [20, 21], measuring moisture of soil [22, 23] and estimating the amount of fluid in a tank [24]. However, when the TDR technique is applied as a leak detection system, it is challenging to interpret the signal through visual checking or through use of a constant threshold-based criterion. Although TDR-based methods can easily interpret the measured signal when only one leak is present, it is difficult to interpret the inexplicit signal that results from a condition with multiple leaks and periphery noise.

To address these challenges, researchers applied the RLCG-based forward model to this detection system and used Bayesian inference-based inverse model to enhance signal analysis [25]. In RLCG, R is resistance, L is inductance, C is capacitance, and G is conductance. The RLCG-based forward model estimates the TDR signal using lossy transmission line (LTL) theory based on finite-difference time-domain (FDTD). Applying Bayesian inference improves detecting ability in light of the uncertainties of the model and errors of measurement [26, 27]. While these findings have improved the ability to interpret TDR signals, the RLCG forward model has other shortcomings, specifically that it takes long time to generate the trained sample signal. In the Bayesian inference, this drawback causes an increase in the time required to build the sample data set that is used for maximum likelihood. The lengthy time required to build trained sample data set results in limitations of this method's usefulness in long-distance pipelines. This is because as the pipeline length increases, the amount of sample data required to measure likelihood in the Bayesian inference increases as well. These restrictions limit or prevent applying this method in the field, where the length of pipelines can reach tens to hundreds of km, such as in the *Los Angeles Aqueduct*. In particular, a robust leak detection system is most needed in the most challenging circumstances – long-distance pipelines – because pipelines in these settings pass through remote places where it is difficult to detect leaks by human inspection.

1.3 Thesis Outline

In this research, computational efficiency of the forward model is improved by lessening the time required to build the sample data set. This achievement makes it possible to apply the TDR technique for leak detection in long-distance pipelines. This work also proposes a newly developed algorithm to estimate the time required to build the sample data. The detection system proposed in this study is focused only on detecting leaks in the pipe connections, or flanges; it does not attempt to detect leaks in the main "body" of pipes. Leaks in the pipe body are typically easily recognizable, as they usually occur from artificial impacts such as by workers or heavy equipment. Because we can make this assumption based on real-world experience, we can propose a more focused model that benefits from an ability to decrease both the number of leak detectors and the size of the sample data set.

The rest of the paper is organized as follows. First, the background theory is explained in section 2. Next, the proposed multiple-leak inference method using S-parameters is described in section 3. Section 4 outlines an estimation algorithm to calculate the time required to build the sample data. In section 5, the accuracy and efficiency of the suggested model are validated through case studies. Finally, section 6 gives conclusions.

Chapter 2. Background & Literature Review

In this chapter, the theoretical background and literature review is briefly described to enable better understanding of this research. First, the principle of the TDR, which is used to detect leaks, is explained. Second, S-parameters, which are applied to make a forward model, are defined. Finally, the Bayesian inference utilized for locating the leaks in the proposed method is presented.

2.1 Principles of TDR

The TDR was originally proposed as a method to find the location of transmission line faults, such as electrical open, short, or chafe. TDR is, in principle, similar to RADAR, which measures a reflected radio wave to find the locations of objects. Likewise, in TDR, an incident pulse is propagated along the transmission line by TDR instrument and reflected when it meets a fault on the line. This reflected pulse is measured at the TDR instrument. The ultimate cause of the reflection is a disparity of impedance in the transmission line. According to Eq. (1) and Fig. 2, it is clear that a mismatch of impedances between Z_0 and Z_L determines the reflection coefficient between minus one and one, not zero:

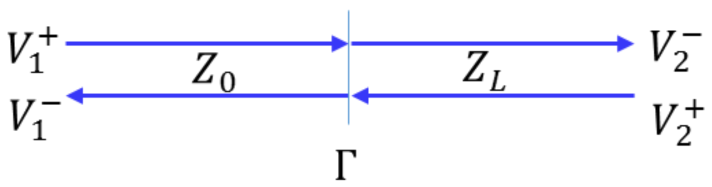
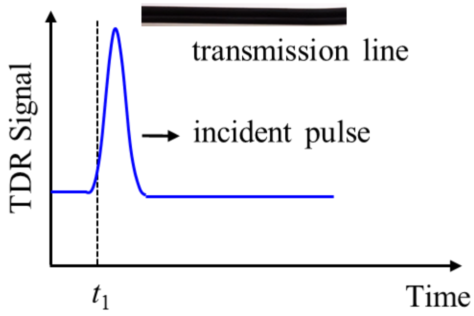


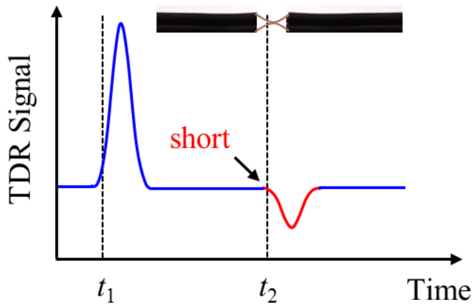
Fig. 2 Impedance disparity and reflected coefficient

$$\Gamma = \frac{Z_L - Z_0}{Z_L + Z_0} = \left[\frac{V_1^-}{V_1^+}\right]_{V_2^+=0} \tag{1}$$

where, Z is the characteristic impedance and Γ is the reflection coefficient. If a Γ is a negative value, the shape of the reflected pulse is upside down for the incident pulse, which indicates an electric short. If the value of Γ is one, the shape of the reflected pulse is the same as that of the incident pulse, which indicates electric open, as shown in Fig. 3.



(a)



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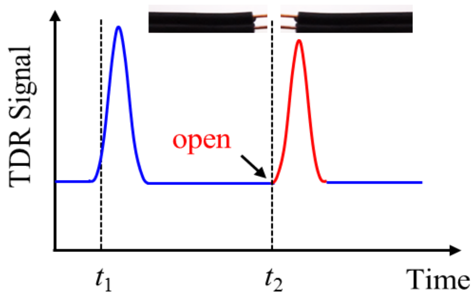


(c)

Fig. 3 TDR signal for electrical: (a) normal, (b) open, and (c) short

The TDR technique can also locate faults, L_f, on the transmission line by calculating the velocity of propagation and pulse traveling time, as in Eq. (2):

$$L_f = v_p \frac{t_2 - t_1}{2} \quad (2)$$

where, t_1 is the incident time when the pulse starts to transmit into the line and t_2 is the arrival time when the reflected pulse is measured at the TDR instrument. v_p is the velocity of propagation of the traveling pulse on the transmission line.

These features of TDR are also useful for a leak detection system. The key here is the similarity between water leakage and an electrical short. An electrical short occurs by abnormal connection of two nodes having different voltages in an electric circuit. Likewise, if the water leakage contacts an electric circuit, it can also cause an electrical short because the leaking water is a good conductor. Fig. 4 shows the proposed operational concept. First, a sensing cable with leak detectors is attached to the pipe. The sensing cable plays the role of the transmission line in traditional TDR technique. Then, the location of leaks can be found by measuring the signal that is reflected from any electrical short that occurs in the leak detection system. This method is described in more detail in sections 3 and 4.

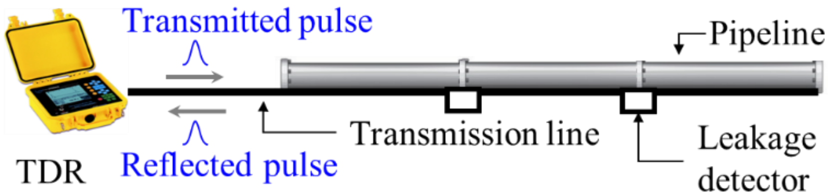


Fig. 4 Concept of leak detection using TDR

2.2 S-parameters

The S-parameters, so called scattering parameters, represent the voltage ratio between the input and output power of an electrical system in the frequency domain. The subscripts of S-parameters signify the port that the electric pulse passes through. The first subscript is an output port where the pulse exits via the port and the second is an input port where the pulse enters the port. S-parameters of two-port units are depicted in Fig. 5 and Eq. (3). Because S-parameters are measured in the frequency domain, the voltage ratio in the time-domain can be acquired by conducting inverse fast Fourier transform (IFFT). In this respect, if the TDR signal is acquired at a specific location on the transmission line in the frequency domain, a time-domain signal at that location can be easily obtained by IFFT. These features of S-parameters are used here to convert the reflected TDR signal that arrives at the TDR instrument into the time domain.

$$\begin{bmatrix} V_1^- \\ V_2^- \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \begin{bmatrix} V_1^+ \\ V_2^+ \end{bmatrix} \tag{3}$$

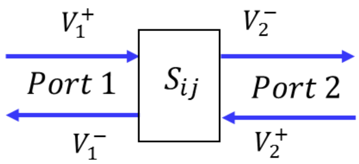


Fig. 5 Concept of S-parameters

2.3 Bayesian Inference

Bayesian Inference is a statistical method that infers posterior distributions of parameters by using prior distributions of those when a new event is given. The basic formula of the Bayesian inference is defined in Eq. (4):

$$\Pr(\theta|y) = \frac{\Pr(y|\theta)\Pr(\theta)}{\int \Pr(y|\theta)\Pr(\theta)\,d\theta} \tag{4}$$

where θ are random variable, y is a new event, and $\Pr(\theta|y)$ is a posterior distribution, which means the updated distribution of θ according to the new event y. $\Pr(\theta)$ are prior distributions, specifically the distributions of each θ before considering the new event y. $\Pr(y|\theta)$ is a likelihood function that stochastically finds the θ that is the most proper to represent y. Because of these features, it is appropriate to stochastically identify an optimal value of each parameter in the numerical models. In addition, it should be noted that this does not have the risk of finding only a locally optimal value of θ because the inference evaluates the likelihood for all samples. A sample means a case determined by θ and the case is compared with y. Generally, a greater sample size has the benefit of more precision in the inference of statistical method. It may have, however, a significant drawback; specifically a significant computational load if generating one sample is time consuming. Thus, to efficiently apply the Bayesian inference in any algorithm, it is important to consider the sample size and the time required to generate each sample. In this research, the sample size of the TDR-based leak detection system is affected by the length of the pipeline. The generating time is also related to the forward model. Therefore, to apply TDR based leak detection system to a long-distance pipeline, the computational efficiency of the forward model is a very important factor in this system.

Chapter 3. Forward Model using S-parameters for Generating a TDR Signal Corresponding to Leakage

This section describes the forward model and an inverse model for detecting pipeline leaks. The purpose of the forward model is to estimate a TDR signal by using information about leaks, such as the number of leaks and their locations. Here, it is important that the modeled signal must well represent the measured signal in real situations. The inverse model then infers the information about leaks using the measured TDR signal. In this research, S-parameters are employed as the method of inducing the forward model to improve computational efficiency. The Bayesian inference is used for the inverse model. This section is comprised of four parts. First, the benefits of the proposed S-parameter based forward model are explained. Second, the operating principle of the forward model is exposited. Third, the method of inducing the forward model is described. Finally, we outline the principle of Bayesian inference based the inverse model. For demonstrating the forward model, the equations established by Stefan Schuet et al [28] are quoted. These equations were originally applied to describe the health state of coaxial cables.

3.1 Advantages of a Forward Model utilizing S-parameters

The TDR signal is a vector of sequent voltages that are measured at the TDR instrument. As shown in Fig. 6, the TDR signal is a white line that is composed of white stars (✰). The white star means a voltage that is measured at the TDR input port per time unit.

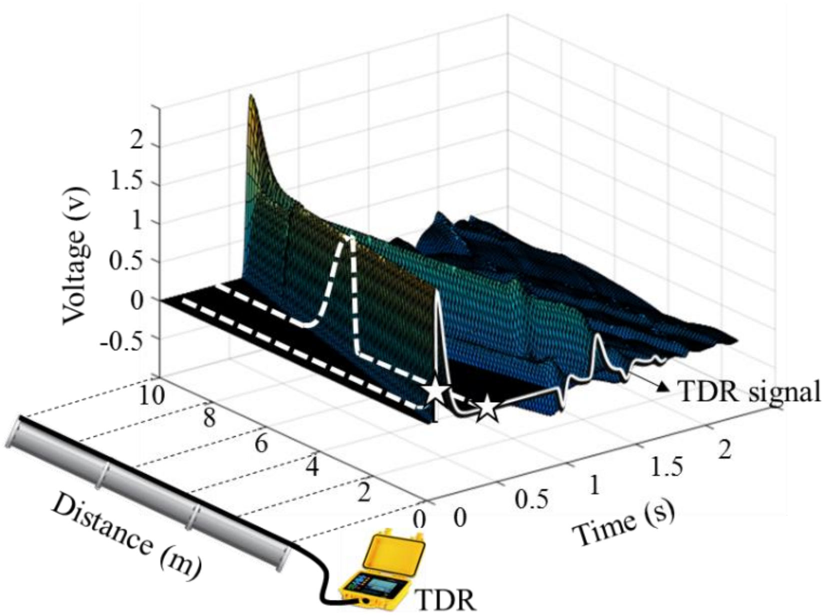


Fig. 6 Voltage distribution on the transmission line in the time domain

(white line: TDR signal; white dotted line: modeled signal based on RLCG)

Thus, the forward model must estimate the white stars. The previous RLCG forward model, based on FDTD, requires calculating the all voltages (- - -, white dotted line) on the attached transmission line to obtain the one voltage (☆, white star) per time unit. However, the S-parameter based forward model does not need to calculate the all voltages. The S-parameter based model obtains the reflected signal in the frequency domain at the distance of zero meter, or the TDR input port. Then, by performing IFFT, the modeled frequency domain signal can be transformed to a reflected signal in the time domain which is same as the white solid line. In other words, the S-parameter based model does not need to consider the white dotted lines.

Thus, the S-parameter based forward model method offers the advantage of reflecting the physical character of the TDR signal. The model also needs also a smaller number of voltage data points to estimate the TDR signal than does the RLCG-based model. For example, if the RLCG forward model has a circuit model comprised of segments of the total transmission line equal to one thousandth of the line, one thousand voltage values are needed to gain one white star per time unit. In this sense, the S-parameter model is a more computationally economical method than the RLCG model.

3.2 Concept of the Forward Model using S-parameters

In As defined in section 3.1, the forward model estimates the TDR signal. The TDR signal is a vector that is composed of sequentially measured voltages. In the Eqs. (5) and (6), $v_M(\mathrm{t})$ is the TDR signal which is a reflected signal in the time domain and V_M is the reflected signal in the frequency domain. The source signal, v_S, is a vector that consists of values of the voltage sequentially generated by TDR instrument in the time domain. V_S is the source signal in the frequency domain. The transfer function, H, generally means a ratio of output values to input values. In this paper, the output values are V_S, the input values are V_M, and H is defined as V_M / V_S. Thus, in the time domain, the forward model, which estimates the TDR signal, v_M, is the right hand side of Eq. (5):

$$v_M(t) = IFFT(H(\omega, \theta) \odot FFT(v_S(t))) \tag{5}$$

where $\odot$ is the element-by-element vector multiplication operation. $v_S(t)$ can be determined by the specifications of the equipment. As in Eq. (6), H is represented in the reflection coefficients, Γ_S and Γ_0, of the connection area between the TDR equipment and the transmission line [28]:

$$H(\omega) = \frac{V_M}{V_S} = \frac{G}{2}(1 + \frac{\Gamma_S + \Gamma_0}{1 + \Gamma_S \Gamma_0} e^{-j2\omega t_M}) \tag{6}$$

where G is the gain factor and t_M is the internal time delay in the TDR instrument. ω is the continuous frequency that corresponds to the sampling period of the TDR. Γ_S is the reflection coefficient between the impedance of the TDR instrument, Z_S, and the characteristic impedance of the transmission line, Z_0, as shown in Fig. 7 and Eq. (7).

$$\Gamma_S = \frac{Z_0 - Z_S}{Z_0 + Z_S} \tag{7}$$

Γ_0 is the reflection coefficient at the starting point of the transmission line (just to the right side of Γ_S). Γ_0 is not constant, but changeable, because it is affected by the health state of the transmission line. Γ_0 and the method of inducing the forward model are explained in the next section.

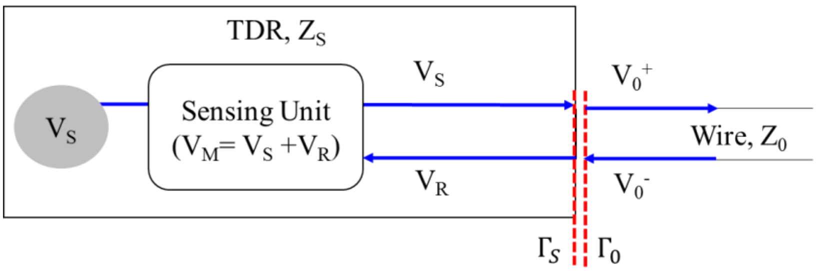


Fig. 7 Operating concept of TDR

3.3 Modeling the Sensing Cable

In this research, the transmission line of the leak detection system is referred to as the sensing cable. The cable can be divided into two types of segments, namely normal segments, N_i, and leakage segments, L_i, as shown in Fig. 8. A disparity of impedance occurs at the boundary between each differing segment due to the electric short caused by the leak. As a result, the reflection of the transmitted pulse occurs at the boundary between segments. As shown in Eq. (6), Γ_0 must be obtained to model the TDR signal. Because the left side reflection coefficient of each segment can be induced from the right side reflection coefficient of it [28], Γ_0 can be inferred from Γ_L. To model the sensing cable, first, a model that can obtain the reflection coefficient of each segment should be made. Next, a totally synthesized model of the sensing cable is completed by connecting the reflection coefficient of each segment. The method of modeling the segments is as follows.

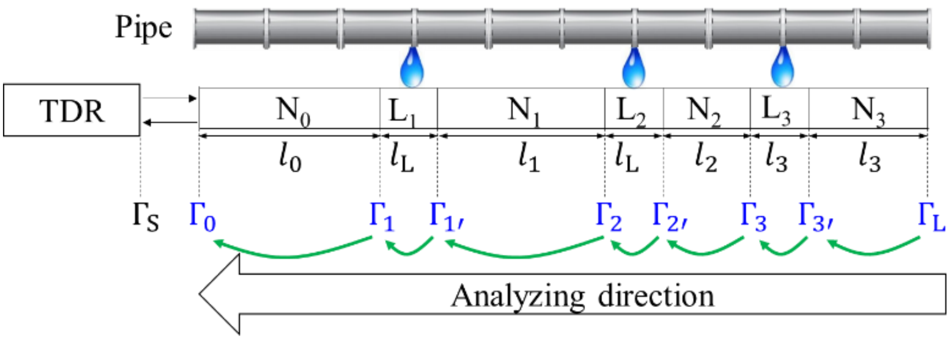
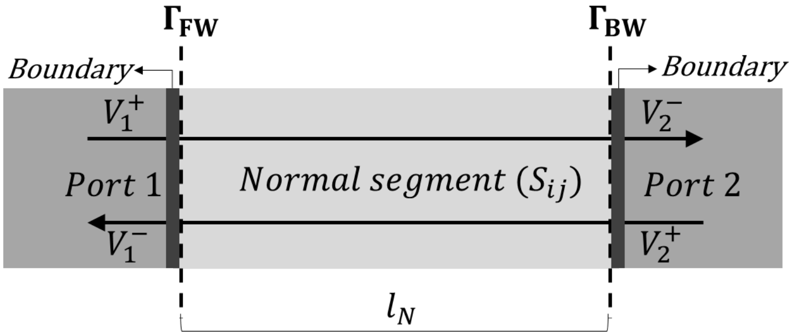
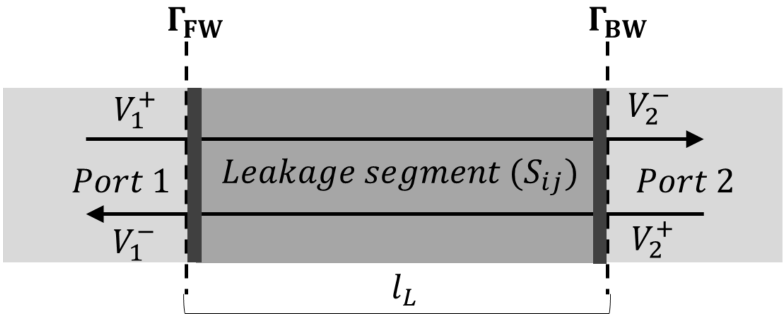


Fig. 8 Model synthesis



(a)



(b)

Fig. 9 Modeling the segments of the transmission line: (a) normal segment, (b) leakage segment

Normal segment - As shown in Fig. 9 (a), the area of a normal segment is defined inside the domain, excluding both side boundaries. Thus, Γ_{FW} is just to the right of the front boundary and Γ_{BW} is just to the left of the rear boundary. In addition, the segment can be regarded as a two-port device that has S-parameters. Generally, in a two-port device, Γ_{FW} is defined by S-parameters and Γ_{BW} can be found using Eq. (8) [29]:

$$\Gamma_{\mathrm{FW}} = S_{11} + \frac{S_{12}S_{21}\Gamma_{\mathrm{BW}}}{1 - S_{22}\Gamma_{\mathrm{BW}}} \tag{8}$$

where Γ_{BW} is the same as Γ_{FW} of its backward segment. S_{11} and S_{22} are zero because there is no change of impedance in the normal segment. S_{12} and S_{21} are not zero, but rather represent transmission loss during the travel of the pulse along the segment, as in Eq. (9) [28]:

$$\mathrm{S}_{12} = S_{21} = e^{-\gamma l_k} \tag{9}$$

where γ is propagation constant and l_k is the length of the segment. Thus, Γ_{FW} is defined as $e^{-2\gamma l_k} \cdot \Gamma_{BW}$ where γ is defined as Eq. (10):

$$\gamma = \sqrt{[R + j\omega L][G + j\omega C]} \tag{10}$$

where RLCG is a property of the sensing cable. The RLCG of two parallel cables is defined in Table 1.

Table 1 R, L, G, and C of two parallel cables

R[Ω/m]	L[H/m]	G[S/m]	C[F/m]
$\frac{1}{\pi a \sigma_c \delta}$	$\frac{\mu}{\pi}\mathrm{acosh}(\frac{d}{2a})$	$\frac{\pi\sigma_d}{\mathrm{acosh}(\frac{d}{2a})}$	$\frac{\pi\varepsilon}{\mathrm{acosh}(\frac{d}{2a})}$

μ: permeability of dielectric; σ_c: conductivity of conductor; σ_d: conductivity of dielectric; ε: permittivity of dielectric; a: radius of conductor; d: distance between conductors; δ: $1/\sqrt{\pi f \mu_c \sigma_c}$ (μ_c: permeability of conductor; *f*: input bandwidth)

Leak segment - As shown in Fig. 8(b), the area of a leak segment is a defined domain that includes both side boundaries. Thus, Γ_{FW} is the left side of the front boundary and Γ_{BW} is the right side of the rear boundary. This segment can be also analyzed as a two-port device. Unlike a normal segment, here S_{11} and S_{22} are not zero because there are disparities of impedance in the segment. As shown in Eq. (11) and (12), the S-parameters are calculated similarly to S-parameters of a faulty segment in a coaxial cable, as established by Stefan Schuet et al [28].

$$\mathrm{S}_{11} = \mathrm{S}_{22} = \frac{\Gamma_2\left(e^{-j\omega 2t_d} - 1\right)}{1 - \Gamma_2^2 e^{-j\omega 2t_d}}, \quad (t_d = l_L/v_p) \tag{11}$$

$$\mathrm{S}_{12} = \mathrm{S}_{21} = \frac{(1 - \Gamma_2^2)e^{-j\omega 2t_d}}{1 - \Gamma_2^2 e^{-j\omega 2t_d}} \tag{12}$$

where t_d is travel time, which is taken while the pulse passes the leak segment, l_L is the length of the segment, and v_p is the propagation velocity of the pulse. The Γ_{FW} of this segment can be also calculated using Eq. (8). Γ_{BW} of this segment can also be acquired from Γ_{FW} of its backward segment.

Model Synthesis - The entire sensing cable can be thus modeled by combining these two types of segments. Fig. 8 shows an example of a pipeline with three leaks. The pipeline has four normal segments, N_i, and three leakage segments, L_i. Γ_{BW} of each segment overlaps with Γ_{FW} of its backward segment. The value of Γ_L, as is already known, is one as it is the reflection coefficient of the open circuit at the end point of the sensing cable. Γ_0 can then be induced from Γ_L by acquiring Γ_{FW} for each segment. Using the obtained Γ_0, $H(\omega)$ can be found using Eq. (6). When $H(\omega)$ is substituted into Eq. (5), the S-parameter based forward model is completed.

Chapter 4. Estimation Algorithm to Determine the Time required to Build the Trained Sample Data Set

This section explains the algorithm used to estimate the time required to build the trained sample data set. The training data set includes modeled TDR signals of all cases covering all possible leak situations. The training data can then be compared to the measured TDR signal to determine the likelihood of leak locations. To detect leaks in real time, the comparison must be performed rapidly. To that end, the whole data set must be built in advance before completion of construction of the water distribution system because building the training data set is a surprisingly time-consuming process. Once built, the training data set can be used repeatedly, because the data set doesn't change as long as the configuration of pipeline doesn't change. However, the time required to build the data set is significant. Thus, the training data set may not be built during the construction period of the pipeline due to the design conditions of the system, such as the total length of the pipeline, the length of each pipe unit, the number of maximum detectable leaks, K, and the computational efficiency of the forward model. With this in mind, an estimate of the time required to build the data set is useful before construction starts.

The total time required to build the trained sample data set, T_{tot}, is defined by multiplying the total number of training data, $N_{training\ data}$, by the time required to generate one instance of trained sample data, t_{sample}.

$$T_{tot} = N_{training\ data} \cdot t_{sample} \tag{13}$$

$N_{training\ data}$ is determined by the number of leak detectors needed in the system, $N_{detector}$, and the number of maximum detectable leaks, K. In this system, $N_{detector}$ is the same as the number of flanges in the pipeline except for the beginning and end flanges. This number is obtained by dividing the length of the total pipeline by the length of each pipe unit and subtracting one, because a detector is installed on each connecting flange. The formula of $N_{training\ data}$ then follows, as shown in Eq. (14):

$$N_{training\ data} = \left(\sum_{i=1}^{K} C(N_{detector}, i) \right) + 1 \tag{14}$$

where C is the combination operator. $C(N_{detector}, k)$ refers to the number of cases when the number of leaks is k. The last term (+ 1) adds to the formula to account for the case of a normal situation without any leaks. Thus, the formula of $N_{training\ data}$ accounts for the total number of all possible leakage situations, from no leakage to the maximum number of leaks. Thus, t_{sample} can be obtained by averaging the consumed time for various case studies, as described in the next section.

Chapter 5.   Case Study

In this section, the accuracy and efficiency of the suggested leak detection system are validated through case studies. First, the experimental test bed is briefly described. The test bed is then validated by applying a real leak situation to the test bed. Next, parameters of the forward model are calibrated by using experimental data acquired from the experimental results of both the normal and single-leak situations. Next, the accuracy of the forward model is validated by comparing the modeled signal with the measured signal under a two-leak situation. Further, the accuracy of the Bayesian inference is demonstrated by comparing the training data set and the measured TDR signal under a three-leak situation. The three-leak situation generates an inexplicit TDR signal that is hard to interpret through visual inspection due to the overlapped reflection. Finally, the time required to build trained sample data set is estimated according to various lengths of pipeline by using t_{sample}, which is obtained through the case studies.

5.1   Description of the Experimental Test Bed

A custom test bed was designed at the lab scale, as shown in Fig. 10. This system is comprised of three parts, including the pipeline, the leak detectors, and a data acquisition system. The pipeline is made up of four 3 meter-long pipes with 12 centimeter radius and additional components to enable the TDR technique to be applied, including a sensing cable and an outer housing case at the joints. These components are not found in a regular pipeline. A twin parallel cable that is made from copper wire with 0.4 millimeter radius is used as the sensing cable in the test bed.

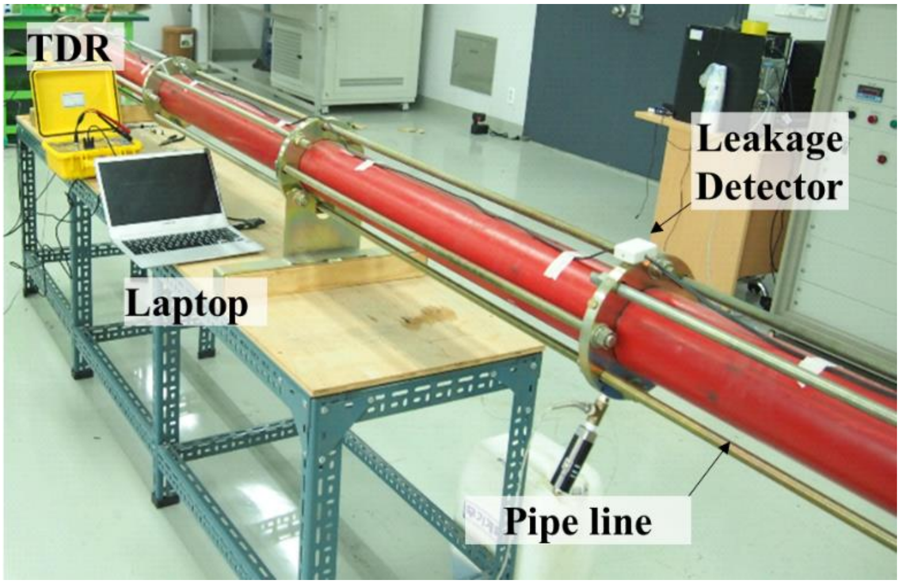
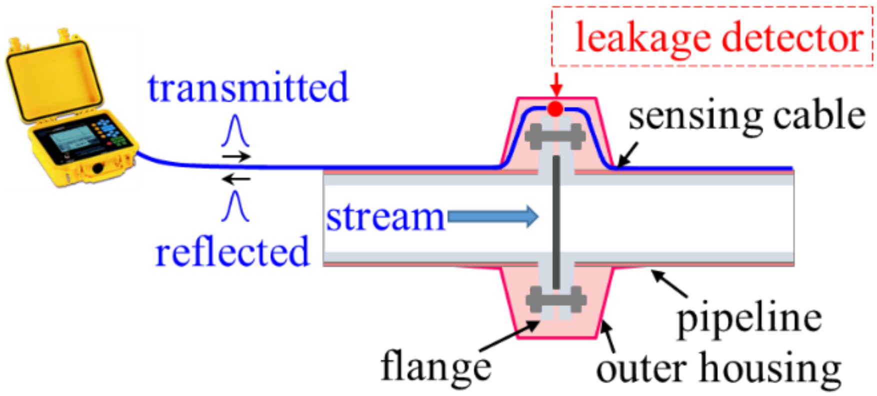
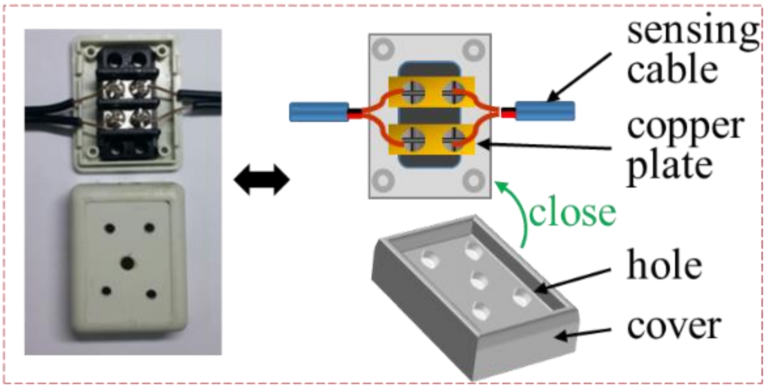


Fig. 10 Experimental test bed for validating the forward model

The outer housing case is installed around joints where leakage is likely to occur. The housing plays the role of a reservoir for the leaking water, ensuring the leak detector gets wet. This wetness in turn causes an electrical short at the detector and the reflection of the pulse at the location of the short. The leak detector consists of two copper plates and a plastic case with holes, as shown in Fig. 11. The detector is isolated from external moisture by the outer housing, and is thus only affected by leaking water at the joint. The copper plate is also exposed to contact with the leaking water; the water then plays the role of a conductor between the two plates. The data acquisition part is composed of the TDR instrument and a laptop. The model of TDR instrument in the test setup is an mTDR-070 from Nanotrinics Corp. with an input bandwidth of 300 MHz, output pulse of two volts, rising time of 1ns, maximum effective distance of 20 kilometers, and a characteristic impedance of 75 Ω. The laptop specifications include an Intel core i5 3.1 GHz processor with eight GRAM. The TDR instrument is connected to the start of the sensing cable to transmit the pulse and receive the reflected pulse. The TDR instrument is connected also to the laptop for analyzing the acquired data.



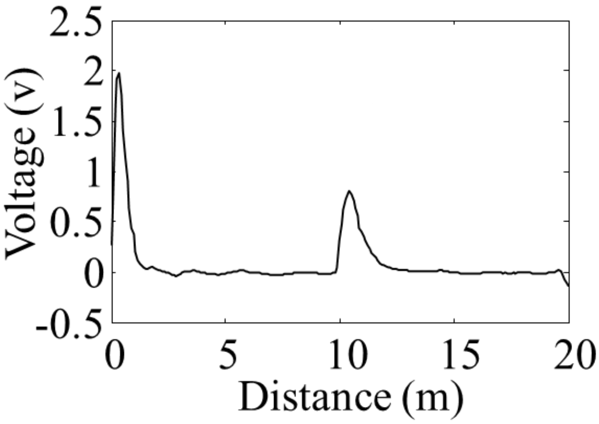
(a)



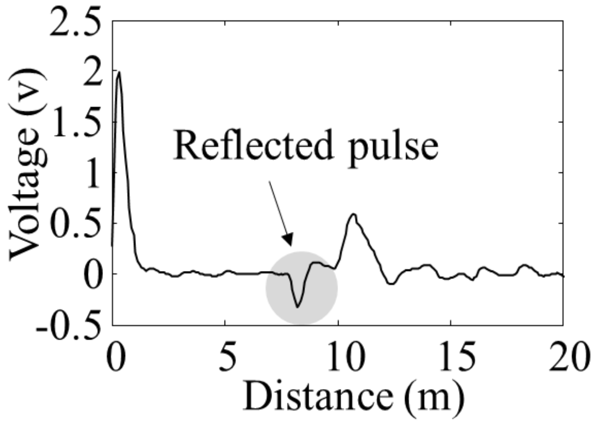
(b)

Fig. 11 Leak detection system: (a) system components, (b) leak detector

Normal operation of this system was demonstrated through a simple experiment that was conducted using a 10 meter cable with one leak detector installed 8 meters along the cable. Then, the leak detector was attached to the flange and a leakage situation was applied to the system. The reflected pulse signal from the leakage was observed as shown in Fig. 12. To test a situation with multiple leakage signals under various situations with several detectors, tests were manually performed to intentionally change the gap between the leaks.



(a)

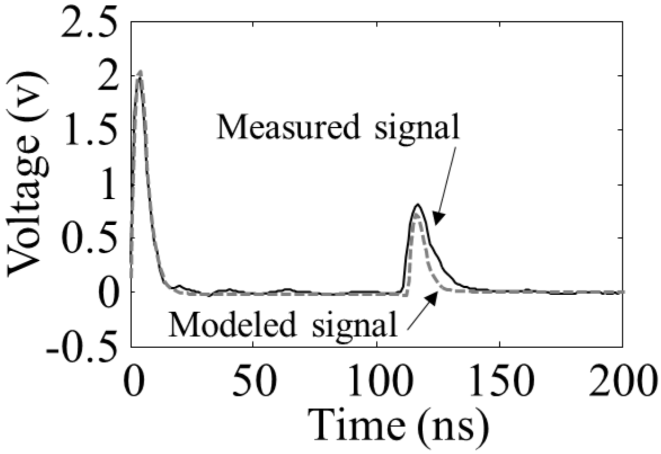


(b)

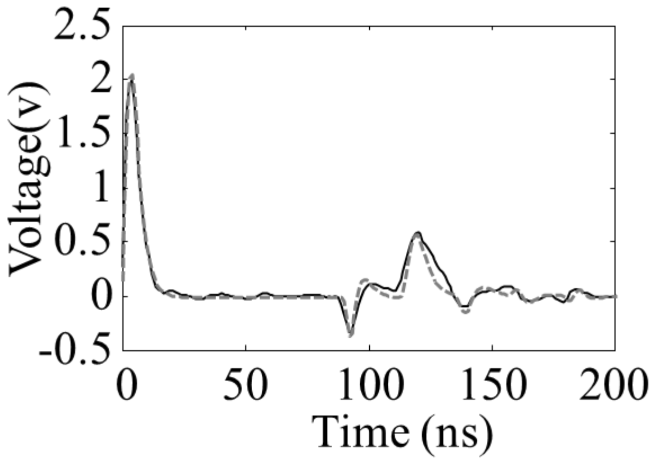
Fig. 12 Operation check of the leak detector: (a) no leak, (b) single leak at 8m

5.2 Validation of Accuracy of the Forward Model and the Bayesian Inference

Before the developed forward model is used, the constant parameters in the forward model need to be calibrated. Although these parameters were determined based on a review of the literature, known properties of the material, and specifications of the chosen equipment, some parameters inevitably have uncertainties.



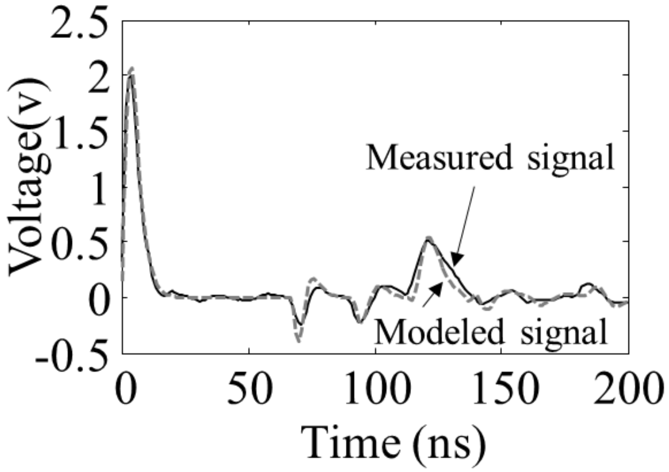
(a)



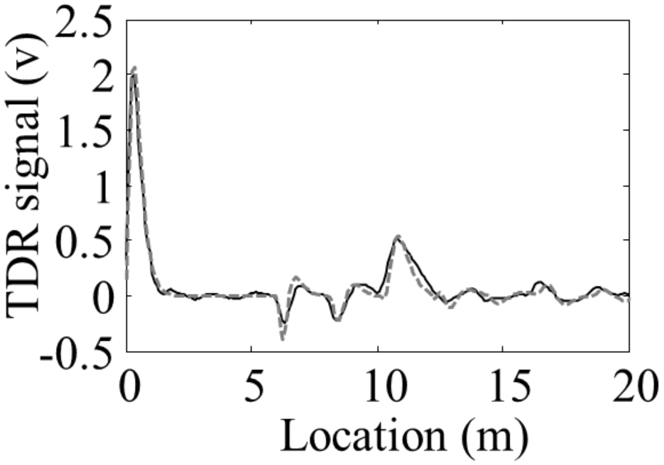
(b)

Fig. 13 Comparison between measured signal and modeled signal: (a) no leak, (b) single leak at 8m

In order to decrease the effect of the uncertainties, calibration of the parameters was conducted using the *least square method* (LSM) between the measured and the modeled signal under situations with no leaks and with a single leak, as shown Fig. 13. After calibration, the accuracy of the forward model was validated by comparing the measured signal to the modeled signal under the multiple-leak situation. The pipe in the experimental setup is 10m long with two leaks at 6m and 8m. As shown in Fig. 14, the forward model accurately represents the TDR signal. It is also converted to the distance domain to arrive at more practical information, specifically, the predicted leak locations. Table 2 examines the accuracy of the forward model by comparing the TDR signal estimated by the model and the signal measured by the TDR instrument. The stochastic measures used are *Correlation Coefficient, Weighted Integrated Factor* (WIFac) and standard deviation of noise (σ_M). The *Correlation Coefficient* and WIFac represent the accuracy of the model in the aspect of shape and σ_M represents the error of the model. The *Correlation Coefficient* has a value between minus one and one. Here, minus one is total negative correlation, zero is no correlation, and one is total positive correlation. The WIFac has a value between zero and one. In case of the WIFac, the value means a degree of match between the two signals and one means perfect match. As shown Table 2, the WIFac value falls a little short of one because of difference of magnitude of the signals caused by periphery noise and physical uncertainties included in this system. The *Correlation Coefficient* related to tendency of peaks of the signals is close to one. The peak locations of the signals is important factor for inferring the leak locations in this detection system. Thus, the suggested forward model is appropriate to use the proposed leak detection system.



(a)



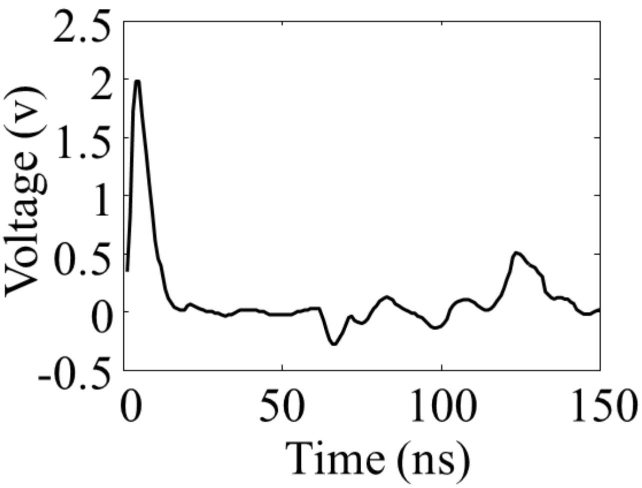
(b)

Fig. 14 Validation of the forward model with two leaks (6m and 8m) on the 10 m cable: (a) time domain, (b) distance domain

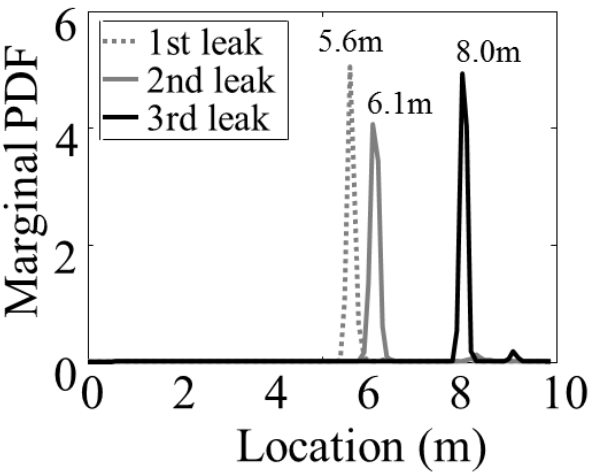
Table 2 Comparison of similarity between real measured TDR signal and virtually generated TDR signal

Measure	Correlation coefficient	WIFac	σ_M
value	0.9869	0.8621	0.06

The Bayesian inference was then validated using the training data set, which was made using the forward model, as described in the section 4. The given condition is a multiple-leak situation that has three leaks in a 10 meter pipe. The locations of the leaks are at 5.5 meters, six meters, and eight meters. As shown in Fig. 15 (a), the signal is not explicit and thus cannot be interpreted by visual inspection. However, the location of the leaks can be stochastically found through Bayesian inference, as shown in Fig. 15 (b), which shows the marginal PDFs of each parameter around the location of the leaks.



(a)



(b)

Fig. 15 Bayesian inference for finding the location of leaks: (a) measured TDR signal, (b) location of leaks

5.3 Estimating the Time required to Build Sample Data Set for a Long-Distance Pipeline

As described in section 4, to estimate T_{tot}, t_{sample} must be obtained. The t_{sample} is calculated using the results of case studies that are performed for various lengths of pipelines. However, a lab setting limits the opportunity to extend a sample pipeline. Thus, to examine various situations, we assumed that the length of each pipe unit ranged from one meter to 0.1 meter under the given length of our sample pipeline, 10m. This enabled us to examine different numbers of flanges and allowed $N_{detector}$ to increase, achieving the same effect as extending the length of the pipeline. As shown in Table 3, $N_{detector}$, $N_{training\ data}$, T_{tot} and T_{sample} were acquired according to the length of each unit pipeline with three maximum detectable leaks, K. The average of t_{sample} was approximately 0.00263 second. This result was also calculated using the laptop with an Intel core i5 3.1GHz processor and eight GRAM and MATLAB. Thus, the t_{sample} can be a changeable value depending on computer performance. If this system were to be used with a high-performance computer such as a supercomputer, t_{sample} can also be reduced. This also means that the system suggested in this research can be effectively applied to actual field situations that use higher-performance computers than the laptop used in this research.

Table 3 The T_{tot} and t_{sample} with three maximum detectable leaks, as predicted by each forward model

Length of unit pipe	1 m	0.5 m	0.2 m	0.1 m
$N_{detector}$	9	19	49	99
$N_{training\ data}$	130	1,160	19,650	161,800
T_{tot} [s]	0.34	3.03	51.42	433.15
t_{sample} [s]	0.002615	0.002612	0.002617	0.002677

Table 4 The T_{tot} in the field with three maximum detectable leaks

Length of pipeline	t_{sample}	1 km	5 km	10 km	20 km	30 km
$N_{detector}$	-	99	499	999	1,999	2,999
$N_{training\ data}$	1	161,800	20,709,000	166,168,000	1,331,336,00	4,495,504,000
T_{tot} ($t_{\mathrm{sample}} \times N_{training\ data}$)	0.00263s	0.12h	15.22h	122.15h (5.09 days)	978.63h (40.78 days)	3,304.53h (137.69 days)

Table 4 shows the total estimated T_{tot} of all training data for various lengths of pipeline, using Eqs. (15) and (16), with a 10m pipe and 3 maximum detectable leaks.

T_{tot} is obtained by multiplying $N_{training\ data}$ by t_{sample}. If the length of the pipeline is same, the T_{tot} depends on the K which affect the $N_{\mathrm{training\ data}}$. When the K increases, the T_{tot} also increases. On the other hand, when the K decreases, the T_{tot} must also decrease. The K and T_{tot} relationship reflects the trade-off between multi-detection capabilities and the cost of the time required to generate the sample data set. This process can be applied in practice to various lengths of pipelines and different numbers of maximum detectable leaks.

Chapter 6.   Conclusion

A novel TDR-based leak detection system using an S-parameter forward model has been presented in this paper. The application of S-parameters improves the computational efficiency of the forward model and shortens the T_{sample} of the trained sample data needed for Bayesian inference. The Bayesian inference based inverse model can stochastically detect the location of leaks from an inexplicit TDR signal that includes noise and overlapped reflection. Moreover, the time estimation algorithm developed here predicts the T_{tot}, using the configuration information for the particular pipeline of interest. To demonstrate the performance of the suggested leak detection system, laboratory experiments were conducted using a sample pipeline, leak detectors, a sensing cable, and TDR instrument. To simulate a long-distance pipeline, the length of each pipe unit was intentionally controlled at various lengths from one meter to 0.1 meter. Through the case study, the accuracy of the proposed S-parameter based forward model was validated by various measures and t_{sample} was also obtained by averaging the results of different case studies. Using the t_{sample}, the T_{tot} for various conditions, including different lengths of pipeline and a varying number of maximum detectable leaks can be estimated.

As a result of this research, it is significantly meaningful that a multiple-leak detecting technique can be applied to a water distribution system. Some people may think that a conventional TDR-based leak detection method is sufficient to detect pipeline leaks because the possibility of multiple leaks occurring simultaneously in any given pipeline is low. In addition, if it is easy to access the location of a particular leak, maintenance can be quickly performed as soon as a leak is detected and before another leak occurs. However, in actual pipeline applications if other leaks occur before an existing leak is repaired the usefulness of the conventional TDR-based method is limited. In addition, it can be difficult to perform quick maintenance on pipelines due to difficult accessibility (e.g., pipelines installed underwater or in desert or alpine regions). Moreover, the crustal movement of an area with installed pipelines, such as an earthquake, uplift of strata, ground sinking, or various external shocks, can force a change in the geometry of a long-distance pipeline. These phenomena may cause misalignment of a pipeline and generate multiple leaks at the flanges. Even though the non-trivial procedure of building a training data set is required for use of our proposed system, the suggested multiple-leak detection system offers significant long-term advantages, particularly in situations involving long-distance pipelines.

In terms of return on investment (ROI), the economic feasibility of the proposed detection system is superior to any existing method, including LNC, GPR, and PMA methods. While the TDR installation of this leak detection system, in terms of investment, *could* be regarded as an additional cost, the TDR installation, in terms of return, should not be regarded as an additional cost, but rather as an investment that will pay back in economic profits. In this regard, the installation of TDR system should be analyzed from the perspective of its long-term cost savings. First, in terms of operational cost reduction, the suggested method doesn't require surveyors and equipment to be dispatched for detecting leaks, unlike existing detection methods, because the proposed system can remotely monitor a wide area in real time. This advantage could derive benefits such as substantial labor cost savings. Second, in terms of cost avoidance, the price of the TDR instrument installed in the leak detection system is cheaper than it would be for electronic monitoring because the latter requires the TDR instrument with high resolution. In contrast, our suggested detection system requires only the TDR with moderate-resolution, which is able to accurately identify the distance between the detectors. In addition, our more robust system can also prevent the occurrence of costs related to economic, social, or environmental issues caused by being continuously unaware of leaks. Third, in terms of revenue growth, the net profit of the water industry is expected to gradually increase because of the reduction of non-revenue water (NRW) losses through more rapid maintenance to fix leaks.

If the economic efficiency of installation of the system is demonstrated in the long term, this leak detection system is also expected to be useful for sewer lines and wastewater pipelines. Generally, a leak of a sewer line or wastewater pipeline system is not related to an economic cost in the short term, so the effort put toward preventing leaks in these systems is relatively less than that observed for water distribution systems. However, leakage of sewage and wastewater may cause various environmental, economic, and social problems. First, the leakage causes soil and underground water contamination. It negatively impacts human health through agricultural products and can contaminate drinking water. Second, the contamination of soil and underground water leads to considerable remediation costs in the long term. Finally, the continuous leakage of wastewater pipelines can cause disasters such as sinkholes, in which a hole is made by the collapse of the ground surface as a result of a leaking pipeline below ground [30]. This situation may result in great a catastrophe causing many casualties. Thus, applying the proposed TDR system to sewer lines and wastewater pipelines could prevent these problems in the long term.

Future work related to this research will be expanded to examine the network structure of pipelines because this research is only applicable to a single pipeline. As a result, this method would need multiple TDR instrument stations to cover a networked pipeline structure. In the case of coaxial cable, Xiaolong Zhang has examined the failure diagnosis technique of a cable network using a TDR-based system using a modeling splitter and tap [31]. However, to be robust to noise and improve interpretability of the TDR signal for multiple leaks, a Bayesian inference based network detection technique must be developed. Thus, to reduce the amount of required equipment and cost, the authors will seek to develop a method that efficiently detects leaks in a networked water distribution system.

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국문 초록

상수도 파이프라인에서 발생하는 누수들은 경제적, 환경적, 사회적 문제들을 발생시킨다. 이러한 누수를 감지하기 위해서 베이지안 추론을 활용한 시간영역반사계(time domain reflectometry: TDR) 기반의 누수탐지 기술이 연구되고 있다. 그러나 이 기술은 베이지안 추론 시 필요한 샘플데이터를 구축하는데 걸리는 소요시간과 샘플데이터의 방대한 크기로 인해서 장거리 파이프를 포함하여 실제 적용하는데 실용적이지 못하다.

이러한 문제점을 해결하기 위해서 본 연구에서는 두 가지 새로운 방법을 제안한다. 첫 번째는 샘플데이터의 크기를 감소하기 위해 S-파라미터 기반의 전진모델 개발이며, 두 번째는 전체 샘플데이터를 구축하는데 걸리는 소요시간 예측 알고리즘 개발이다. 기존 전진모델의 경우, TDR 장비와 탐지 케이블의 모든 전압에 대한 모델링이 필요하였지만, 제안한 S-파라미터 기반의 전지모델은 탐지 케이블은 제외한 TDR 장비의 입력 전압에 대해서만 모델링이 필요하다. 따라서 제안한 누수탐지 방법에서는 탐지선의 전압은 TDR 신호를 모델링은 필요하지 않다. 그러므로 각 전진모델에서 필요로 하는 샘플데이터의 크기를 고려하였을 때 S-파라미터 기반의 전진모델이 기존의 전진모델보다 계산비용 관점에서 훨씬 효율적인 모델이라고 할 수 있다. 게다가, 샘플데이터 구축시간을 예측하기 위해 제안된 알고리즘은 시스템 사용자에게 TDR 기반 누수탐지 시스템이 특정 조건에서 파이프 라인의 공사기간과 구축소요시간을 비교하여 실용적인지를 판단할 수 있게 해준다.

이 제안된 방법은 실험실 규모에서 파이프, 누수탐지기, 탐지선, TDR 장비를 사용하여 검증을 하였다. 실험을 통해서 장거리 파이프라인에서 제안된 S-파라미터 기반 전진 모델의 실용성 또한 검증하였다.

주요어: 누수탐지 시스템
상수도 시스템
S-파라미터
장거리 파이프라인
시간영역반사계
베이지안 추론
전진모델
역 모델

학 번: 2014-20662

공학석사학위논문

베이지안 S-파라미터 모델을 이용한 시간영역반사계 기반 파이프 다중누수 감지 시스템 개발

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이 논문을 공학석사 학위논문으로 제출함

2016 년 2 월

서울대학교 대학원

기계항공공학부

우 시 형

우시형의 공학석사 학위논문을 인준함

2016 년 2 월

위 원 장 ______ 김 윤 영 ______ (인)

부위원장 ______ 윤 병 동 ______ (인)

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Abstract

Time-Domain Reflectometry based Multiple Leak Detection System using Bayesian S-parameters Model for Pipelines

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Leaks in water distribution systems cause economic, environmental, and social problems. In order to detect leaks in pipelines, techniques have been developed based on time-domain reflectometry (TDR) combined with Bayesian inference. However, these techniques are not practical for applications involving long-distance pipelines due to the large size and significant time required to build the training sample data set required for Bayesian inference in these settings. To solve these challenges, this study proposes two approaches: (a) an S-parameter based forward model to reduce the size of sample data, and (b) an algorithm to estimate the time required to build an training sample data set. Unlike existing methods that model the voltage from both the TDR instrument and the sensing cable, the proposed S-parameter based model has only to estimate the voltage measured at only the input port of TDR instrument without considering the sensing cable. Thus, the voltage of the sensing cable is not required for modeling the TDR signal in this proposed detection system. In terms of the amount of training data required by each method, therefore, the S-parameter based model is much more efficient than existing models from a computational point of view. In addition, the algorithm proposed here to predict the time required to build the sample data allows the user to determine the feasibility of the TDR-based leak detection technique for a particular setting. To validate the proposed method, lab experiments were conducted using a pipeline, leak detectors, sensing cable, and TDR instrument. Through the experiments, the applicability of the suggested S-parameter based model in a long-distance pipeline was validated.

Keywords: Leak Detection System

Water Distribution System

S-parameters

Long Distance Pipeline

Time-Domain Reflectometry

Bayesian Inference

Forward Model

Inverse Model

Student Number: 2014-20662

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Nomenclatures

α	direction of footstep
R	resistance
L	inductance
C	capacitance
G	conductance
Z_0	characteristic impedance
Z_L	changed impedance
Z_S	source impedance of TDR instrument
Γ	reflection coefficient
V	voltage
L_f	location of fault
v_p	velocity of propagation
t	time
S	scattering (S)-parameter
Pr	probability
y	measured TDR signal
θ	random variable related to leaks

v_M	modeled voltage signal in the time domain
V_M	modeled voltage signal in the frequency domain
V_S	modeled transmitted signal in the frequency domain
H	transfer function
G	gain factor of TDR instrument
t_M	internal time delay in the TDR instrument
ω	continuous frequency
N_i	normal segment
L_i	leakage segment
Γ_{FW}	forward reflection coefficient of segment
Γ_{BW}	backward reflection coefficient of segment
γ	propagation constant
l_k	length of segment
μ	permeability of dielectric
σ_c	conductivity of conductor
σ_d	conductivity of dielectric
ε	permittivity of dielectric
a	radius of conductor
d	distance between conductors
μ_c	permeability of conductor

f	input bandwidth
l_L	length of leakage segment
t_d	travel time of pulse
T_{tot}	total time required to build sample data set
$N_{training\ data}$	total number of training data
t_{sample}	time required to model one instance of trained data
$N_{detector}$	number of detectors
K	number of maximum detectable leaks
C	combination operator
V	voltage
σ_M	standard deviation of noise

Chapter 1. Introduction

1.1 Motivation

In the water distribution system, water is supplied from its source to users through a pipeline. During water transfer, often a large amount of water is not supplied to the end user but instead leaks from the pipeline along the pipeline route. According to the International Water Supply Association (IWSA), 20-30 percent of total produced water is not supplied to users [1-4] as a result of several causes including leaks. For example, 250 billion liters of water annually leak from pipelines in the Great Lakes states; this quantity of water could serve the needs of 1.9 million Americans for a year [5]. Unaddressed leaks not only waste resources and money but also cause environmental and social problems, such as sinkholes. Thus, it is very important to quickly and accurately detect leaks to avoid these problems. However, this is not an easy task because most pipelines are buried underground or – in the case of long-distance pipelines – installed in remote regions.

Many methods have been proposed for accurately detecting pipeline leaks. For example, methods include acoustic emission, leak noise correlators (LNC) [6], ground penetrating radar (GPR) [7-9] and pig-mounted acoustic (PMA) sensing [10]. These methods are not suitable for detection of leaks over a wide area or in long-distance pipelines; rather, they are only suitable for inspecting a specific area where leaks are suspected based on prior information, such as a civil complaint. In addition, in cases of these prior methods, surveyors must also be dispatched to the suspected leak area, resulting in significant personnel costs and inspection time.

(a)

(b)

Fig. 1 Existing leak detection system for local area: (a) acoustic emission method, (b) ground penetrating radar method

Other researchers have proposed techniques for monitoring leaks in pipelines over wider areas. Some researchers suggest that analyzing the pressure change of a transient wave can detect the location of a leak [11-14]. However, this method contains uncertainties that are caused by disparities of pipe connectors, foreign substances like rust in the pipe, bending of the pipeline, etc. These uncertainties reduce detection accuracy. To increase the accuracy, detailed information can be added to the numerical algorithm used in the method; however, these additions cause other problems, including increasing the computational load in the numerical model. The added information must also be continually updated as the uncertainties change over time. To overcome these limitations, the time-domain reflectometry (TDR) based leak detection method has been researched.

1.2 Overview of existed TDR Leak Detection System

The suggested methods in this research use time-domain reflectometry (TDR) [15-17], which has fewer uncertainties caused by the configuration conditions of a pipeline than are found in the former method. The TDR technique can inform observers about the state of a transmission line or its periphery through the measurement of a reflected signal on the line. Thus, researchers utilize this method in various situations, such as for monitoring the health state of electronic devices [18, 19], monitoring bridge scour [20, 21], measuring moisture of soil [22, 23] and estimating the amount of fluid in a tank [24]. However, when the TDR technique is applied as a leak detection system, it is challenging to interpret the signal through visual checking or through use of a constant threshold-based criterion. Although TDR-based methods can easily interpret the measured signal when only one leak is present, it is difficult to interpret the inexplicit signal that results from a condition with multiple leaks and periphery noise.

To address these challenges, researchers applied the RLCG-based forward model to this detection system and used Bayesian inference-based inverse model to enhance signal analysis [25]. In RLCG, R is resistance, L is inductance, C is capacitance, and G is conductance. The RLCG-based forward model estimates the TDR signal using lossy transmission line (LTL) theory based on finite-difference time-domain (FDTD). Applying Bayesian inference improves detecting ability in light of the uncertainties of the model and errors of measurement [26, 27]. While these findings have improved the ability to interpret TDR signals, the RLCG forward model has other shortcomings, specifically that it takes long time to generate the trained sample signal. In the Bayesian inference, this drawback causes an increase in the time required to build the sample data set that is used for maximum likelihood. The lengthy time required to build trained sample data set results in limitations of this method's usefulness in long-distance pipelines. This is because as the pipeline length increases, the amount of sample data required to measure likelihood in the Bayesian inference increases as well. These restrictions limit or prevent applying this method in the field, where the length of pipelines can reach tens to hundreds of km, such as in the *Los Angeles Aqueduct*. In particular, a robust leak detection system is most needed in the most challenging circumstances – long-distance pipelines – because pipelines in these settings pass through remote places where it is difficult to detect leaks by human inspection.

1.3 Thesis Outline

In this research, computational efficiency of the forward model is improved by lessening the time required to build the sample data set. This achievement makes it possible to apply the TDR technique for leak detection in long-distance pipelines. This work also proposes a newly developed algorithm to estimate the time required to build the sample data. The detection system proposed in this study is focused only on detecting leaks in the pipe connections, or flanges; it does not attempt to detect leaks in the main “body” of pipes. Leaks in the pipe body are typically easily recognizable, as they usually occur from artificial impacts such as by workers or heavy equipment. Because we can make this assumption based on real-world experience, we can propose a more focused model that benefits from an ability to decrease both the number of leak detectors and the size of the sample data set.

The rest of the paper is organized as follows. First, the background theory is explained in section 2. Next, the proposed multiple-leak inference method using S-parameters is described in section 3. Section 4 outlines an estimation algorithm to calculate the time required to build the sample data. In section 5, the accuracy and efficiency of the suggested model are validated through case studies. Finally, section 6 gives conclusions.

Chapter 2. Background & Literature Review

In this chapter, the theoretical background and literature review is briefly described to enable better understanding of this research. First, the principle of the TDR, which is used to detect leaks, is explained. Second, S-parameters, which are applied to make a forward model, are defined. Finally, the Bayesian inference utilized for locating the leaks in the proposed method is presented.

2.1 Principles of TDR

The TDR was originally proposed as a method to find the location of transmission line faults, such as electrical open, short, or chafe. TDR is, in principle, similar to RADAR, which measures a reflected radio wave to find the locations of objects. Likewise, in TDR, an incident pulse is propagated along the transmission line by TDR instrument and reflected when it meets a fault on the line. This reflected pulse is measured at the TDR instrument. The ultimate cause of the reflection is a disparity of impedance in the transmission line. According to Eq. (1) and Fig. 2, it is clear that a mismatch of impedances between Z_0 and Z_L determines the reflection coefficient between minus one and one, not zero:

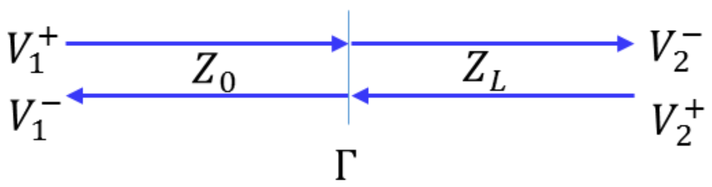
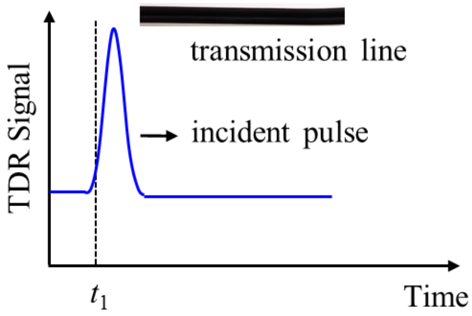


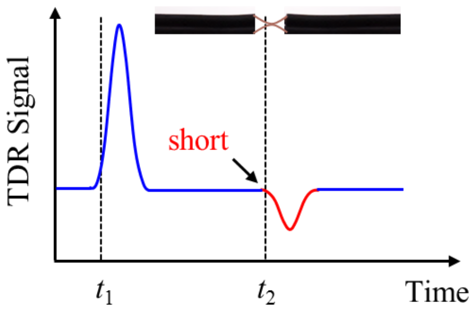
Fig. 2 Impedance disparity and reflected coefficient

$$\Gamma = \frac{Z_L - Z_0}{Z_L + Z_0} = \left[\frac{V_1^-}{V_1^+}\right]_{V_2^+=0} \tag{1}$$

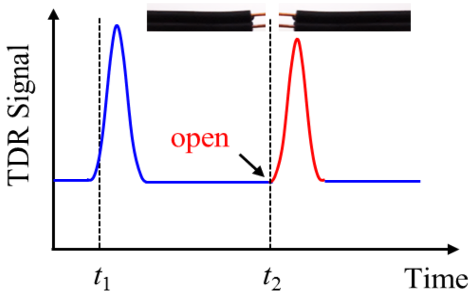
where, Z is the characteristic impedance and Γ is the reflection coefficient. If a Γ is a negative value, the shape of the reflected pulse is upside down for the incident pulse, which indicates an electric short. If the value of Γ is one, the shape of the reflected pulse is the same as that of the incident pulse, which indicates electric open, as shown in Fig. 3.



(a)



(b)



(c)

Fig. 3 TDR signal for electrical: (a) normal, (b) open, and (c) short

The TDR technique can also locate faults, L_f, on the transmission line by calculating the velocity of propagation and pulse traveling time, as in Eq. (2):

$$L_f = v_p \frac{t_2 - t_1}{2} \tag{2}$$

where, t_1 is the incident time when the pulse starts to transmit into the line and t_2 is the arrival time when the reflected pulse is measured at the TDR instrument. v_p is the velocity of propagation of the traveling pulse on the transmission line.

These features of TDR are also useful for a leak detection system. The key here is the similarity between water leakage and an electrical short. An electrical short occurs by abnormal connection of two nodes having different voltages in an electric circuit. Likewise, if the water leakage contacts an electric circuit, it can also cause an electrical short because the leaking water is a good conductor. Fig. 4 shows the proposed operational concept. First, a sensing cable with leak detectors is attached to the pipe. The sensing cable plays the role of the transmission line in traditional TDR technique. Then, the location of leaks can be found by measuring the signal that is reflected from any electrical short that occurs in the leak detection system. This method is described in more detail in sections 3 and 4.

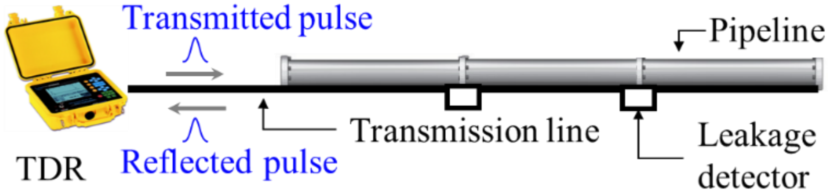


Fig. 4 Concept of leak detection using TDR

2.2 S-parameters

The S-parameters, so called scattering parameters, represent the voltage ratio between the input and output power of an electrical system in the frequency domain. The subscripts of S-parameters signify the port that the electric pulse passes through. The first subscript is an output port where the pulse exits via the port and the second is an input port where the pulse enters the port. S-parameters of two-port units are depicted in Fig. 5 and Eq. (3). Because S-parameters are measured in the frequency domain, the voltage ratio in the time-domain can be acquired by conducting inverse fast Fourier transform (IFFT). In this respect, if the TDR signal is acquired at a specific location on the transmission line in the frequency domain, a time-domain signal at that location can be easily obtained by IFFT. These features of S-parameters are used here to convert the reflected TDR signal that arrives at the TDR instrument into the time domain.

$$\begin{bmatrix} V_1^- \\ V_2^- \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \begin{bmatrix} V_1^+ \\ V_2^+ \end{bmatrix} \tag{3}$$

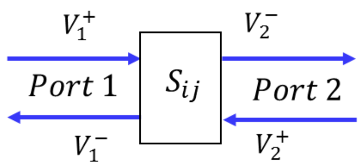


Fig. 5 Concept of S-parameters

2.3 Bayesian Inference

Bayesian Inference is a statistical method that infers posterior distributions of parameters by using prior distributions of those when a new event is given. The basic formula of the Bayesian inference is defined in Eq. (4):

$$\Pr(\theta|y) = \frac{\Pr(y|\theta)\Pr(\theta)}{\int \Pr(y|\theta)\Pr(\theta)\,d\theta} \tag{4}$$

where θ are random variable, y is a new event, and $\Pr(\theta|y)$ is a posterior distribution, which means the updated distribution of θ according to the new event y. $\Pr(\theta)$ are prior distributions, specifically the distributions of each θ before considering the new event y. $\Pr(y|\theta)$ is a likelihood function that stochastically finds the θ that is the most proper to represent y. Because of these features, it is appropriate to stochastically identify an optimal value of each parameter in the numerical models. In addition, it should be noted that this does not have the risk of finding only a locally optimal value of θ because the inference evaluates the likelihood for all samples. A sample means a case determined by θ and the case is compared with y. Generally, a greater sample size has the benefit of more precision in the inference of statistical method. It may have, however, a significant drawback; specifically a significant computational load if generating one sample is time consuming. Thus, to efficiently apply the Bayesian inference in any algorithm, it is important to consider the sample size and the time required to generate each sample. In this research, the sample size of the TDR-based leak detection system is affected by the length of the pipeline. The generating time is also related to the forward model. Therefore, to apply TDR based leak detection system to a long-distance pipeline, the computational efficiency of the forward model is a very important factor in this system.

Chapter 3. Forward Model using S-parameters for Generating a TDR Signal Corresponding to Leakage

This section describes the forward model and an inverse model for detecting pipeline leaks. The purpose of the forward model is to estimate a TDR signal by using information about leaks, such as the number of leaks and their locations. Here, it is important that the modeled signal must well represent the measured signal in real situations. The inverse model then infers the information about leaks using the measured TDR signal. In this research, S-parameters are employed as the method of inducing the forward model to improve computational efficiency. The Bayesian inference is used for the inverse model. This section is comprised of four parts. First, the benefits of the proposed S-parameter based forward model are explained. Second, the operating principle of the forward model is exposited. Third, the method of inducing the forward model is described. Finally, we outline the principle of Bayesian inference based the inverse model. For demonstrating the forward model, the equations established by Stefan Schuet et al [28] are quoted. These equations were originally applied to describe the health state of coaxial cables.

3.1 Advantages of a Forward Model utilizing S-parameters

The TDR signal is a vector of sequent voltages that are measured at the TDR instrument. As shown in Fig. 6, the TDR signal is a white line that is composed of white stars (✰). The white star means a voltage that is measured at the TDR input port per time unit.

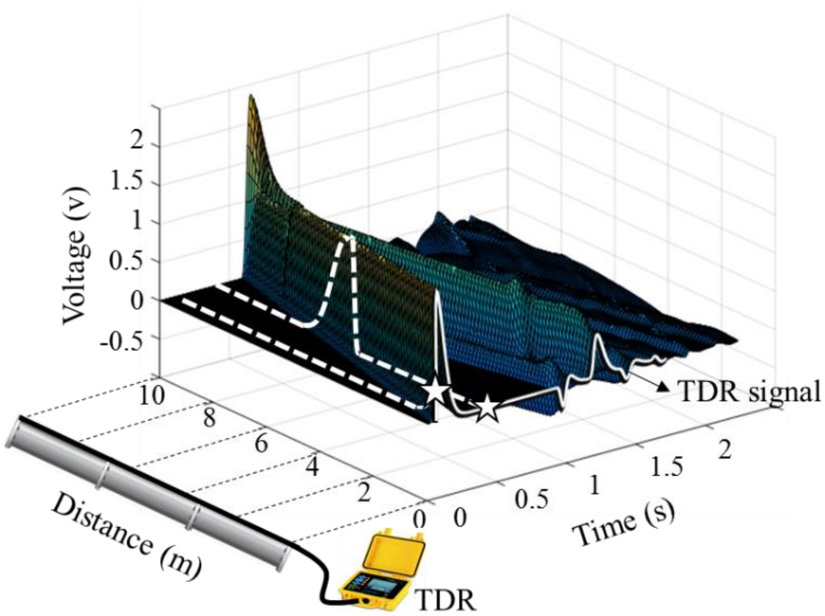


Fig. 6 Voltage distribution on the transmission line in the time domain

(white line: TDR signal; white dotted line: modeled signal based on RLCG)

Thus, the forward model must estimate the white stars. The previous RLCG forward model, based on FDTD, requires calculating the all voltages (- - -, white dotted line) on the attached transmission line to obtain the one voltage (☆, white star) per time unit. However, the S-parameter based forward model does not need to calculate the all voltages. The S-parameter based model obtains the reflected signal in the frequency domain at the distance of zero meter, or the TDR input port. Then, by performing IFFT, the modeled frequency domain signal can be transformed to a reflected signal in the time domain which is same as the white solid line. In other words, the S-parameter based model does not need to consider the white dotted lines.

Thus, the S-parameter based forward model method offers the advantage of reflecting the physical character of the TDR signal. The model also needs also a smaller number of voltage data points to estimate the TDR signal than does the RLCG-based model. For example, if the RLCG forward model has a circuit model comprised of segments of the total transmission line equal to one thousandth of the line, one thousand voltage values are needed to gain one white star per time unit. In this sense, the S-parameter model is a more computationally economical method than the RLCG model.

3.2 Concept of the Forward Model using S-parameters

In As defined in section 3.1, the forward model estimates the TDR signal. The TDR signal is a vector that is composed of sequentially measured voltages. In the Eqs. (5) and (6), $v_M(t)$ is the TDR signal which is a reflected signal in the time domain and V_M is the reflected signal in the frequency domain. The source signal, v_S, is a vector that consists of values of the voltage sequentially generated by TDR instrument in the time domain. V_S is the source signal in the frequency domain. The transfer function, H, generally means a ratio of output values to input values. In this paper, the output values are V_S, the input values are V_M, and H is defined as V_M / V_S. Thus, in the time domain, the forward model, which estimates the TDR signal, v_M, is the right hand side of Eq. (5):

$$v_M(t) = IFFT(H(\omega, \theta) \odot FFT(v_S(t))) \tag{5}$$

where $\odot$ is the element-by-element vector multiplication operation. $v_S(t)$ can be determined by the specifications of the equipment. As in Eq. (6), H is represented in the reflection coefficients, Γ_S and Γ_0, of the connection area between the TDR equipment and the transmission line [28]:

$$H(\omega) = \frac{V_M}{V_S} = \frac{G}{2}\left(1 + \frac{\Gamma_S + \Gamma_0}{1 + \Gamma_S \Gamma_0} e^{-j2\omega t_M}\right) \tag{6}$$

where G is the gain factor and t_M is the internal time delay in the TDR instrument. ω is the continuous frequency that corresponds to the sampling period of the TDR. Γ_S is the reflection coefficient between the impedance of the TDR instrument, Z_S, and the characteristic impedance of the transmission line, Z_0, as shown in Fig. 7 and Eq. (7).

$$\Gamma_S = \frac{Z_0 - Z_S}{Z_0 + Z_S} \tag{7}$$

Γ_0 is the reflection coefficient at the starting point of the transmission line (just to the right side of Γ_S). Γ_0 is not constant, but changeable, because it is affected by the health state of the transmission line. Γ_0 and the method of inducing the forward model are explained in the next section.

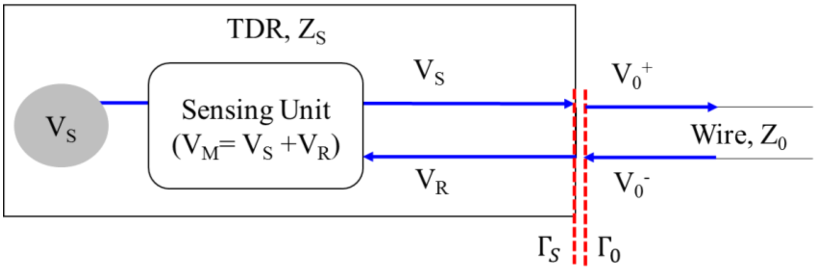


Fig. 7 Operating concept of TDR

3.3 Modeling the Sensing Cable

In this research, the transmission line of the leak detection system is referred to as the sensing cable. The cable can be divided into two types of segments, namely normal segments, N_i, and leakage segments, L_i, as shown in Fig. 8. A disparity of impedance occurs at the boundary between each differing segment due to the electric short caused by the leak. As a result, the reflection of the transmitted pulse occurs at the boundary between segments. As shown in Eq. (6), Γ_0 must be obtained to model the TDR signal. Because the left side reflection coefficient of each segment can be induced from the right side reflection coefficient of it [28], Γ_0 can be inferred from Γ_L. To model the sensing cable, first, a model that can obtain the reflection coefficient of each segment should be made. Next, a totally synthesized model of the sensing cable is completed by connecting the reflection coefficient of each segment. The method of modeling the segments is as follows.

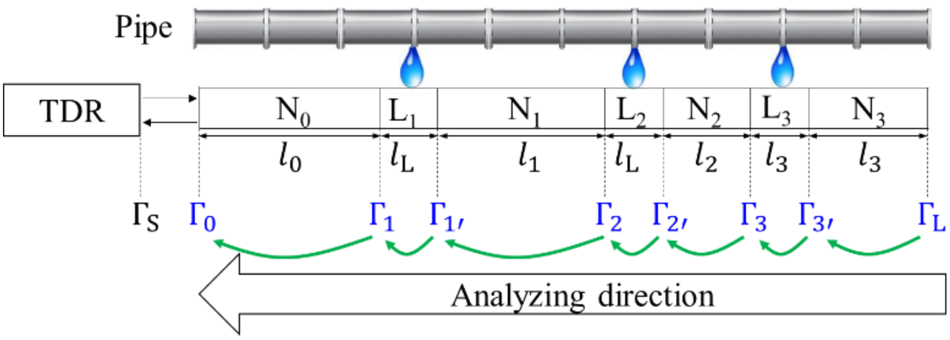


Fig. 8 Model synthesis

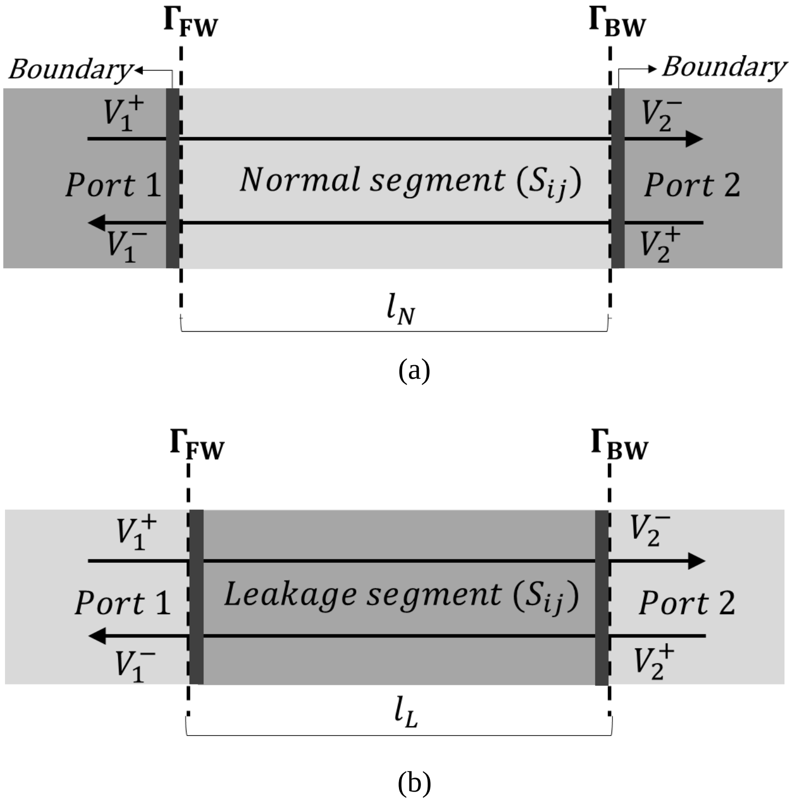


Fig. 9 Modeling the segments of the transmission line: (a) normal segment, (b) leakage segment

Normal segment - As shown in Fig. 9 (a), the area of a normal segment is defined inside the domain, excluding both side boundaries. Thus, Γ_{FW} is just to the right of the front boundary and Γ_{BW} is just to the left of the rear boundary. In addition, the segment can be regarded as a two-port device that has S-parameters. Generally, in a two-port device, Γ_{FW} is defined by S-parameters and Γ_{BW} can be found using Eq. (8) [29]:

$$\Gamma_{\mathrm{FW}} = S_{11} + \frac{S_{12}S_{21}\Gamma_{\mathrm{BW}}}{1 - S_{22}\Gamma_{\mathrm{BW}}} \tag{8}$$

where Γ_{BW} is the same as Γ_{FW} of its backward segment. S_{11} and S_{22} are zero because there is no change of impedance in the normal segment. S_{12} and S_{21} are not zero, but rather represent transmission loss during the travel of the pulse along the segment, as in Eq. (9) [28]:

$$S_{12} = S_{21} = e^{-\gamma l_k} \tag{9}$$

where γ is propagation constant and l_k is the length of the segment. Thus, Γ_{FW} is defined as $e^{-2\gamma l_k} \cdot \Gamma_{BW}$ where γ is defined as Eq. (10):

$$\gamma = \sqrt{[R + j\omega L][G + j\omega C]} \tag{10}$$

where RLCG is a property of the sensing cable. The RLCG of two parallel cables is defined in Table 1.

Table 1 R, L, G, and C of two parallel cables

R[$\boldsymbol{\Omega/m}$]	**L[H/m]**	**G[S/m]**	**C[F/m]**
$\frac{1}{\pi a \sigma_c \delta}$	$\frac{\mu}{\pi}\mathrm{acosh}(\frac{d}{2a})$	$\frac{\pi\sigma_d}{\mathrm{acosh}(\frac{d}{2a})}$	$\frac{\pi\varepsilon}{\mathrm{acosh}(\frac{d}{2a})}$

μ: permeability of dielectric; σ_c: conductivity of conductor; σ_d: conductivity of dielectric; ε: permittivity of dielectric; a: radius of conductor; d: distance between conductors; δ: $1/\sqrt{\pi f \mu_c \sigma_c}$ (μ_c: permeability of conductor; *f*: input bandwidth)

Leak segment - As shown in Fig. 8(b), the area of a leak segment is a defined domain that includes both side boundaries. Thus, Γ_{FW} is the left side of the front boundary and Γ_{BW} is the right side of the rear boundary. This segment can be also analyzed as a two-port device. Unlike a normal segment, here S_{11} and S_{22} are not zero because there are disparities of impedance in the segment. As shown in Eq. (11) and (12), the S-parameters are calculated similarly to S-parameters of a faulty segment in a coaxial cable, as established by Stefan Schuet et al [28].

$$S_{11} = S_{22} = \frac{\Gamma_2\left(e^{-j\omega 2t_d} - 1\right)}{1 - \Gamma_2^2 e^{-j\omega 2t_d}}, \quad (t_d = l_L/v_p) \tag{11}$$

$$S_{12} = S_{21} = \frac{(1 - \Gamma_2^2)e^{-j\omega 2t_d}}{1 - \Gamma_2^2 e^{-j\omega 2t_d}} \tag{12}$$

where t_d is travel time, which is taken while the pulse passes the leak segment, l_L is the length of the segment, and v_p is the propagation velocity of the pulse. The Γ_{FW} of this segment can be also calculated using Eq. (8). Γ_{BW} of this segment can also be acquired from Γ_{FW} of its backward segment.

Model Synthesis - The entire sensing cable can be thus modeled by combining these two types of segments. Fig. 8 shows an example of a pipeline with three leaks. The pipeline has four normal segments, N_i, and three leakage segments, L_i. Γ_{BW} of each segment overlaps with Γ_{FW} of its backward segment. The value of Γ_L, as is already known, is one as it is the reflection coefficient of the open circuit at the end point of the sensing cable. Γ_0 can then be induced from Γ_L by acquiring Γ_{FW} for each segment. Using the obtained Γ_0, $H(\omega)$ can be found using Eq. (6). When $H(\omega)$ is substituted into Eq. (5), the S-parameter based forward model is completed.

Chapter 4. Estimation Algorithm to Determine the Time required to Build the Trained Sample Data Set

This section explains the algorithm used to estimate the time required to build the trained sample data set. The training data set includes modeled TDR signals of all cases covering all possible leak situations. The training data can then be compared to the measured TDR signal to determine the likelihood of leak locations. To detect leaks in real time, the comparison must be performed rapidly. To that end, the whole data set must be built in advance before completion of construction of the water distribution system because building the training data set is a surprisingly time-consuming process. Once built, the training data set can be used repeatedly, because the data set doesn't change as long as the configuration of pipeline doesn't change. However, the time required to build the data set is significant. Thus, the training data set may not be built during the construction period of the pipeline due to the design conditions of the system, such as the total length of the pipeline, the length of each pipe unit, the number of maximum detectable leaks, *K*, and the computational efficiency of the forward model. With this in mind, an estimate of the time required to build the data set is useful before construction starts.

The total time required to build the trained sample data set, T_{tot}, is defined by multiplying the total number of training data, $N_{training\ data}$, by the time required to generate one instance of trained sample data, t_{sample}.

$$T_{tot} = N_{training\ data} \cdot t_{sample} \tag{13}$$

$N_{training\ data}$ is determined by the number of leak detectors needed in the system, $N_{detector}$, and the number of maximum detectable leaks, K. In this system, $N_{detector}$ is the same as the number of flanges in the pipeline except for the beginning and end flanges. This number is obtained by dividing the length of the total pipeline by the length of each pipe unit and subtracting one, because a detector is installed on each connecting flange. The formula of $N_{training\ data}$ then follows, as shown in Eq. (14):

$$N_{training\ data} = \left(\sum_{i=1}^{K} C(N_{detector}, i) \right) + 1 \tag{14}$$

where C is the combination operator. $C(N_{detector}, k)$ refers to the number of cases when the number of leaks is k. The last term (+ 1) adds to the formula to account for the case of a normal situation without any leaks. Thus, the formula of $N_{training\ data}$ accounts for the total number of all possible leakage situations, from no leakage to the maximum number of leaks. Thus, t_{sample} can be obtained by averaging the consumed time for various case studies, as described in the next section.

Chapter 5. Case Study

In this section, the accuracy and efficiency of the suggested leak detection system are validated through case studies. First, the experimental test bed is briefly described. The test bed is then validated by applying a real leak situation to the test bed. Next, parameters of the forward model are calibrated by using experimental data acquired from the experimental results of both the normal and single-leak situations. Next, the accuracy of the forward model is validated by comparing the modeled signal with the measured signal under a two-leak situation. Further, the accuracy of the Bayesian inference is demonstrated by comparing the training data set and the measured TDR signal under a three-leak situation. The three-leak situation generates an inexplicit TDR signal that is hard to interpret through visual inspection due to the overlapped reflection. Finally, the time required to build trained sample data set is estimated according to various lengths of pipeline by using t_{sample}, which is obtained through the case studies.

5.1 Description of the Experimental Test Bed

A custom test bed was designed at the lab scale, as shown in Fig. 10. This system is comprised of three parts, including the pipeline, the leak detectors, and a data acquisition system. The pipeline is made up of four 3 meter-long pipes with 12 centimeter radius and additional components to enable the TDR technique to be applied, including a sensing cable and an outer housing case at the joints. These components are not found in a regular pipeline. A twin parallel cable that is made from copper wire with 0.4 millimeter radius is used as the sensing cable in the test bed.

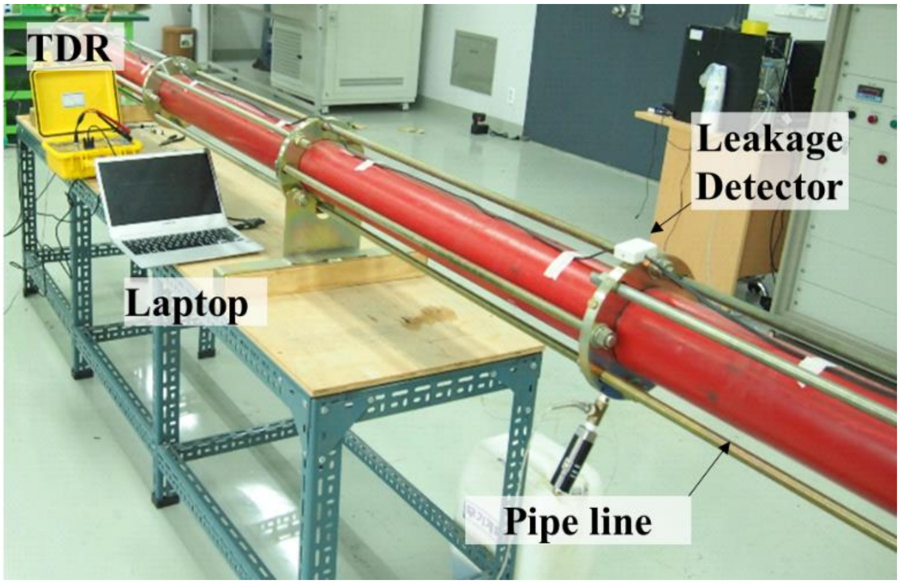
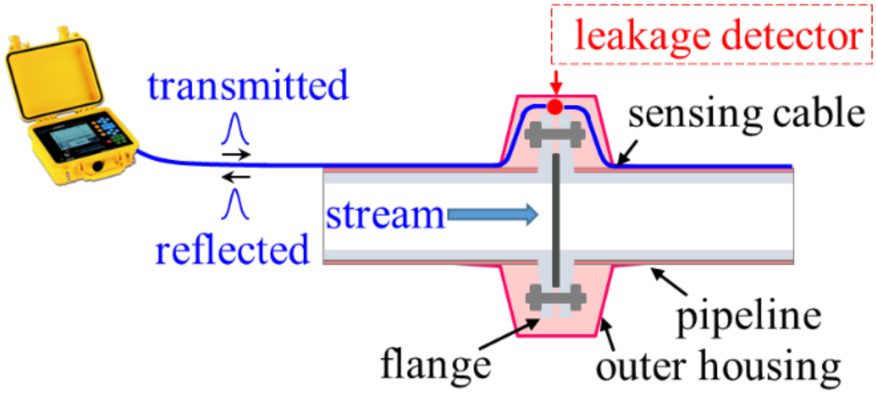
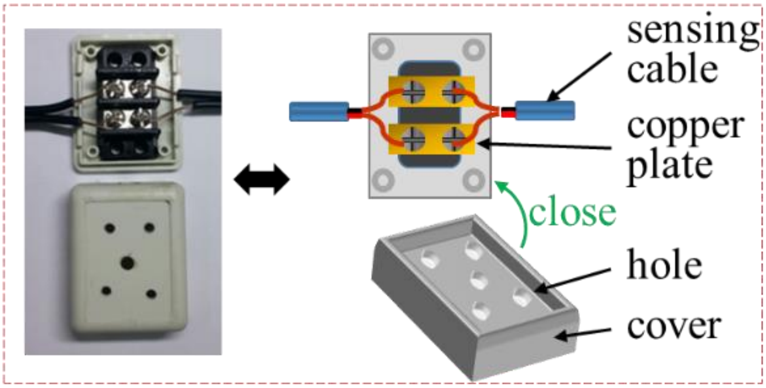


Fig. 10 Experimental test bed for validating the forward model

The outer housing case is installed around joints where leakage is likely to occur. The housing plays the role of a reservoir for the leaking water, ensuring the leak detector gets wet. This wetness in turn causes an electrical short at the detector and the reflection of the pulse at the location of the short. The leak detector consists of two copper plates and a plastic case with holes, as shown in Fig. 11. The detector is isolated from external moisture by the outer housing, and is thus only affected by leaking water at the joint. The copper plate is also exposed to contact with the leaking water; the water then plays the role of a conductor between the two plates. The data acquisition part is composed of the TDR instrument and a laptop. The model of TDR instrument in the test setup is an mTDR-070 from Nanotrinics Corp. with an input bandwidth of 300 MHz, output pulse of two volts, rising time of 1ns, maximum effective distance of 20 kilometers, and a characteristic impedance of 75 Ω. The laptop specifications include an Intel core i5 3.1 GHz processor with eight GRAM. The TDR instrument is connected to the start of the sensing cable to transmit the pulse and receive the reflected pulse. The TDR instrument is connected also to the laptop for analyzing the acquired data.



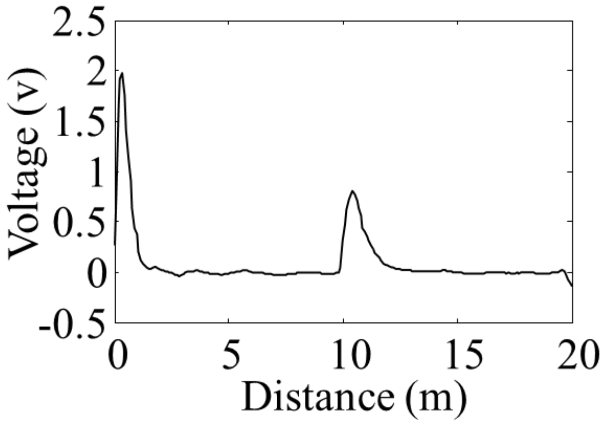
(a)



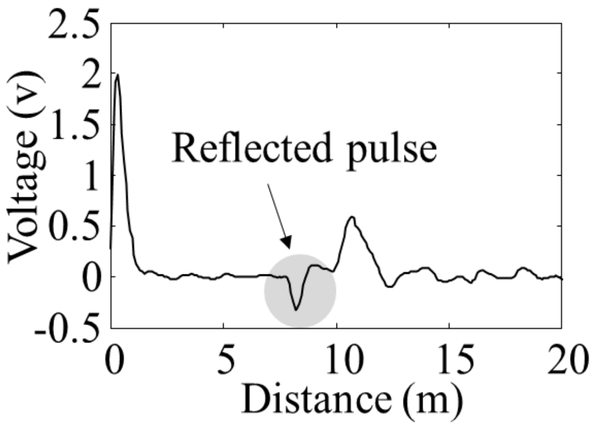
(b)

Fig. 11 Leak detection system: (a) system components, (b) leak detector

Normal operation of this system was demonstrated through a simple experiment that was conducted using a 10 meter cable with one leak detector installed 8 meters along the cable. Then, the leak detector was attached to the flange and a leakage situation was applied to the system. The reflected pulse signal from the leakage was observed as shown in Fig. 12. To test a situation with multiple leakage signals under various situations with several detectors, tests were manually performed to intentionally change the gap between the leaks.



(a)

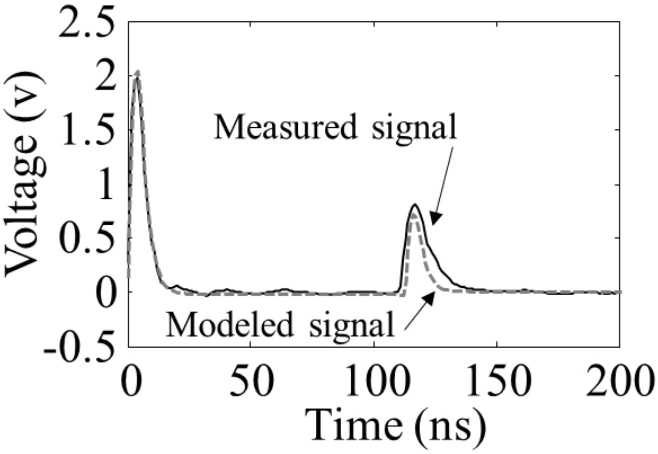


(b)

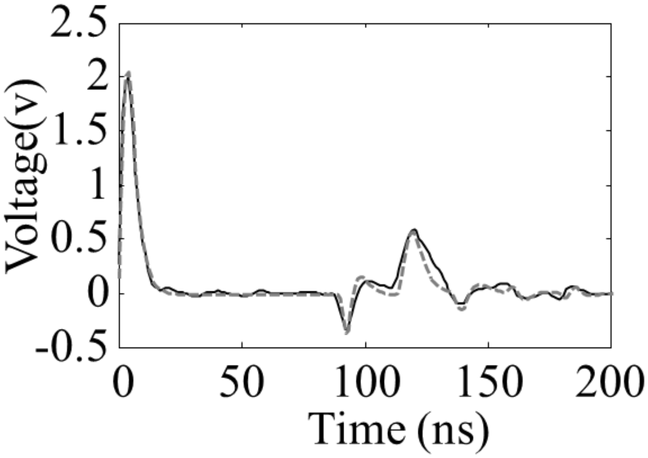
Fig. 12 Operation check of the leak detector: (a) no leak, (b) single leak at 8m

5.2 Validation of Accuracy of the Forward Model and the Bayesian Inference

Before the developed forward model is used, the constant parameters in the forward model need to be calibrated. Although these parameters were determined based on a review of the literature, known properties of the material, and specifications of the chosen equipment, some parameters inevitably have uncertainties.



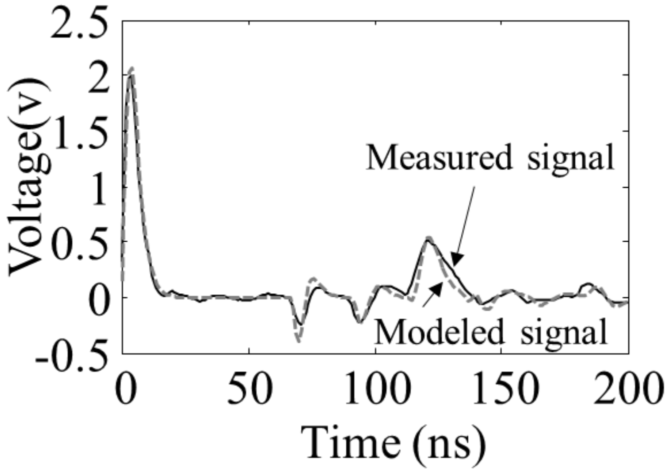
(a)



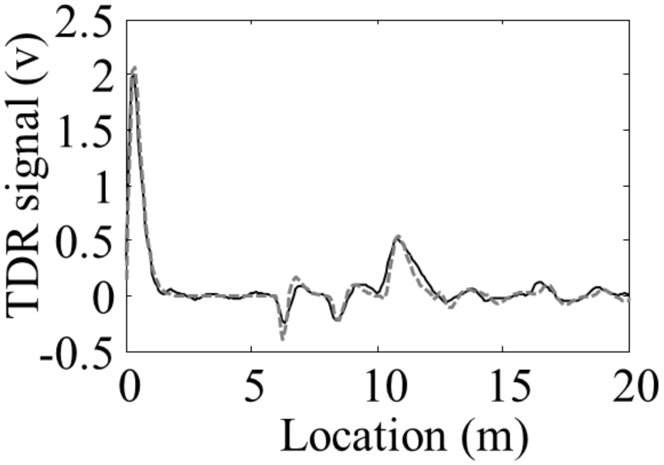
(b)

Fig. 13 Comparison between measured signal and modeled signal: (a) no leak, (b) single leak at 8m

In order to decrease the effect of the uncertainties, calibration of the parameters was conducted using the *least square method* (LSM) between the measured and the modeled signal under situations with no leaks and with a single leak, as shown Fig. 13. After calibration, the accuracy of the forward model was validated by comparing the measured signal to the modeled signal under the multiple-leak situation. The pipe in the experimental setup is 10m long with two leaks at 6m and 8m. As shown in Fig. 14, the forward model accurately represents the TDR signal. It is also converted to the distance domain to arrive at more practical information, specifically, the predicted leak locations. Table 2 examines the accuracy of the forward model by comparing the TDR signal estimated by the model and the signal measured by the TDR instrument. The stochastic measures used are *Correlation Coefficient, Weighted Integrated Factor* (WIFac) and standard deviation of noise (σ_M). The *Correlation Coefficient* and WIFac represent the accuracy of the model in the aspect of shape and σ_M represents the error of the model. The *Correlation Coefficient* has a value between minus one and one. Here, minus one is total negative correlation, zero is no correlation, and one is total positive correlation. The WIFac has a value between zero and one. In case of the WIFac, the value means a degree of match between the two signals and one means perfect match. As shown Table 2, the WIFac value falls a little short of one because of difference of magnitude of the signals caused by periphery noise and physical uncertainties included in this system. The *Correlation Coefficient* related to tendency of peaks of the signals is close to one. The peak locations of the signals is important factor for inferring the leak locations in this detection system. Thus, the suggested forward model is appropriate to use the proposed leak detection system.



(a)



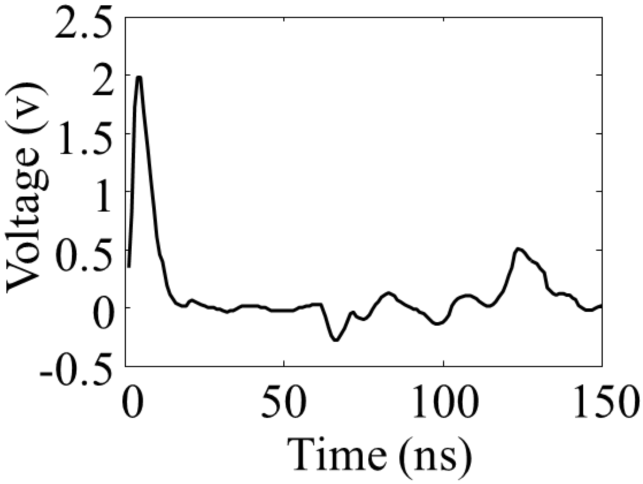
(b)

Fig. 14 Validation of the forward model with two leaks (6m and 8m) on the 10 m cable: (a) time domain, (b) distance domain

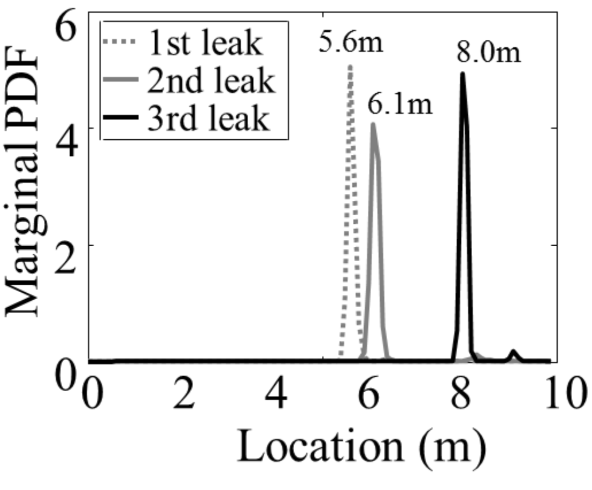
Table 2 Comparison of similarity between real measured TDR signal and virtually generated TDR signal

Measure	Correlation coefficient	WIFac	σ_M
value	0.9869	0.8621	0.06

The Bayesian inference was then validated using the training data set, which was made using the forward model, as described in the section 4. The given condition is a multiple-leak situation that has three leaks in a 10 meter pipe. The locations of the leaks are at 5.5 meters, six meters, and eight meters. As shown in Fig. 15 (a), the signal is not explicit and thus cannot be interpreted by visual inspection. However, the location of the leaks can be stochastically found through Bayesian inference, as shown in Fig. 15 (b), which shows the marginal PDFs of each parameter around the location of the leaks.



(a)



(b)

Fig. 15 Bayesian inference for finding the location of leaks: (a) measured TDR signal, (b) location of leaks

5.3 Estimating the Time required to Build Sample Data Set for a Long-Distance Pipeline

As described in section 4, to estimate T_{tot}, t_{sample} must be obtained. The t_{sample} is calculated using the results of case studies that are performed for various lengths of pipelines. However, a lab setting limits the opportunity to extend a sample pipeline. Thus, to examine various situations, we assumed that the length of each pipe unit ranged from one meter to 0.1 meter under the given length of our sample pipeline, 10m. This enabled us to examine different numbers of flanges and allowed $N_{detector}$ to increase, achieving the same effect as extending the length of the pipeline. As shown in Table 3, $N_{detector}$, $N_{training\ data}$, T_{tot} and T_{sample} were acquired according to the length of each unit pipeline with three maximum detectable leaks, K. The average of t_{sample} was approximately 0.00263 second. This result was also calculated using the laptop with an Intel core i5 3.1GHz processor and eight GRAM and MATLAB. Thus, the t_{sample} can be a changeable value depending on computer performance. If this system were to be used with a high-performance computer such as a supercomputer, t_{sample} can also be reduced. This also means that the system suggested in this research can be effectively applied to actual field situations that use higher-performance computers than the laptop used in this research.

Table 3 The T_{tot} and t_{sample} with three maximum detectable leaks, as predicted by each forward model

Length of unit pipe	1 m	0.5 m	0.2 m	0.1 m
$N_{detector}$	9	19	49	99
$N_{training\ data}$	130	1,160	19,650	161,800
T_{tot} [s]	0.34	3.03	51.42	433.15
t_{sample} [s]	0.002615	0.002612	0.002617	0.002677

Table 4 The T_{tot} in the field with three maximum detectable leaks

Length of pipeline	t_{sample}	1 km	5 km	10 km	20 km	30 km
$N_{detector}$	-	99	499	999	1,999	2,999
$N_{training\ data}$	1	161,800	20,709,000	166,168,000	1,331,336,00	4,495,504,000
T_{tot} ($t_{\text{sample}} \times N_{training\ data}$)	0.00263s	0.12h	15.22h	122.15h (5.09 days)	978.63h (40.78 days)	3,304.53h (137.69 days)

Table 4 shows the total estimated T_{tot} of all training data for various lengths of pipeline, using Eqs. (15) and (16), with a 10m pipe and 3 maximum detectable leaks.

T_{tot} is obtained by multiplying $N_{training\ data}$ by t_{sample}. If the length of the pipeline is same, the T_{tot} depends on the K which affect the $N_{\text{training data}}$. When the K increases, the T_{tot} also increases. On the other hand, when the K decreases, the T_{tot} must also decrease. The K and T_{tot} relationship reflects the trade-off between multi-detection capabilities and the cost of the time required to generate the sample data set. This process can be applied in practice to various lengths of pipelines and different numbers of maximum detectable leaks.

Chapter 6. Conclusion

A novel TDR-based leak detection system using an S-parameter forward model has been presented in this paper. The application of S-parameters improves the computational efficiency of the forward model and shortens the T_{sample} of the trained sample data needed for Bayesian inference. The Bayesian inference based inverse model can stochastically detect the location of leaks from an inexplicit TDR signal that includes noise and overlapped reflection. Moreover, the time estimation algorithm developed here predicts the T_{tot}, using the configuration information for the particular pipeline of interest. To demonstrate the performance of the suggested leak detection system, laboratory experiments were conducted using a sample pipeline, leak detectors, a sensing cable, and TDR instrument. To simulate a long-distance pipeline, the length of each pipe unit was intentionally controlled at various lengths from one meter to 0.1 meter. Through the case study, the accuracy of the proposed S-parameter based forward model was validated by various measures and t_{sample} was also obtained by averaging the results of different case studies. Using the t_{sample}, the T_{tot} for various conditions, including different lengths of pipeline and a varying number of maximum detectable leaks can be estimated.

As a result of this research, it is significantly meaningful that a multiple-leak detecting technique can be applied to a water distribution system. Some people may think that a conventional TDR-based leak detection method is sufficient to detect pipeline leaks because the possibility of multiple leaks occurring simultaneously in any given pipeline is low. In addition, if it is easy to access the location of a particular leak, maintenance can be quickly performed as soon as a leak is detected and before another leak occurs. However, in actual pipeline applications if other leaks occur before an existing leak is repaired the usefulness of the conventional TDR-based method is limited. In addition, it can be difficult to perform quick maintenance on pipelines due to difficult accessibility (e.g., pipelines installed underwater or in desert or alpine regions). Moreover, the crustal movement of an area with installed pipelines, such as an earthquake, uplift of strata, ground sinking, or various external shocks, can force a change in the geometry of a long-distance pipeline. These phenomena may cause misalignment of a pipeline and generate multiple leaks at the flanges. Even though the non-trivial procedure of building a training data set is required for use of our proposed system, the suggested multiple-leak detection system offers significant long-term advantages, particularly in situations involving long-distance pipelines.

In terms of return on investment (ROI), the economic feasibility of the proposed detection system is superior to any existing method, including LNC, GPR, and PMA methods. While the TDR installation of this leak detection system, in terms of investment, *could* be regarded as an additional cost, the TDR installation, in terms of return, should not be regarded as an additional cost, but rather as an investment that will pay back in economic profits. In this regard, the installation of TDR system should be analyzed from the perspective of its long-term cost savings. First, in terms of operational cost reduction, the suggested method doesn't require surveyors and equipment to be dispatched for detecting leaks, unlike existing detection methods, because the proposed system can remotely monitor a wide area in real time. This advantage could derive benefits such as substantial labor cost savings. Second, in terms of cost avoidance, the price of the TDR instrument installed in the leak detection system is cheaper than it would be for electronic monitoring because the latter requires the TDR instrument with high resolution. In contrast, our suggested detection system requires only the TDR with moderate-resolution, which is able to accurately identify the distance between the detectors. In addition, our more robust system can also prevent the occurrence of costs related to economic, social, or environmental issues caused by being continuously unaware of leaks. Third, in terms of revenue growth, the net profit of the water industry is expected to gradually increase because of the reduction of non-revenue water (NRW) losses through more rapid maintenance to fix leaks.

If the economic efficiency of installation of the system is demonstrated in the long term, this leak detection system is also expected to be useful for sewer lines and wastewater pipelines. Generally, a leak of a sewer line or wastewater pipeline system is not related to an economic cost in the short term, so the effort put toward preventing leaks in these systems is relatively less than that observed for water distribution systems. However, leakage of sewage and wastewater may cause various environmental, economic, and social problems. First, the leakage causes soil and underground water contamination. It negatively impacts human health through agricultural products and can contaminate drinking water. Second, the contamination of soil and underground water leads to considerable remediation costs in the long term. Finally, the continuous leakage of wastewater pipelines can cause disasters such as sinkholes, in which a hole is made by the collapse of the ground surface as a result of a leaking pipeline below ground [30]. This situation may result in great a catastrophe causing many casualties. Thus, applying the proposed TDR system to sewer lines and wastewater pipelines could prevent these problems in the long term.

Future work related to this research will be expanded to examine the network structure of pipelines because this research is only applicable to a single pipeline. As a result, this method would need multiple TDR instrument stations to cover a networked pipeline structure. In the case of coaxial cable, Xiaolong Zhang has examined the failure diagnosis technique of a cable network using a TDR-based system using a modeling splitter and tap [31]. However, to be robust to noise and improve interpretability of the TDR signal for multiple leaks, a Bayesian inference based network detection technique must be developed. Thus, to reduce the amount of required equipment and cost, the authors will seek to develop a method that efficiently detects leaks in a networked water distribution system.

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국문 초록

상수도 파이프라인에서 발생하는 누수들은 경제적, 환경적, 사회적 문제들을 발생시킨다. 이러한 누수를 감지하기 위해서 베이지안 추론을 활용한 시간영역반사계(time domain reflectometry: TDR) 기반의 누수탐지 기술이 연구되고 있다. 그러나 이 기술은 베이지안 추론 시 필요한 샘플데이터를 구축하는데 걸리는 소요시간과 샘플데이터의 방대한 크기로 인해서 장거리 파이프를 포함하여 실제 적용하는데 실용적이지 못하다.

이러한 문제점을 해결하기 위해서 본 연구에서는 두 가지 새로운 방법을 제안한다. 첫 번째는 샘플데이터의 크기를 감소하기 위해 S-파라미터 기반의 전진모델 개발이며, 두 번째는 전체 샘플데이터를 구축하는데 걸리는 소요시간 예측 알고리즘 개발이다. 기존 전진모델의 경우, TDR 장비와 탐지 케이블의 모든 전압에 대한 모델링이 필요하였지만, 제안한 S-파라미터 기반의 전지모델은 탐지 케이블은 제외한 TDR 장비의 입력 전압에 대해서만 모델링이 필요하다. 따라서 제안한 누수탐지 방법에서는 탐지선의 전압은 TDR 신호를 모델링은 필요하지 않다. 그러므로 각 전진모델에서 필요로 하는 샘플데이터의 크기를 고려하였을 때 S-파라미터 기반의 전진모델이 기존의 전진모델보다 계산비용 관점에서 훨씬 효율적인 모델이라고 할 수 있다. 게다가, 샘플데이터 구축시간을 예측하기 위해 제안된 알고리즘은 시스템 사용자에게 TDR 기반 누수탐지 시스템이 특정 조건에서 파이프 라인의 공사기간과 구축소요시간을 비교하여 실용적인지를 판단할 수 있게 해준다.

이 제안된 방법은 실험실 규모에서 파이프, 누수탐지기, 탐지선, TDR 장비를 사용하여 검증을 하였다. 실험을 통해서 장거리 파이프라인에서 제안된 S-파라미터 기반 전진 모델의 실용성 또한 검증하였다.

주요어: 누수탐지 시스템
상수도 시스템
S-파라미터
장거리 파이프라인
시간영역반사계
베이지안 추론
전진모델
역 모델

학 번: 2014-20662