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NON-DESTRUCTIVE TESTING OF CIPP DEFECTS USING A MACHINE LEARNING APPROACH

NEPORUŠNO TESTIRANJE CIPP NAPAK Z UPORABO PRISTOPA STROJNEGA UČENJA

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In civil engineering, retrofitting actions involving repairs to pipes inside buildings and in extravehicular locations present complex and challenging tasks. Traditional repair procedures typically involve disassembling the surrounding structure, leading to technological pauses and potential work environment disruptions. An alternative approach to these procedures uses the cured-in-place-pipe (CIPP) technology for repairs. Unlike standard repairs, CIPP repairs do not require a disassembly of the surrounding structures; only the access points at the beginning and end of the pipe need to be accessible. However, this method introduces the possibility of different types of defects.[1] This research aims to observe the defects between the host and newly cured pipes. The presence of holes, cracks, or obstacles prevents achieving a desired close-fit state, ultimately reducing the life expectancy of the retrofitting. This paper focuses on the non-destructive observation of these defects using the non-destructive testing (NDT) impact-echo (IE) method. The study explicitly applies this method to the composite segments inside concrete host pipes, forming a testing polygon. Previous results have indicated that the mechanical behaviour of cured composite pipes can vary in stiffness depending on factors such as the curing procedure and environmental conditions.[2] The change in acoustic parameters such as resonance frequency, attenuation and other features of typical IE signals can describe the stiffness evolution. This study compares different sensors used for the proposed IE testing, namely piezoceramic and microphone sensors. It evaluates their ability to distinguish between the defects present in the body of a CIPP via a machine-learning approach using random tree classifiers.

Keywords: retrofitting, cured-in-place pipes, non-destructive testing, impact-echo method, pipe defects, acoustic parameters, machine learning, classification

Popravila in modifikacije (angl.: retrofitting actions) starih cevovodov v že izdelanih zgradbah in na posebej obremenjenih zunanjih vozliščih predstavlja poseben in zahteven gradbeniški poseg. Običajni ali standardni postopki popravljanja cevovodov so sestavljeni iz celotnega razstavljanja okoliške strukture. To vodi do tehnoloških premorov in potencialno tudi do neželenih motenj v okolju. Alternativa k tem pristopom je uporaba tehnologije oz. postopka popravila cevovoda na licu mesta (CIPP; angl.: cured-in-place pipes). Za razliko od standardnega postopka popravila cevovodov, CIPP ne zahteva celotne demontaže okoliške strukture. Potrebno je zagotoviti dostop do začetka in konca cevovoda. Vendar pa s to metodo lahko popravimo le določene vrste napak na cevovodih.[1] V članku avtorji opisujejo opazovanje napak med obstoječimi in na novo popravljenimi cevovodi. Vendar pa prisotnost lukenj, razpok ali ovir preprečuje, da bi dosegli popolen dostop, ki bi omogočal idealen postopek popravila. To pa dokončno zmanjšuje pričakovano dobo trajanja popravljenega cevovoda. V tem članku se avtorji osredotočajo na neporušna opazovanja napak v cevovodih s pomočjo NDT (angl.: non-destructive testing) udarno-odbojne zvočne metode (IE; angl.: Impact-Echo method). Pri tej metodi mehanski udarci povzročajo valovanje zvoka skozi medij, ki je moteno zaradi prisotnih napak v materialu. V pričujoči študiji so avtorji to metodo uporabili direktno za testiranje posameznih segmentov kompozitnih CIPP cevovodov. Predhodni rezultati raziskav[2] so pokazali, da je mehansko obnašanje oziroma togost popravljenih CIPP kompozitnih cevovodov odvisno od izbranega postopka popravila in okoljskih pogojev. Sprememba akustičnih parametrov kot so resonančna frekvenca, atenuacija (pojemanje) in druge karakteristike tipičnih IE signalov lahko opišejo razvoj togosti. V članku avtorji opisujejo primerjavo med različnimi senzorji (piezokeramičnimi in mikrofonskimi), ki so jih uporabili za predlagan način IE testiranja. S tem so ovrednotili njihovo sposobnost razlikovanja med prisotnimi napakami v jedru CIPP s pomočjo pristopa strojnega učenja in z uporabo treh naključnih klasifikatorjev.

Ključne besede: retrofiting, obdelava oziroma popravilo cevovodov na licu mesta, neporušno testiranje, vpliv metode "mehanski udarec in odboj zvoka", napake na cevovodih, akustični parametri, strojno učenje, klasifikacija

1 INTRODUCTION

The IE method has found wide application in the construction industry due to its simplicity, low cost of implementation and relatively wide range of applications.[3] At the same time, the IE method is dependent on the correct interpretation of the measured data. In practice, it has been found to be applicable in measuring pile lengths, localizing cracks in massive monolithic structures, delaminating bridge bodies, diagnosing the condition of concrete elements, etc. Due to its simple principle of testing, there are many variations of the IE method, for example, the low-frequency pulse-echo method.

So far, however, the IE method has not found significant application in measuring defects in sewer lines and product pipelines. These are linear structures made of concrete, ceramics or steel, which can, in principle, be measured using similar methods to those commonly used for structural concrete. For example, a typical concrete oven may be designed for type XF4 (highly saturated

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with de-icing agents or seawater) and XA1 (weakly aggressive chemical environments). These ovens commonly suffer from degradation due to abrasion, chemical exposure, mechanical stresses, wear and tear, and need to be repaired over time. This can be done by excavating and replacing the entire pipe or with a trenchless technology. The CIPP method can be used in this area.[4]

During this process, the host pipe is lined with a resin-saturated insert forced into the pipe by water or air pressure. This liner is then cured with elevated temperature (above 60 °C) using air or water. The high pressure of the medium also allows the liner to make close contact with the host pipe. The elevated temperature starts the polymerization reaction, and the liner is cured, forming a new pipe profile.

However, due to the nature of the curing process, defects may occur. For example, in large diameter pipes, resin washout may happen in the event of high water pressure in the ground body. Caverns and longitudinal thin cavities are formed in some areas of the pipe, reducing the pipe's overall life.

Depending on the type of pipeline, holes will be cut into the branch and connection pipelines using a manual or robotic cutter. In some cases, however, not all of the original connections are connected, creating blind connections and, therefore, a cavity behind them.

The condition of pipelines is currently most often assessed visually using camera surveys, and it must be emphasised that the poor condition of a pipeline can only be recognised when the degradation is intolerable. At selected locations, for example, semi-destructive tear tests can be carried out with some reliability, but often only to confirm the poor condition of the pipeline. Other tools are not used in the domestic market to assess the extent of pipeline degradation or locate this degradation. From this perspective, it would be helpful to have a tool that can determine the state of degradation of a host pipeline or defects in a newly repaired pipeline, and monitor selected sections over time to assess the evolution of their conditions.

2 EXPERIMENTAL PART

As part of field measurements on two pipe liners at the test polygon, using the KAWO liner in collaboration with company WOMBAT s.r.o., a test measurement was carried out using the impact-echo method and a microphone. This measurement was focused on trying to recognize different types of common defects on the CIPP liner. The testing polygon with all simulated defects is shown in **Figure 1**. The whole polygon is shown in **Figure 1a**. The KAWO liner tightly fitted to the host pipe (referred to as the "wall") is shown in **Figure 1b**. The cavern defect behind the KAWO liner is presented in **Figure 1c**. When there is a big thin gap between the host pipe and the liner, the defect is defined as a free-end, shown in **Figure 1d**. Defects are defined based on retrofitting practices. The cavity is a typical defect, where the space behind the liner wall allows the accumulation of debris. The free-end represents the state where there is a thin space between the host pipe and the liner and it is a specific type of cavern defect. The whole polygon was 14 m long, the inner height was 1350 mm, and the width of the largest span was 900 mm.

The microphone was hand-held, and the hammer impacts were done from a 100-mm distance. Each signal was composed of inputs from the microphone and the force sensor.

The longitudinal axis of the measured pipe was chosen along different parts of the estimated profile. The axis is shown in **Figure 2** and **Figure 3**. It was determined according to previous measurements on the free part of the cured liner, accessible from the inside and outside between the concrete tubes. A broadband piezoceramic transducer measured the natural resonant frequency on these parts. The frequency at the estimated point E was 470 Hz. At points C and G, it was 731 Hz; at the upper part, at point A, the resonant frequency was 789 Hz. This insert part is not dampened against self-vibration, and its natural resonant frequency is measurable. However, this situation is artificially created by the design of the test polygon.

(a) (b) (c) (d)

Figure 1: Illustration of tested materials and structures: a) testing polygon with concrete sewage pipes and a cured-in-place pipe; b) representation of the close-fit state; b) cavern behind the polymer pipe; c) free-end without a close-fit state

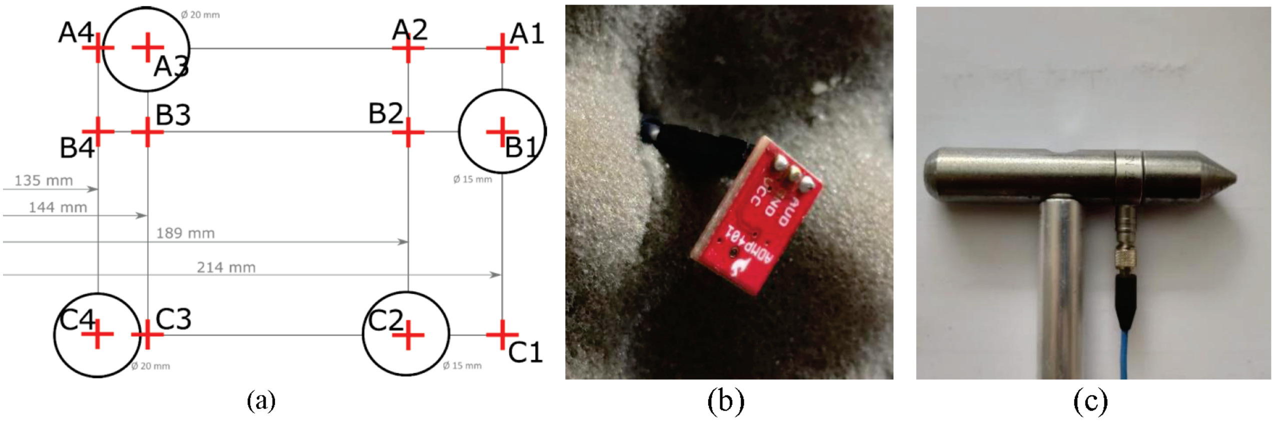

Figure 2: Set-up for axis testing and the used measuring devices: a) testing points at the first cross-section of the CIPP; b) microphone used for recording; c) hammer with a piezoelectric ring for signal excitation

A MEMS microphone ADMP401 and a modal hammer with a built-in ring force sensor for exciting signals were used to acquire signals. The signals were recorded by a Handyscope HS3 digital oscilloscope with 16-bit resolution and sampling frequency of 193 kHz. The recorded data were processed using the MATLAB software, namely Machine Learning Toolbox, Statistics, and Feature Extraction Toolbox, and for continuous wavelet transforms, a fast wavelet library was used.[5]

For the feature extraction, a Predictive Maintenance Toolbox was used, which allows us to design functions for extracting features from both signal and frequency spectra. This toolbox is designed to create a feature extraction algorithm, which focuses on several acoustic metrics.

The root mean square (RMS) is a statistical measure used in acoustics to quantify the magnitude of a varying signal. It is particularly useful for measuring the average power of an audio signal over time. By squaring the signal values, averaging them, and then taking the square root, the RMS provides a single value that represents a signal's overall energy level. This metric is crucial in assessing the sound intensity and ensuring consistent audio levels in various applications, from music production to noise monitoring.[6]

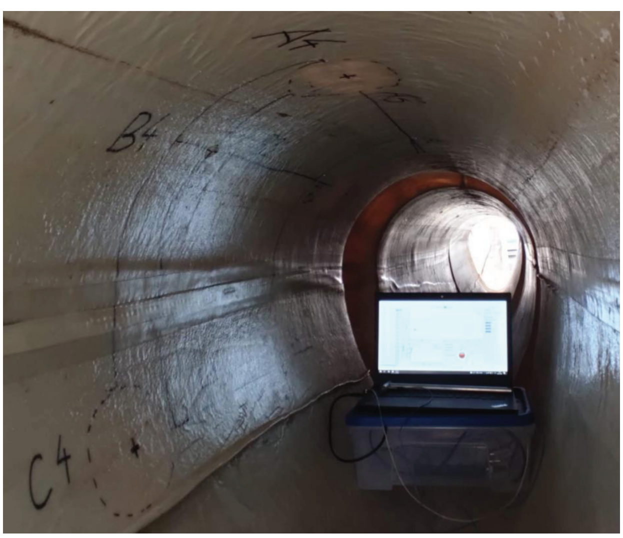

Figure 3: Image from the inside of the pipe, with a testing grid of a semi-section of the tube. The light is coming through the A4 testing point, where a 'cavern' type of defect is present

The signal-to-noise ratio (SNR) is a key metric in acoustics that quantifies the relationship between the desired signal and the background noise. Expressed in decibels (dB), the SNR measures how much a signal stands out from the noise. A higher SNR indicates a clearer, more distinguishable signal, essential for high-fidelity audio reproduction, speech intelligibility, and effective communication systems. Improving the SNR is a primary goal in audio engineering, leading to better sound quality and listener experience.[7]

To further support the differences between the signals of all three classes, band power and signal frequency are also extracted from the signals. For training the models, the whole set of variables, supported by the Predictive Maintenance Toolbox was used: Clearance Factor, Sensor Crest Factor, Sensor Impulse Factor, Sensor Kurtosis, Sensor Mean, Sensor Peak Value, Root Mean Square (RMS), Sensor SINAD, Signal-to-Noise Ratio (SNR), Sensor Shape Factor, Sensor Skewness, Sensor Standard Deviation (Std), Sensor Total Harmonic Distortion (THD), Sensor Peak Amplitude 1 (PS), Sensor Peak Frequency 1 (PS), Sensor Band Power (PS), Sensor Peak Amplitude 1 (PS Spec 1), Sensor Peak Amplitude 2 (PS Spec 1), Sensor Peak Amplitude 3 (PS Spec 1), Sensor Peak Amplitude 4 (PS Spec 1), Sensor Peak Amplitude 5 (PS Spec 1), Frequency Peak, Sensor Peak Frequency 2 (PS Spec 1), Sensor Peak Frequency 3 (PS Spec 1), Sensor Peak Frequency 4 (PS Spec 1), Sensor Peak Frequency 5 (PS Spec 1), Band Power (BP).

To illustrate the variables with the highest relevance for the classification, the Band Power, Frequency, SNR and RMS are selected for the visualization of results.

3 RESULTS

In total, 379 signals were recorded, which consisted of 196 close-fit signals, 76 free-end signals, and 107 cavern signals. From the recorded signals, 27 variables were extracted using the Feature Extraction Toolbox. These features were then assessed with 4-way ANOVA to find the variables with the highest overall variance. An example of representative signals is presented in **Figure 4a**. From the time-frequency domain, the main differences between different states of the CIPP composite classes can be recognized.

The healthy close-fit has a strong resonance response at 1 kHz. The cavern can be distinguished by a lower RMS and higher signal-to-noise ratio, where the dominant frequency is scattered around 0.8–1.4 kHz. The free-end is most distinguishable with the highest RMS, band power and lowest signal-to-noise ratio. This corresponds to a fairly stable oscillation when excited by an impact hammer, with consistent response frequencies at 0.65 kHz and 1.2 kHz. A standard classification model with the observed dataset can be designed using the Machine Learning Toolbox. Among the possible models, the Tree Bag[8] reaches the highest accuracy of 0.93, using a five-fold cross-validation algorithm on the given dataset.[9]

Figure 5 shows the variance in the selected four variables. Each class is marked with a different colour, and the overlapping and typical numeric range of the classes can be observed. From the plot, it can be seen that the RMS and band power allow us to clearly distinguish the free-end and close-fit and these two classes are most different from each other. The cavern, on the other hand, overlaps with both the close-fit and free-end classes. To decide which model was the most optimal, a hyper-parameter tunning approach was utilized showing a comparison between the first four most precise models. The training was done using k-fold cross-validation with 5 folds. In this procedure, the whole dataset is divided into five groups, where each time a different portion of the dataset is the validation group and the rest is the training group. The resulting accuracy is an average of these five training sessions. This procedure ensures the robustness

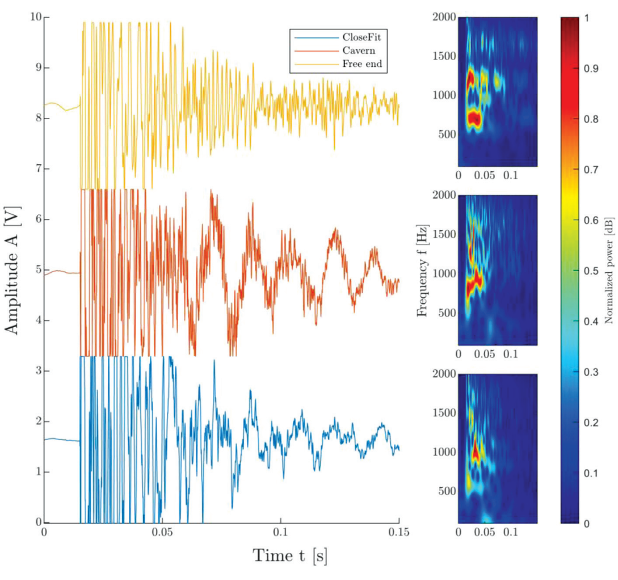

Figure 4: Example of representative signals for each class, based on lower Pearson residuals observed in all acquired signals: measured signals and their time-frequency domain illustrated by fast continuous wavelet transformation

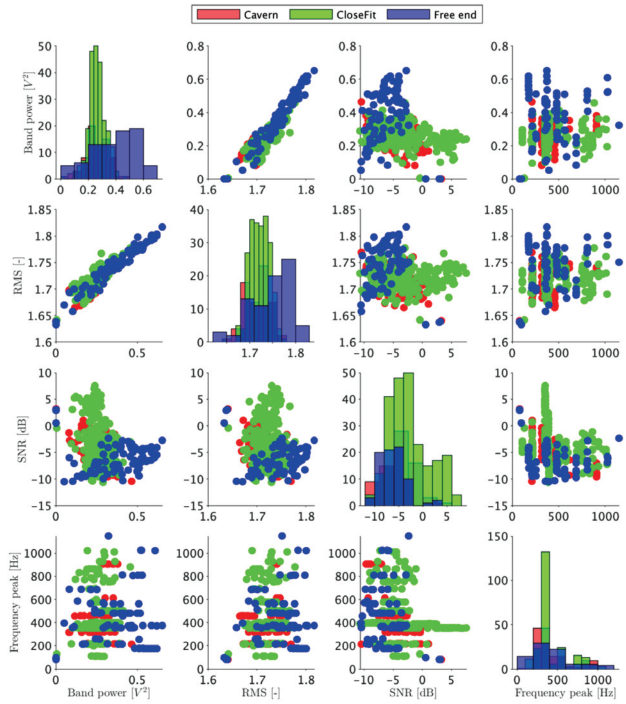

Figure 5: Correlation plot of selected representative variables: band power, root mean square, signal-to-noise ratio and dominant frequency

Table 1: Example of different classifiers and their accuracy used for the dataset

Classifier	Accuracy
Ensemble of bagged trees	93 %
Cubic support vector machine	88 %
Fine K-NN	87 %
Coarse Gaussian SVM	69 %

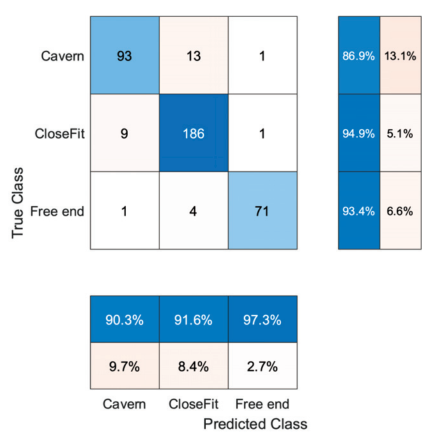

Figure 6: Confusion matrix of the designed model: bagged tree, validation accuracy of 0.93

of the training procedure, which could be biased if the distribution of some of the classes is uneven.

The resulting model can be visualized using the confusion matrix from **Figure 6**, which shows true-false predictions and prediction accuracy for each selected class. The most successful classification can be observed in the close-fit class, where only 5.1 % was misclassified. This indicates that the designed model can be used to localize healthy parts of the CIPP in the tested polygon. The lowest accuracy can be seen in the cavern class, where 13.1 % of this class was misclassified as a close-fit or free-end.

5 CONCLUSIONS

The paper presents a methodology for designing a machine-learning algorithm for determining the state of the inner wall of the cured-in-place pipe used for trenchless retrofitting of sewage pipes. The methodology uses data acquisition using the impact-echo NDT method and a non-contact microphone, creating a training dataset of signals and their features. The paper shows that training a machine learning classification model is possible and can achieve high validation accuracy. However, construction details and other defects, apart from the set classes including close-fit, cavern and free-end, can influence classification accuracy. Possible accuracy and reliability of such a classification model can be achieved by testing various types of pipes and their details regarding the geometry of pipe, using the composition of the CIPP and other conditions such as acoustic noise inside the sewage system. The proposed method shows that the heuristic models used for impact-echo classification can be replaced by a machine-learning classification model, which can increase classification accuracy and provide testing procedures requiring less human experience as they can be automated.

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