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Hybrid Transient-Machine Learning Methodology for Leak Detection in Water Transmission Mains †

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Abstract: This contribution proposes a hybrid approach integrating transient test-based techniques with machine learning for automatic leak detection in water transmission mains. Transient numerical simulations calibrated using experimental tests are used to develop a data-driven method based on neural networks to identify leak locations and characteristics. The accuracy of leak localization is demonstrated using three different degrees of noise in terms of mean absolute error, ranging between 0.54 m and 2.1 m. This proposed hybrid approach shows prospects for in-field applications.

Keywords: transmission mains; pressure transient; anomaly detection; experimental tests; machine learning

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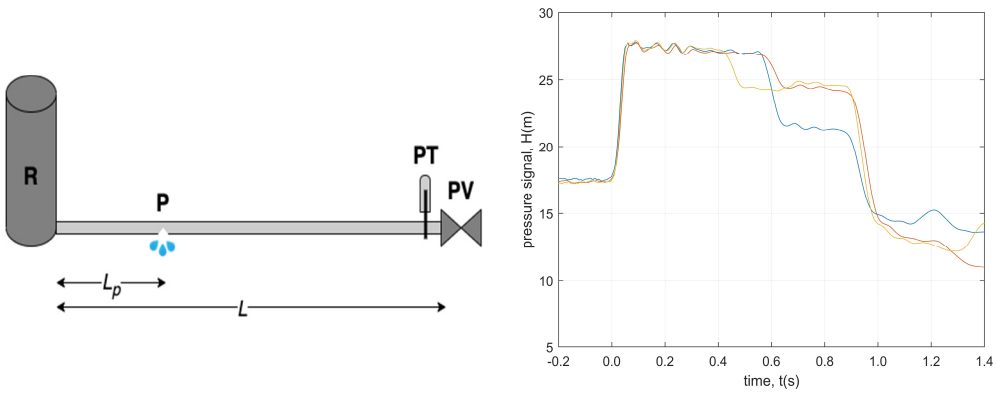
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1. Introduction

Worldwide, transmission mains lose an average of 40% of the transported water because of low maintenance and the limitations of current leak detection methods [1]. Water losses in conveyance systems cost money and energy, representing an effective reduction in the available water resources, putting more stress on the environment in addition to the impacts of climate change. However, attention to these transmission pipelines has recently increased due to the urgent need for sustainable use of freshwater resources, requiring appropriate inspection techniques and diagnosis methodologies. These pipes are often located in remote areas with limited accessibility, therefore causing more difficulties in monitoring and check-ups. The most suitable inspection solutions for this aim are inline sensors, such as swimming sensors or acoustic correlators, infrared thermographs, satellite technology, and transient test-based techniques (TTBTs). TTBTs involve analyzing transient pressure signals to identify anomalies in water systems by propagating small amplitude pressure waves through the system, exploring and collecting valuable information about the pipeline's "status". The analysis of pressure signals allows fault detection, as each anomaly leaves a distinct fingerprint [2,3]. TTBTs offer advantages such as low instrumentation costs, minimal required measurement sections, and short test durations, minimizing interference with the system's normal functioning [4]. While various models exist for transient pressure signal analysis, the integration of TTBTs with machine learning methodologies is still in its early stages [5–7]. In the context of the TANDEM project (i.e., hybrid transient-machine learning approach for anomaly detection and classification in water transmission mains), the authors intend to investigate this topic and present their preliminary results via this contribution.

2. Materials and Methods

At the Water Engineering Laboratory of the University of Perugia, a campaign of variable velocity experimental tests was conducted on the installation illustrated in Figure 1a. The system consists of a DN110 high-density polyethene pipe with a length L = 164.93 m, internal diameter D = 93.3 mm, and thickness e = 8.1 mm. The pipe is fed by a pressurized tank (R), while a pneumatic valve (PV) is installed at the downstream end to perform rapid closure maneuvers and generate the transient phenomenon. The pressure signal is measured using a piezoresistive transducer (PT) at the section immediately upstream of PV. A leak (P) with an effective area A_P is placed at a distance L_P from tank R. During the tests involved in this study, both the size of the leak (A_P) and the location (L_P) were varied in three test configurations. Specifically, in test$_{(1)}$ $A_P = 4.5 \times 10^{-4}$ m^2 and $L_P = 61.3$ m, in test$_{(2)}$ $A_P = 1.85 \times 10^{-4}$ m^2 and $L_P = 61.3$ m, and in test$_{(3)}$ $A_P = 1.1 \times 10^{-4}$ m^2 and $L_P = 72.62$ m. The initial hydraulic conditions of the experiment are fixed as follows: the piezometric head H_{PT} at PT is around 17.5 m, and the outflow Q_{PV} is around 2 L/s. Figure 1b shows the pressure transient signal acquired during the three campaign tests. At time t = 0, the overpressure generated by the sudden closure of P_V is recorded, while at t ≈ 0.5–0.7 s, a pressure reduction is observed corresponding to the interaction of the generated wave with the reflection of the leak (in fact, a negative reflected wave is generated). The subsequent pressure reduction t ≈ 1 s is instead due to the wave reflected from the tank.



(**a**) (**b**)

Figure 1. (**a**) Schematic diagram of the experimental setup at the Water Engineering Laboratory of the University of Perugia; (**b**) three pressure signals recorded during the experimental test campaign.

The second step of the proposed methodology consists of setting up an unsteady hydraulic simulator to reproduce the experimental tests in Figure 1b, with the final aim of increasing the sample of transient signal with different combinations of leak positions and sizes along the pipe. The hydraulic model used in this study is based on a semi-implicit finite volume–finite difference scheme for pressurized pipes, capable of ensuring mass conservation, thus allowing the representation of a precise mass loss due to pipe breakage [8]. Furthermore, in the developed hydraulic model, a noise generator is integrated to replicate the laboratory signal noise. Thus, three datasets of 2000 simulations for the training and 400 for the testing for each level of noise were performed. The noise in the simulated PT signals follows a normal distribution with a standard deviation equal to 0.05 m (dataset$_{(1)}$), 0.1 m (dataset$_{(2)}$), and 0.5 m (dataset$_{(3)}$), respectively.

The last step consists of training and then testing a Feed Forward Neural Network (FFNN) to identify the leak position along the pipe, e.g., [9,10]. The data-driven method based on FFNN uses transient signals as input, and the leak position is the output.

3. Results

Since the calibrated hydraulic model proved to be reliable, three levels of noise datasets were performed. Figure 2a,b show 10 of the 2400 samples of simulated pressure transient

in PT belonging to dataset$_{(1)}$ and dataset$_{(3)}$ with a corresponding low and high level of noise. These figures show the transient signals generated through simulations that include uniformly randomly distributed leaks along the pipe that also vary in magnitude.

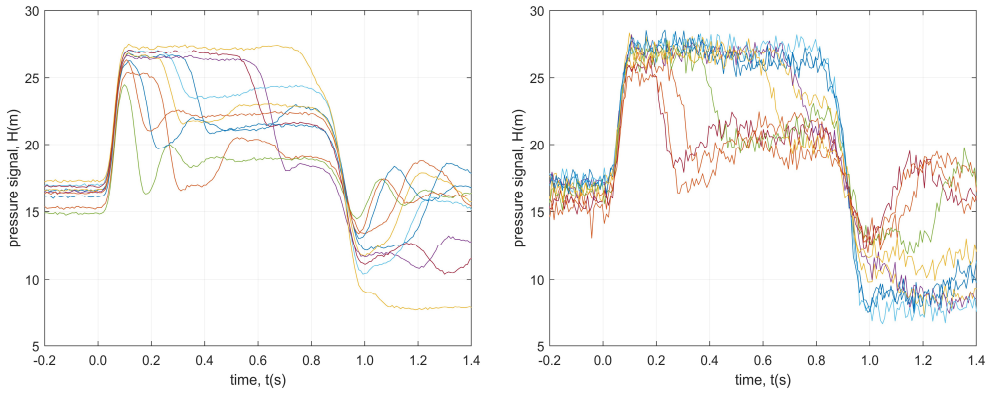


Figure 2. Pressure transient signals in PT simulated using the numerical model with different leak positions and sizes: (**a**) 10 samples of data from dataset$_{(1)}$ and (**b**) 10 samples from dataset$_{(3)}$.

Due to the three synthetic datasets with different levels of noise, three different ML models were trained. The selected neural network model consists of an FFNN architecture with an input layer with 256 pressure signal values, three hidden layers, and an output layer with one value, i.e., the leak position. The FFNN configuration comprises 32, 16, and 12 neurons, respectively, for each of the hidden layers, with 100 epochs. The training data are divided into 80% for training and 20% for validation in order to avoid overfitting. The 400 testing simulations were used to assess the accuracy of the FFNN models for each dataset. Thus, Figure 3 reports the results of the machine learning algorithm as a Q-Q plot between the predicted and the real leak position, using the three different levels of noise. The accuracy of the prediction model for dataset$_{(1)}$ presents a mean absolute error of 0.54 m, while for dataset$_{(2)}$ and dataset$_{(3)}$, the mean absolute errors are 0.82 m and 2.1 m, respectively.

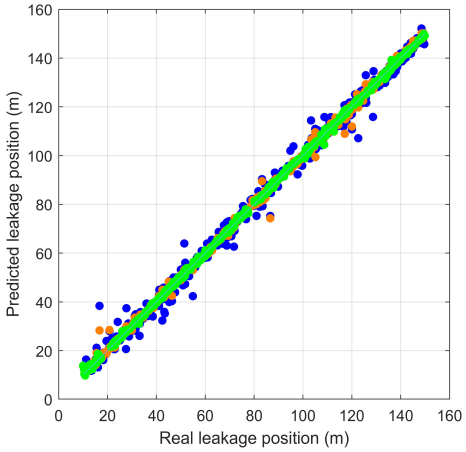


Figure 3. FFNN results as a Q-Q plot of the predicted against real leak positions for the three datasets: dataset$_{(1)}$ in green, dataset$_{(2)}$ in orange, and dataset$_{(3)}$ in blue.

4. Conclusions

This contribution provides an overview of the TANDEM project, highlighting how the potential of TTBT can be boosted through ML signal processing techniques. This hybrid transient-machine learning approach seeks to pave the way for an on-demand diagnosis of water mains, enabling a real-time response about upcoming anomalies along the pipeline.

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