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Proceeding Paper

Real-Time Burst Localization in Complex Water Transmission Lines Using Hydraulic Gradient Analysis †

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Abstract: This study introduces a methodology for the real-time detection and localization of bursts in water transmission lines by comparing estimated and measured Hydraulic Gradient (HG) values across pipe segments. Employing a deep learning approach, the method analyzes the complex relationships between system states such as flows, HGs, pump and valve operations. The approach capitalizes on the difference in HG values before and after a burst, enabling precise burst localization. Tested on a real incident, the method proved effective in accurately identifying burst locations, offering a practical solution for operators.

Keywords: hydraulic gradient; burst localization; water transmission line

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1. Introduction

Water transmission lines (WTLs) play a pivotal role in delivering substantial volumes of water; thus, their failure can significantly disrupt water supply and damage additional infrastructure. Consequently, the rapid detection and accurate localization of bursts are fundamental for an effective response strategy. Meanwhile, to enhance the reliability of water supply, recent innovations in WTL design have focused on parallelization and interconnections [1]. These advancements complicate burst localization due to increased network complexity. Furthermore, although sensors generate large volumes of data, the lack of data analysis methods suitable for real-world conditions leads operators to primarily concentrate on basic monitoring and trend analysis [2].

Research on WTL bursts has primarily employed the transient method, which analyzes the pressure waves from sudden flow changes such as a burst. However, despite their precision, their implementation in real-world networks is challenging due to the need for specialized equipment and numerous sample points [3]. Kim et al. [4] predicted the pressure values at various points within complex WTLs using deep neural networks (DNNs) to analyze data from sensors such as flows and pressures. Although this method showed accuracy in detection, there were certain limitations in localization. Traditionally, data analysis in this field has depended on pressure and flow data, while the hydraulic gradient (HG) is mainly utilized for network construction and operation optimization [5,6]. Although a few researchers have applied HG for leak detection [7,8], it has generally been implemented on simplified laboratory experiments that do not fully reflect real-world system complexities. Addressing this identified research gap, this study introduces an innovative method for real-time burst detection and localization by integrating HG data with deep learning in complex WTLs.

2. Materials and Methods

This paper proposes a method aimed at identifying and precisely locating leaks within water transmission lines (WTLs). This approach hinges on the analysis of discrepancies between measured and estimated HG values. It is designed for use in WTLs equipped with pressure and flow meters at key points such as service reservoirs and water treatment plants. Since historical data on WTLs rarely include burst incidents, the model learns from regular operational data to spot unusual occurrences. The approach uses real-time data in the real world, sent to SCADA systems every minute, for analysis.

2.1. Hydraulic Gradient

The Hazen–Williams equation (Equation (1)) indicates that the hydraulic gradient (HG), which reflects the head loss $(H_i - H_j)$ between nodes i and j per pipe length (L_{ij}), changes with the flow rate (Q). It includes the pipe diameter (D), flow rate (Q), a constant (K), and a friction factor (C), showing that HG can act as an effective surrogate value for detecting the flow change within a segment when the heads at both ends of a pipe are known.

$$HG_{ij} = \frac{H_i - H_j}{L_{ij}} \approx 10.666 D^{-4.87} C^{-1.85} Q^{1.85} \approx K \times Q^{1.85} \quad (1)$$

2.2. Deep Neural Network

Determining whether changes in the HGs result from operational adjustments due to demand variations or a burst is essential. HG fluctuations are influenced by the pump operations, flow rate and valve activities, necessitating an analysis of their complex interactions. A deep neural network (DNN) with a multilayer perceptron (MLP) architecture was used to analyze these relationships, estimating HGs in real time based on operational data. Since the model aims to estimate the HG values for each segment, the number of models corresponds to the number of segments. For example, to estimate a specific HG value, the input data include the flow rate, pump and valve operations, and measurements from other HGs. The model was trained for one hundred epochs, using data collected over three weeks, with the first two weeks for training and the last for validation. This validation set helped in hyperparameter tuning and evaluating the model's performance.

2.3. Burst Detection and Localization

Burst detection is based on comparing actual HG measurements with estimates. A difference (HG_{diff}) exceeding a threshold indicates a potential burst. This threshold is set at 1.2 times the range observed during a three-week training and validation period. To enhance the accuracy and reduce false alarms, alerts are generated when multiple sensors simultaneously detect anomalies or when a single sensor consistently surpasses the threshold in three successive readings. The method evaluates HG_{diff} across segments, as outlined in a sensor map. A positive HG_{diff} indicates increased flow from a burst, while a negative HG_{diff} reflects reduced flow due to energy losses. This analysis enables the burst segment to be pinpointed by observing the patterns of HG_{diff}, where the burst segment exhibits an increase in HG, followed by a decrease in downstream segments.

3. Results

This methodology was examined on a WTL system with 3–4 parallel pipelines, as illustrated in Figure 1. The network supplies two water treatment plants, two pump stations, and one commercial facility (F14), typically operating 5 of 18 pumps at the intake pump station. It is equipped with 12 pressure meters, and five flow meters.

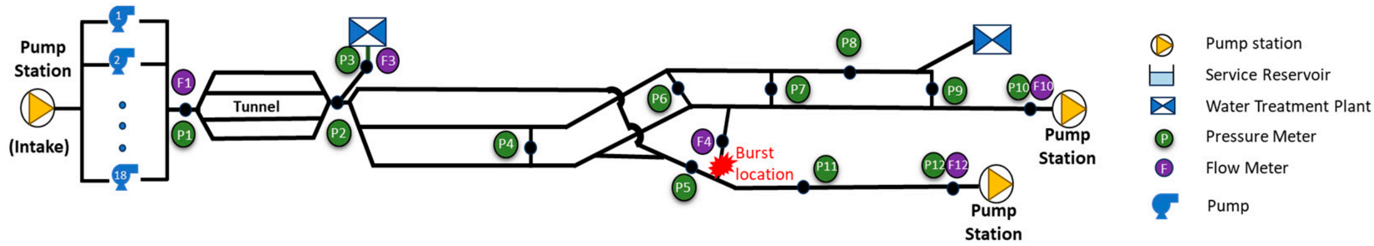
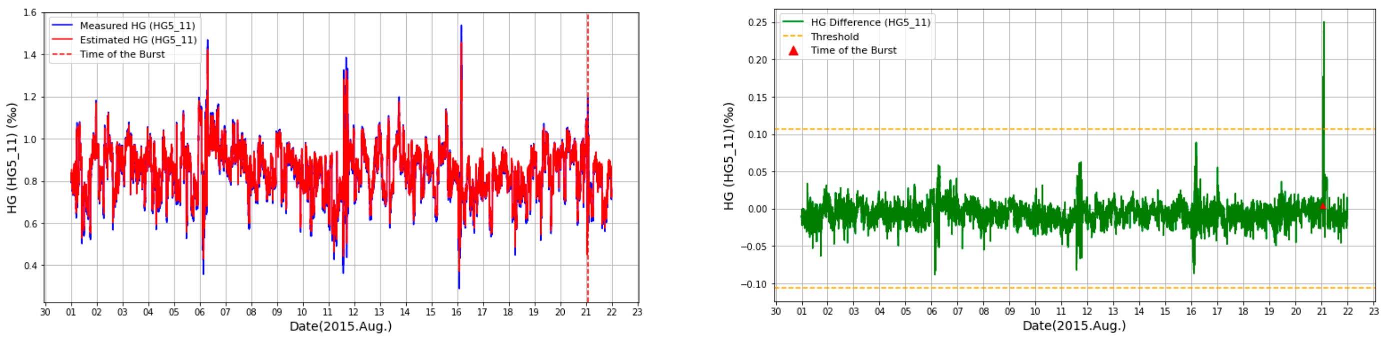


Figure 1. Sensor network map of the WTL.

Based on pressure meter placement and pipe connectivity, it is divided into 13 segments (models) with the start and end pressure meters denoted as below.

$$HG_{i\_j} = [HG_{1\_2}, HG_{2\_3}, HG_{2\_4}, HG_{2\_5}, HG_{4\_5}, HG_{4\_6}, HG_{6\_7}, HG_{7\_8}, HG_{8\_9}, HG_{9\_10}, HG_{7\_9}, HG_{5\_11}, HG_{11\_12}]$$

This study analyzed data from 18 variables, incorporating four flow sensors, 13 HGs, and one variable for the number of operational pumps considering the parallel operation of pumps with identical capacity. Serving as an example, Figure 2 shows the HG changes in one (HG_{5_11}) of the thirteen segments where the burst occurred. During the burst event, the actual HG values exhibited normal fluctuations, as seen in Figure 2a. However, the differences in HG estimated by the DNN model, which has three hidden layers and 64 input nodes, was trained in under 7 min, and as shown in Figure 2b, were considerably larger, surpassing the threshold. Minor spikes were observed between the 6th and 17th day due to sudden flow changes at certain water treatment plants, yet these were negligible compared to the significant variation caused by the burst on the 21st.



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

Figure 2. Hydraulic gradient changes in the model (HG_{5_11}): (**a**) Measured HG and estimated HG in the model; (**b**) HG difference and threshold in the model.

To compare deviations across all MLP models, a heatmap (Figure 3) was used, highlighting values exceeding the threshold in bold. This heatmap indicates that alarms for two segments (HG_{4_5}, HG_{5_11}) were triggered at 01:18 on 21 October and that anomalies were detected in additional segments over time. The sensor map (Figure 4) represents the flow directions derived from the heatmap, using the red arrow for segments with HG_{diff} surpassing the threshold, indicating a potential increase in flow, and blue arrows for segments below the threshold, signaling a decrease. It shows a significant HG increase in three segments, suggesting that the burst flow primarily moved through HG_{2_5} and HG_{4_5} to HG_{5_11}. Subsequently, the connected segment, HG_{11_12}, experiences a sharp decline in HG. Thus, this method accurately identifies HG_{5_11} as the burst segment, characterized by a pattern of HG increase followed immediately by a decrease in the subsequent downstream segments.

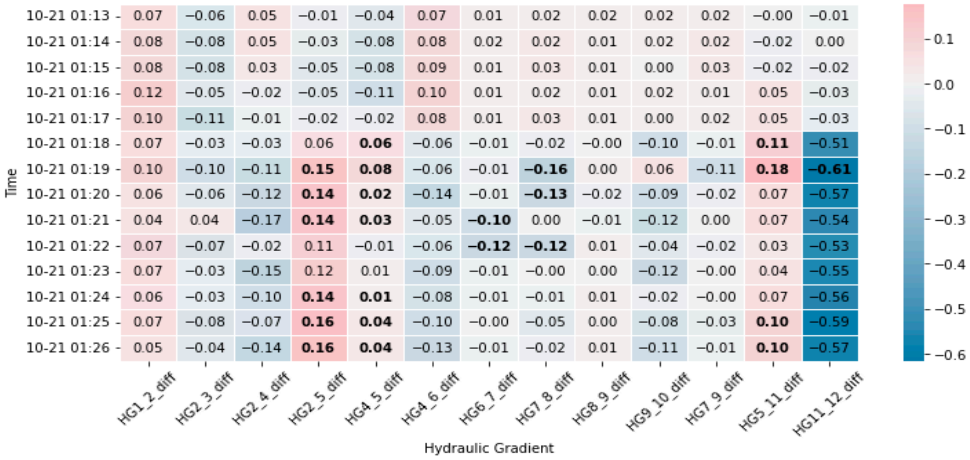


Figure 3. Heatmap of HG_{diff} across the models.

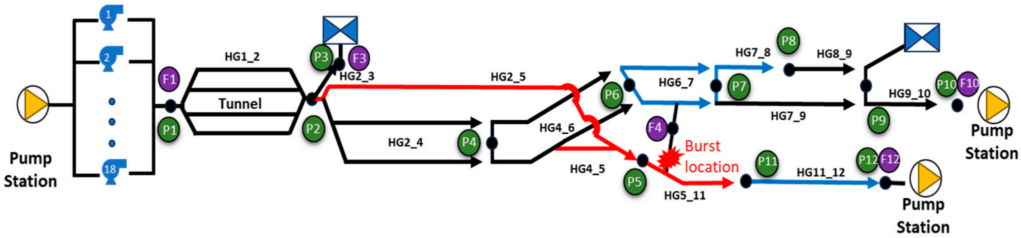


Figure 4. HG_{diff} map for the burst localization.

4. Conclusions

This study introduces a novel approach to detecting and pinpointing a burst in WTLs, utilizing neural networks to analyze HG variations and their correlations with influencing factors in the network. In contrast, traditional methods relying on pressure measurements [4], which require the isolation of connected pipes around pressure sensors that have an abnormal reading, segment-based burst detection enables precise localization, isolating only the affected segment. This approach requires the strategic placement of pressure meters at crucial points like branches and service reservoirs. Considering the cost-effectiveness of pressure meters and their increasing deployment, this method holds significant promise for widespread adoption and future advancements in the field.

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