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Scientific Note

ANN-based Model for Aiding Leak Detection in Water Distribution Networks

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Abstract: Industrial and municipal water distribution networks often have a considerable amount of water lost in transit, particularly in a country like India. Several attempts are being made to detect leaks, of which the physical methods are more commonly employed. However, such methods are reported to be less efficient and time consuming. This paper presents a Neural Network based approach to aid the physical methods. The methodology is demonstrated in a hypothetical unsymmetrical water distribution network. EPANET is chosen to model the hydraulic behaviour of the system. The effect of non-operative/defective pressure meter in the leaking pipe is also studied. It is seen that the proposed methodology performs remarkably well in predicting the exact leaking pipe, the location of leak in the pipe and the leak size. The prediction of leak location in the leaking pipe is more sensitive to the pressure signals from the leaking pipe. Thus, it is concluded that a simple simulation study can be very effective in considerably reducing the time in field methods of leak identification.

Key words: Leak detection, neural network, EPANET, water distribution network.

Introduction

Leakage from a water distribution pipeline network may be defined as that water which escapes accidentally than by deliberate action. In many water distribution systems (such as municipal and industrial) a significant percentage of water is lost while in transit from treatment plants to consumers. Unaccounted water is usually attributed to several causes including leakage, metering errors, and theft – leakage is the major cause. The loss of such large volumes of water is environmentally and ecologically damaging and this situation is more likely to be a major issue during the 21st century. Realizing the seriousness of the problem the water service companies have begun to develop leakage detection strategies in order to reduce leakages to an optimum level.

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For single pipelines carrying liquid or gas, many methods for leak detection have been proposed based on process variables (pressure and flow rate). Software methods use algorithms based on mass, momentum or energy conservation to find the flow rates, and subsequently using the information to locate leaks. However, mostly research in pipe network distribution is restricted to development of efficient algorithms leading to optimal replacement, rehabilitation for pipe network and assisting in decision making based on statistics and cost information (Rossman, 2000). Only a few works are reported in the area of leak detection. Over the past decade, a rapid increase in the number of new leak detection technologies has been observed (Belsito et al., 1998; Todini and Pilati, 1987). In the present work, Artificial Neural Network (ANN) based method is suggested to aid the physical methods in identifying leak sizing and location. The method involves simulation of the pipe network system to identify process variables (such as pressures and flow rates) at suitable locations in pipelines, which are modelled by ANN to locate the leaking pipe, location of leak in the leaking pipe and leak size. Once this preliminary identification is done, the subsequent details can be carried out with physical methods, which are otherwise very time consuming and less efficient. An unsymmetrical hypothetical pipe network system is selected to demonstrate the methodology. EPANET is used for extended period simulation of hydraulic and water quality behaviour within pressurized pipe networks. The leak in EPANET can be simulated by using the 'emitter' facility. Emitters are devices associated with junctions that model the flow through a nozzle or orifice that discharges to the atmosphere. Emitters at junctions are modelled as a fictitious pipe between the junction and a fictitious reservoir. The pipe's head loss parameters are $n = (1/g)$, $r = (1/C)^n$, and $m = 0$ where C is the emitter's discharge coefficient, m is minor loss coefficient and g is its pressure exponent. The head at the fictitious reservoir is the elevation of the junction. The computed flow through the fictitious pipe becomes the leak at that point. Details on ANN can be found in (Pudar and Liggett, 1992; Todini and Pilati, 1987). The hypothetical pipe network system considered in this study is shown in Figure 1. The system consists of 17 pipes with a roughness coefficient of C = 100 interconnected through nine nodes. The pressure meters are assumed to be located at the centre of each pipeline.

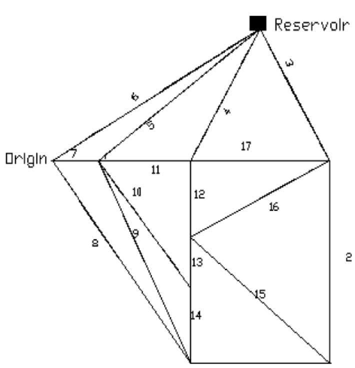


Figure 1: The pipe network system.

Model Development

After generating the training patterns from EPANET simulation viz., the pressures from known pressure meters, ANN is first employed to identify the leaking pipe. Once the leaking pipe is identified, ANN is applied to identify the leak size with flow rate in the leaking pipe (obtained from simulation) as an additional input. The leak size, flow rate, and the pressure measurements are subsequently used to identify the exact location of leak in the pipe. A total of 750 patterns have been generated with EPANET simulation by varying the discharge in pipes, leak size (0%, 1%, 2%, 5% and 10%) and leak location along the 17 pipes in the network. The pressure at the centre of each pipe line is noted for each pattern. Of the 750 patterns, 480 are used for training, 180 for testing and remaining for validation.

ANN Model for Identification of Leaking Pipe

Unlike for a single pipeline or symmetrical pipe network, the foremost difficulty in an unsymmetrical pipe distribution network is to identify the exact pipe where leak is present. Thus, this issue is addressed first. Since the pressure signatures obtained from the pressure meters will be unique for a given flow and leak condition, the leaking pipe can be easily identified by modelling the pressure signatures alone. As seen from Figure 2, ANN is able to identify the pipe accurately (79 cases), except in very few cases (11 cases) where the neighbouring pipe is being identified in lieu of the original pipe.

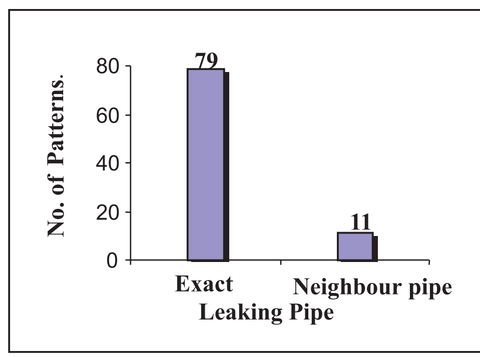


Figure 2: Leaking pipe detection.

ANN Model for Leak Sizing

It is to be noted that leak sizing can be modelled more appropriately by considering pressure drop in the leaking pipe than the absolute pressure values, as there is a drop in the outflow rate with leak. If P_{i0} is the pressure in i^{th} pipe with no leakage (0% leakage) and P_{in}, the pressure corresponding to a leakage of n%, then pressure drop in the i^{th} pipe is given as

$$\Delta p_i = P_{in} - P_{i0}$$

where n = 1%, 2%, 5% or 10%; and i = 1, 2, 3, ……17.

Further, the information of original flow rate (before leak) directly affects the leak in the pipe. Consequently, the input parameters for the leak sizing model are accepted as the pressure difference at 17 pipe centres and the flow rate in the leaking pipe as identified by the leakage pipe identification model. The output parameter is the leak size normalized in the range 0.1-0.9. An output of 0.1 corresponds to no leak condition, while an output of 0.9 means there is a 10% leak in the pipe. The result of the analysis is shown in the bar chart (Figure 3) for the validation data.

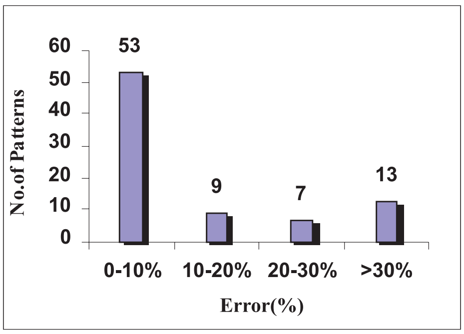


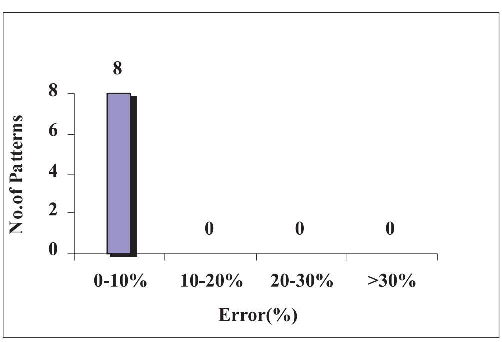
Figure 3: Leak size detection.

ANN Model for dentifying Exact Location of Leak in the Leaking Pipe

The exact location of the leak can be identified only when the leak size and the flow rate in the leaking pipe are known. It is desired that if the model is able to locate even approximately the leak location, this will aid the field methods considerably in saving time. The inputs to ANN model are selected as the pressure signals from 17 pipes, flow rate in the leaking pipe, and leak size. The output is the location of the leak measured as the radial distance from an assumed origin to the leak location. The results of ANN analysis are shown in Figure 4 for validation data. Figure 4 indicates that most of the leak locations (63 test patterns) are predicted within 10%. As seen from scatter plot, leaks have to be accurately modelled even for pipelines farther from the origin of measurement.

Performance of ANN Model under Pressure Meter Failure

It is of interest to know the accuracy in prediction of leaking pipe, leak location and size, when the pressure meter data of the leaking pipe is not available. ANN model is developed for studying the effect of removal of pressure signal from Pipe # 5 for the prediction accuracy in leak sizing and location. A total of 16 input pressure signals are used. As seen from Figure 5, the prediction accuracy certainly gets affected with a non-operative pressure meter in the leaking pipe. The identification of pipe and the leak size doesn't differ drastically, but the effect is more severe in the exact location of the leak.



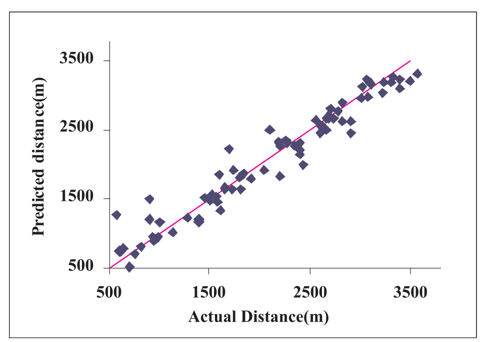
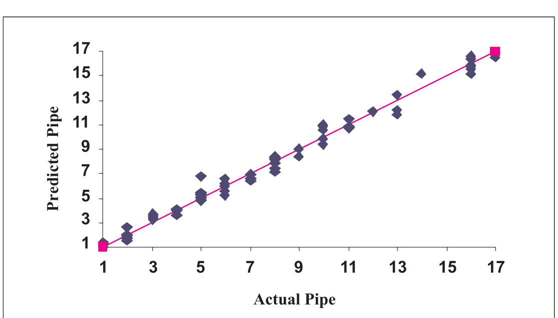


Figure 4: Exact identification of leak location.



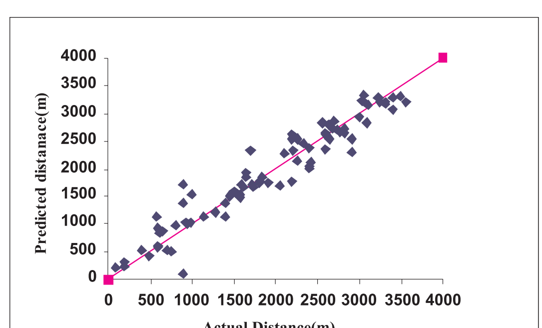


Figure 5: Performance under pressure meter failure.

Conclusion

An ANN-based system is developed for leak detection and location for an unsymmetrical pipe network. EPANET is used for simulating the hydraulics of pipe flow. The following conclusions can be drawn from the study:

1. ANN is suitable for modelling identification of leaking pipe, leak location in the pipe and the leak size. In most of the cases, the exact pipe is identified. The corresponding leak sizes are also accurately identified. The maximum deviation in the prediction of exact location of leak is of the order of half a km, but such cases are very few.
2. The model is able to detect leaks as small as 1% of flow rate, particularly so when the flow rate in the pipe is relatively high.
3. The prediction is found to be sensitive to the pressure signals from the leaking pipe. Though the pipe and leak sizes are predicted relatively correct, the location of leak is poor. However, despite this limitation, the method seems to be robust in aiding the field methods, thereby saving considerable time in leak identification.
4. The leak detection technique presented in this paper has been derived for a single leak in the network. The extension of this technique into real network and multiple leak detection system is under study. The proposed simple model seem to be a viable solution for leak detection for Indian conditions.

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