INTELLIGENT MONITORING OF LOCAL WATER SUPPLY SYSTEM

W referacie przedstawiono badania związane z budową systemu monitorowania sieci wodociągowych, sygnaлизujących pojawienie się awarii i wspomagającego ich lokalizację. Podstawowym założeniem omawianego systemu było przyjęcie metody wykrywania awarii stosowanej dotychczas w diagnostyce technicznej maszyn i procesów przemysłowych, opartej o modele przybliżone obiektu diagnozowanego. Bazując na niewielkiej liczbie czujników przepływu zainstalowanych na sieci wodociągowej i odpowiednio wytrenowanej sztucznej sieci neuronowej pojawiające się awarie sieci są wykrywane i lokalizowane. Opisany został pierwszy etap prac (lokalizacja czujników pomiarowych, przygotowanie i trening klasyfikatora neuronalnego) oraz uzyskane wyniki.

Słowa kluczowe: sieci wodociągowe, diagnostyka, wykrywanie i lokalizacja wycieków, sieci neuronowe.

In the paper an intelligent monitoring system of local water supply system was described. The author took advantage of methods of artificial intelligence and methods known from model-based process diagnostics to decrease the number of indispensable measuring points. Basing on few flow sensors installed on pipeline network and using neural network as a model of pipeline, appeared leakages are approximately localized. The first stage of system building (choosing of sensor localization, neural network preparing and training) and results obtained to-date were shown.

Keywords: water supply systems, diagnostics, leakage detection and localization, artificial neural network.

1. Introduction

Water supply systems are one of the most essential parts of the urban and rural technical infrastructure. It is necessary for them to be reliable, especially because of counteraction of water loss. Finding leaks is one of the typical problems connected with water pipelines maintenance. This task is not simple enough, because quite often leaking water can run deep into ground and therefore pipe failure does not show up on the ground surface. Bearing this in mind one can expect that a diagnostic system, supporting leakage finding would be very useful, especially on an industrial area with coal mining, where leakages are often encountered. Additionally, traditional methods of leakage finding based on leakage noise detecting and analysing, are less efficient with, nowadays very popular, plastic pipes, which are poor sound conductors.

2. Problem description

In fact, mathematical dependencies between flow and pressure loss in a pipe are known, so it is possible to use it for leakage detection. So that theoretically, if we knew water consumption in all the points of network, it would be possible to calculate pressure and flow in any required point of the network. Comparison of calculated and measured parameters could allow finding leakages and other causes of water loss. For example, the method described in [2].

However, to establish such a kind of a monitoring system it is necessary to measure “on line” all legal water consumption. Although it is possible to decrease number of inputs to the water supply system (and then decrease number of measurement points needed), it must result in much worse accuracy of the monitoring system. It is why this idea of monitoring system is not quite good enough for practical implementation.

3. Concept of monitoring system

To avoid necessity of using measuring system which is big, complex and spread out at significant area of the country, with big number of on-line measuring points, the concept of diagnostic system, which uses approximate approach for modeling the pipeline network and recognizes a leak of water was suggested [5]. The idea of this system is based on methods known from model-based process diagnostics where a model of the object being monitored is used for fault detection [3]. Based on measuring flow and/or pressure in chosen points on pipeline networks and appropriate trained artificial neural network (ANN), the diagnostic system in question would suggest if any leakage exists, and where it is possibly located.

4. Practical application of the proposed method

For practical verification of the proposed method, in collaboration with the local water supply system holder, a prototype diagnostic system is being developed.

The considered system will work within one district of town. The monitored network has about 25km of pipelines with different diameters and supplying about one thousand of water consumers. The scheme of this network is shown in Fig. 1. The monitoring system will be finished at the end of 2007.

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4.1. Numeric model of water supply network

Since the artificial neural network was planned to be used as a model of the real network, the problem of preparing training data should be solved. Because it is difficult and inconvenient to simulate leakage and collect data from real object, the numerical model of the network was built. To build this model the EPANET simulation environment [1] was used. Running this model it was possible to calculate flows and pressure in all the points of the network with a leakage located in any point of it or without leakage at all.

To describe temporary water consumption for every water consumer, an accountant data was used. For each user an average consumption was calculated. To describe consumption changes during all day, a daily time pattern consumption, described in [4] was established. To simulate random changes of water consumption, consumption calculated for each time and each user was randomly changed within the range +/-20%.

4.2. Location of the sensors

Because of economical and technical reasons, the owner of the supply system decided to limit the number of used flow sensors to six. The number of pressure sensors, which are cheaper and much easier to mount, was not limited, but as the first examination showed, they are not useful enough for leakage localization (in the considered network). To find the best location of sensors an optimization with genetic algorithm was used [6].

At first allowed sensor localizations were limited to main network junctions only. In all the main junctions potential flow sensors for each connected link were localized. It provided 45 possible flow sensors locations. Next the sets of points of leakages were chosen at random. For each leakage location flows for all potential sensors locations were calculated. Simulations were repeated for every hour for 30 days.

The genetic algorithm chose the best subset of six sensors. For each subset ANN was trained for leakage location. The percentage of correct location was assumed as a value of the fitness function. The best chosen location of six flow sensors was shown on Fig. 2.

4.3. Approximate model of water supply network

As it was described, the ANN as a model of water supply network was established. The multilayer perceptron was used. Water flows, measured in chosen points of network was taken as input to perceptron, the state of the network (no leakage, leakage in first location, leakage in second location, etc) was taken as an output of this ANN. The numbers of neurons in hidden layer was three times greater than a number of outputs. The tan-sigmoid transfer function in the hidden layer and the log-sigmoid transfer function in the output layer were used. To train ANN a data collected during simulation with EPANET was used.

The other problem was to decide how the potential leakage location should be pointed. At first, during ANN training the exact point of leakage was shown. Obtained results were quite good (about 80% of leakages pointed exactly or with small fault). Some of leakages were found as “undistinguished” – because of small number of installed sensors there was no differences in “measured” water flow in the points of sensor localization. But some of leakages, located in absolutely different places were not distinguished, too. Fig. 3, 4, 5 show some examples of results.

To avoid these significant mistakes, it was decided to divide the network into some separated areas and point only some area when leakage is located. At the first stage the network was partitioned as shown in Fig. 6.

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The obtained results show that in the most cases ANN pointed proper area or pointed the nearest one. But more significant errors still occur. In Fig. 7 system errors histogram was shown. The numbers on X-axis means: 0 – proper area was pointed, 1 – nearest area was pointed, 2 – next to nearest area was pointed, etc.

At the second stage partitioning into leakage area was changed. Neighbors areas were separated by network nodes (Fig. 8). Obtained results were shown in Fig. 9.

Leakages located in most areas were pointed good enough, but in some cases results were poor.

To improve this situation instead one ANN a cascade of ANNs was applied. For each area which was not “recognized” good enough, a separate ANN network was prepared and trained. The comparison of results obtained for one ANN and the cascade of ANNs was shown in Fig. 10.

In Fig. 11 histogram of classification errors for ANNs cascade was shown – it is essential, that system points proper area of leakage localizations or the nearest area at least.
10. Further system development

In near future the process of flow sensor installation will be finished, so it will be possible to carry out first practical tests of the monitoring system.

In the next step, after collecting data from installed sensors, it will be possible to improve the system to detect less intensive leakages. The idea is to predict the future flow measured by the given sensor with few hours horizon time. Recurrent errors of prediction can help to determine an additional flow, connected only with potential leakage, and not connected with water consumption.

Fig. 11. Histogram of errors for ANNs cascade

11. References


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