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ROZWÓJ INTELIGENTNEGO SYSTEMU MONITOROWANIA ROZDZIELCZEJ SIECI WODOCIĄGOWEJ

THE DEVELOPMENT OF AN INTELLIGENT MONITORING SYSTEM OF A LOCAL WATER SUPPLY NETWORK

W artykule przedstawiono rozwój inteligentnego systemu monitorowania sieci wodociągowej. Głównym zadaniem systemu jest wykrywanie i lokalizowanie awarii sieci wodociągowej. Wejściami do modelu są dane z czujników przepływu zainstalowanych na sieci, zaś wyjściami informacja o wykryciu wycieku i jego lokalizacji. Podstawową zaletą tej koncepcji systemu diagnozowania sieci wodociągowej jest możliwość przybliżonej lokalizacji uszkodzeń sieci w oparciu o ograniczoną liczbę czujników na niej zainstalowanych. System oparty jest o sztuczne sieci neuronowe, które klasyfikują stany sieci (sprawna, wyciek w zdefiniowanym obszarze sieci). Artykuł przedstawia prace prowadzone w celu ulepszenia metody budowy klasyfikatora, będącego zasadniczym elementem systemu i zwiększenia dokładności jego wskazań.

Słowa kluczowe: *diagnostyka, algorytm genetyczny, sztuczne sieci neuronowe, sieci wodociągowe, wycieki.*

The paper presents the development of monitoring system of intelligent water supply network. The main task of this system is water leakage detection and localization. For inputs, this system uses information from flow sensors, mounted on the pipeline network, while the output is a piece of information about leakage detection and localization. The main advantage of this system is a possibility of approximate leakage localization using only a limited number of installed sensors. The system is based on an artificial neural network which classified the states of network (leakage in defined part of network, no leakage). In the paper, some developments and attempts to improve the sensitivity and accuracy of this system, and develop the method of classifier building were described.

Keywords: *diagnostic, genetics algorithm, neural network, water pipeline, leakage.*

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, because leaking water can quite often run deep into ground and therefore pipe failure does not manifest itself on the ground surface.

Nowadays, to find this leakages, some predominant systems are used: acoustic listening devices, leak noise correlators and tethered hydrophone systems. Usage of there systems requires well trained stuff, which actively work on the spot to find leakages.

Bearing this in mind one can expect that a diagnostic system, supporting leakage finding and working automatically, would be very useful, especially on an industrial area with coal mining, where leakages are often encountered.

Different works dealt with methods possible to be used in such systems have been conducted, but they are still at the theoretical stage.

Generally, all proposed methods based on numerical models of a considered water network and different techniques supporting leakage detecting and finding. For instance, one assumed, that there are leakages, each described by emission coefficient, in network nodes, and GA was used to find the best set of this coefficients, which minimized the difference between real measurements and values obtained from model. In this way the real leakage was detected and localized [5]. Some works was connected with a segmentation of the water network for efficient sensor localization and leakage detection by balancing segment inflow and outflow water [4]. Suggestion of using MultiRegional Principal Component Analysis (MR-PCA), and some trials to practical usage of this method for leakage detection and localization were described in [1,3].

All these methods needs some on-line measuring systems, installed on the water network. Depending on a method, the number of sensors are changing form a several up to teens sensors. In this paper the development of a system, which needs a very low number of sensors to work was described

2. The short description of existing 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 artificial neural network (ANN) for modeling the pipeline network and recognizes a leak of water was suggested [6]. A noncommercial prototype of the monitoring system, which can detect and localize leakages was proposed and built in 2007 under the Sectoral Operational Programme "Improvement of the Competitiveness of Enterprises" – SOP-ICE 1.4.1 under grant "System monitorowania i zarządzania eksploatacją sieci wodociągów i kanalizacji miasta Rybnik" and the Ministry of Education and Scientific Research/Information under grants No. 4 T07B 018 27. The monitored object is a local water pipeline system with about 25km of pipes which supply about 1000 water consumers.

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. Based on measuring flow in chosen points on pipeline networks, diagnostic system supported on a specially trained artificial neural network (ANN), will suggest if and where the leakage is.

To pointing potential leakage location, it was decided to divide the network into some separated areas (zones) and point only some area where the leakage is located.

To find the best localization of sensors which should be installed on water pipeline, the genetic algorithm (GA) described in [7,8] was used. The chosen sensor location was shown in Fig. 1.

The described system indicated only an area of the leakage - different leakages located in one area would be undistinguishable. To partition water network into areas, at the first stage the network was "divided" into small pieces and next, it was tested if these areas can be recognized. Undistinguished areas were joined together. The final division of the pipeline network was shown in Fig.2.

Obtained results showed, that leakages located in most zones were pointed out good enough, but in the case of few zones the results appeared poor. To improve this situation instead of one ANN (multi classes classifier) a cascade of ANNs was applied. For seven zones which were not "recognized" good enough, a separate ANN (binary classifiers, which recognize leakage in distinguished zone) was prepared and trained. When the main classifier was not able to recognize the state of the network satisfactorily, binary classifiers completed the diagnosis. The comparison of results obtained for one ANN and the cascade of ANNs was shown in Fig. 3.

3. The proposed developments of the system description

3.1. Pipeline network partitioning

During the first months of operating time, some problems with the system were encountered.

Planning the development of the system and its expansion for next parts of the town, the problem of pipeline network partitioning into areas should be reconsidered. Manual partitioning is difficulty and time-consuming. To improve this process and

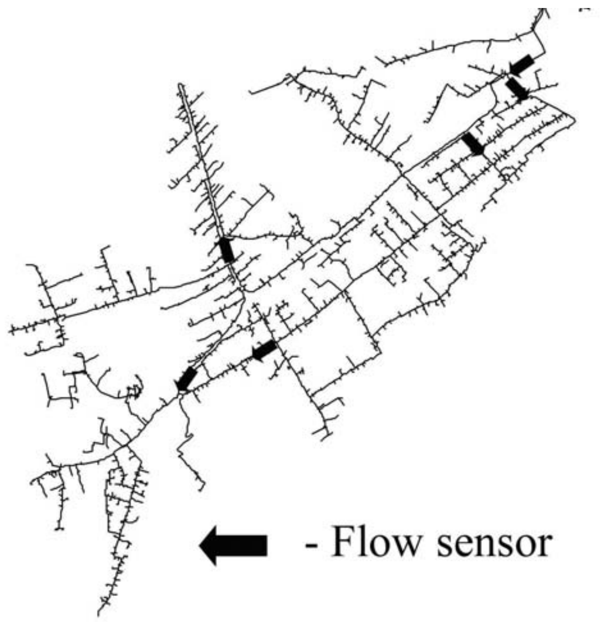

Fig. 1. The flow sensors locations chosen [6]

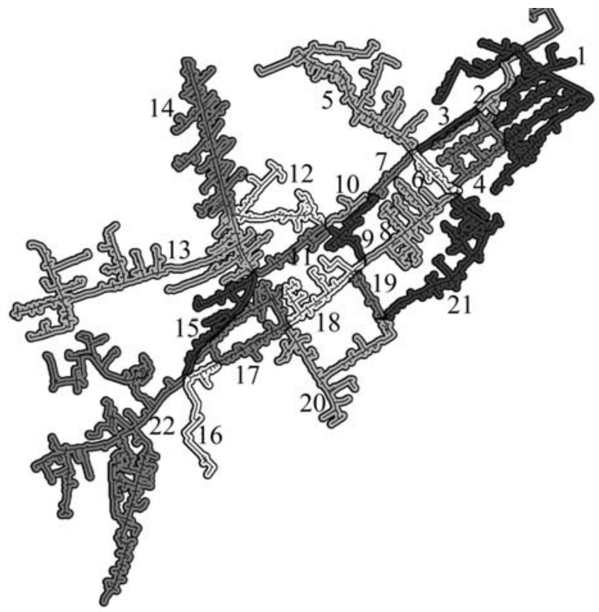

Fig. 2. The final division of pipeline network [6]

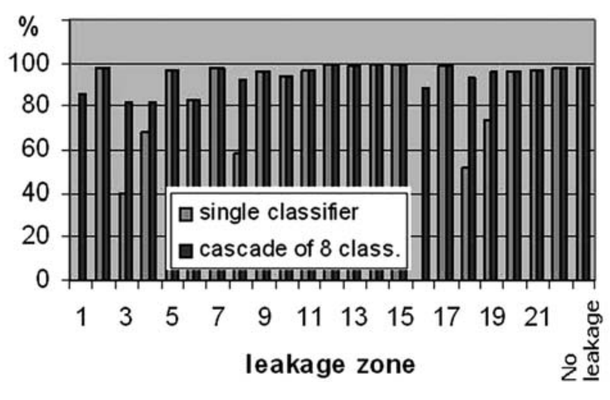

Fig. 3. Classification efficiency [6]

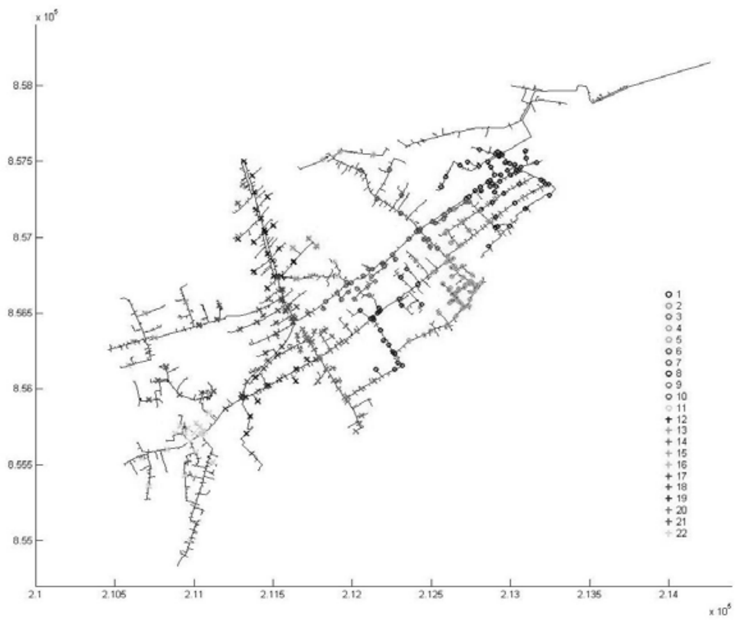

Fig. 4. The division of pipeline network obtained during hierarchical clustering

Fig. 5. Classification efficiency for division of pipeline network obtained during hierarchical clustering

made it more automatic, some methods of clustering were taken into consideration.

To test these methods the group of few hundred point of potential leakage were chosen randomly. The points were spread on all the network. Dividing this set of leakage points into similar classes, we automatically divide the pipeline network into partitions.

A first step, using simulation application [2], for each leakage flows in all sensor location was calculated. Simulations were repeated for every hour for 30 days. For every simulation, individual water consumption for each consumer was randomly modified, but changes never exceeded 20% of the expected value.

Using this data the classification process was made. During research the two classification methods were used:

- hierarchical clustering,
- k-means method.

The first method was chosen, because there is no need to make preliminary clustering in his method. To avoid problems with class dividing, the bottom-up approach was used,

The results of hierarchical clustering were used as a first initial step for k-means method.

The essential problem was to decide how to describe the similarity of leakages points.

At first the distance between points was taken as a measure of similarity, but the results were not good. Next the difference between an average flow into two tested points was considered.

At the end, both the measures were taken. To have an equal participation of both components in the final results, the weighted sum of both the quantities was used.

To test the obtained pipeline network partitioning, the neural network classifier was prepared and it was tested how many emitters were properly associated to the appropriate area. The division of the pipeline network obtained by the hierarchical clustering, and classification efficiency of ANN classifier based on this network division was shown in Fig.4 and Fig.5. The received partitioning was quite similar to this from Fig. 1, but three areas (5, 14, 16) could not be separated at all.

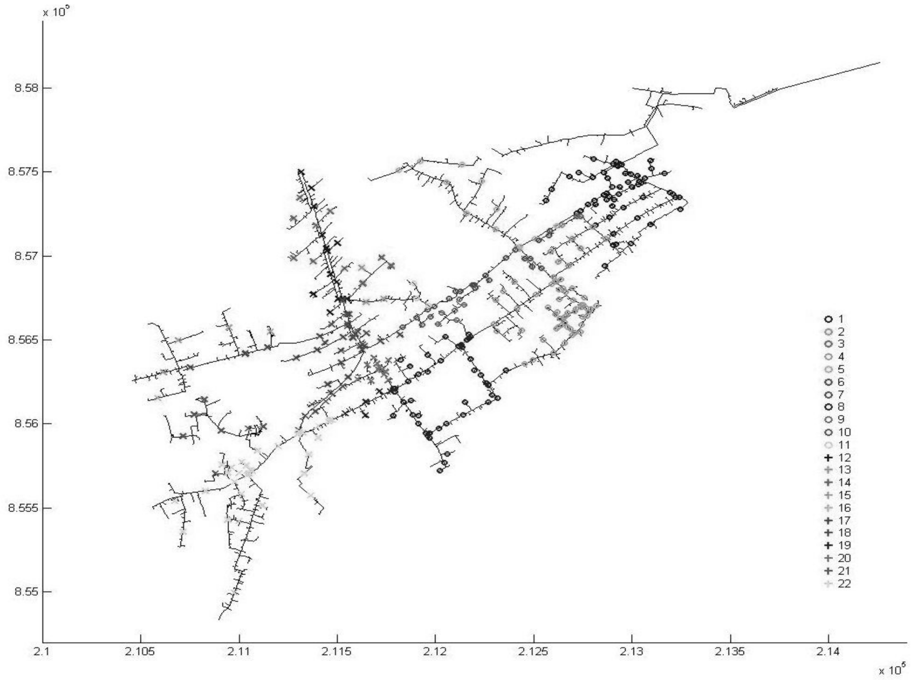

Fig. 6. The division of pipeline network obtained during k-mean clustering

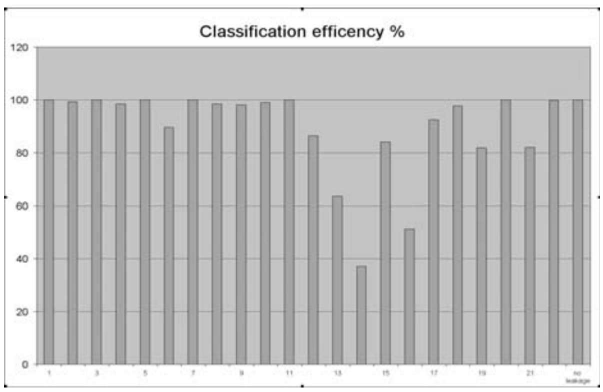

Fig. 7. Classification efficiency for division of pipeline network obtained during k-mean clustering

By using k-means method the obtained results were improved. All expected areas were separated and classification efficiency increased (Fig.6 and Fig.7). But in both the cases the classification efficiency for areas 13, 14 and 16 was significantly worse than the one obtained for the previous network division.

3.2. System sensitivity increasing

To increase the sensitivity of the monitoring system, new inputs were added to the classifier. Up to now, only a value of water flow measured in the chosen points was taken as an input for the classifier. In the next step, the time of the day was added as an input.

After testing the real (measured on the real water network) flows, the daily, average profile of flowing changes was precised (Fig. 8).

According to this profile, there is no need to think over all hours of day separately – the all days were divided into three intervals: 10am to 11pm, 3am to 6am, and the rest of the day.

3.3. Increasing classifier fault resistance

During the first tests of the installed data measuring system the problem of data transmission from sensors was identified. The flow sensors used in the system are battery supplied and the data is transferred by GPRS. Because of different problems (battery weakness, insufficient signal strength) the situations when measured data from one sensor was unavailable were often met. Because the used neural classifier needs all inputs to work properly, in these cases the monitoring system do not work at all.

To avoid this situation the other kind of network was tested as a classifier. Because of a possibility of working with incomplete or noisy data the recurrent network was considered as a classifier.

At first Hopfield network was tested. Hopfield network needs 0 or 1 value as an input. To fulfill this requirement and change set of flow values into an vector of zeroes and ones, input values (the measured flows for all the sensors) were nor-

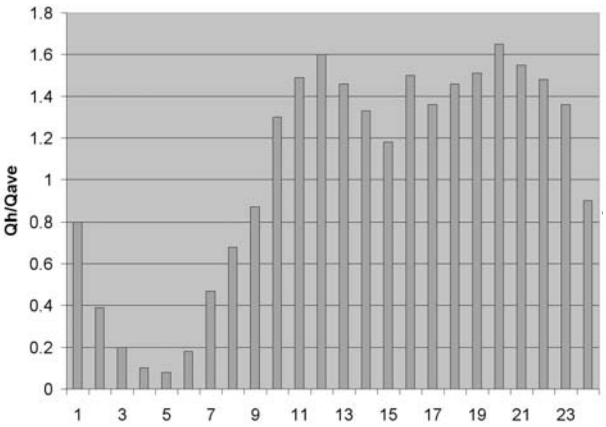

Fig. 8. The average profile of sensor daily flow in considered water network

malized and divided into ranges. If considered value belongs to the selected range, the input vector has value "one" on the adequate position and value zero otherwise.

Hopfield networks were designed to have stable points for the chosen water-network state (an hour of day and emitter location), and were tested, if proper stable point was reach for the similar state.

Obtained results were unsatisfactory, but the authors still work for this problem.

4. Conclusions

The described system was built and tested as an noncommercial prototype, working for one part of town. After a few months of system operating, a first experience was assumed and initial conclusion was made.

At first the problem of building classifier should be resolved. Sensors locations were chosen using GA, and this method can be used for other networks too, but the division of pipeline network was prepared manually, and better, more automatic methods are needed. To automatize this process authors decided to use methods of classification. The obtained results were good enough, but still worse that this, obtained by manual division. It suggests that further studies are needed.

During operation, the problems with measuring system were disclosed. Because of widespread of monitored object, using battery sensors and GPRS data transmission seems to be a good idea, but it causes the system to behave less reliable. So that an idea of using neural networks which can work with incomplete data seems to be interesting.

The sensitivity and accuracy of this system still can be improved. The few ways of improving the system can by developed. Identifying and adding a new, significant inputs the for classifier is one of them.

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