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Application Extreme Learning Machine To Predict Location And Magnitude Of Pipe Leak On Water Distribution Network

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Abstract

Water is an essential requirement in human life than it is required good management and distribution of this resource. However, in the distribution process sometimes there are problems of water loss due to leakage of pipes. Pipeline leak causes pressure changes at each junction / node in the network of water pipes. The pattern of change in pressure can be analyzed in computationally to know the magnitude and location of leakage. One way to analyze the pattern of the pressure change is the use of artificial intelligence methods to identify patterns based on the data of the water pressure measurement. Pressure data obtained from EPANET. It is a modeling hidrolik system. In this study is used methods Extreme Learning Machine (ELM), i.e the machine learning method that new lately developed.
The accuracy of prediction of the magnitude and location of leakage is based on the value RSME. In this case the prediction results from the method of ELM is obtained average RMSE values 0.148 for magnitude of leakage and 0.0518 for the location of leakage.

Keywords: *Leakage of pipe, EPANET, ELM, RMSE.*

1. Introduction

The need for water is increasing every day. To distribute water to consumers with the quantity, quality and sufficient pressure, it requires a good piping system.Therefore, the one that is needed is a system for the adequate distribution piping network. However, in the distribution process sometimes there are problems of water loss due to leakage of pipes.

One of the significant losses experienced by the processing and distribution in the water network system is a leakage of pipe problem. In general, leaking of pipe classified into two categories, namely technical leakage and leakage of non-technical. Leakage of technical is a leakage in pipeline that occurs primarily in the soil, while non-technical leakage such in the form of recording incorrect, the water thief (illegal consumption / connection) and others.

The water leakage problem has become a problem in big cities in the World. Particularly in the city of Makassar, Indonesia, water leakage reaches 30-40%. Various attempts have been made to suppress the leakage rate. All this time, in order to solve the technical leakage, the regional Waterwork Company conducted 2 stages to detect the leakages, i.e. step test analysis method and sounding method. Step test method is a method applied at the scoping stage of the network to restrict the area of water flow to predict the location or the size of the leakages. The step test method is needed to determine the network monitoring priority to the leakages. The implementation of the step test method is one of the most effective ways to identify water leakages on the distribution network. The next stage conducted to determine the location of the leakages is absolutely conducted by using sounding technique. Sounding technique is a technique which uses a portable tool which detects the sound wave emerged throughout the pipe indicated the leakage on the pipe. However, both methods are proven to be less effective in solving the leakages. It was caused by the lack of experienced manpower and limited detection tools.

The effect of the pipe leakage is the change of the pressure on each junction node in the water pipe. This pattern of change in pressure change patterns can be analyzed computationally to be able to detect the location and large leaks that occur in the pipeline.

Today has been a growing research on pipeline leak detection methods with the use of artificial intelligence. There have been many studies that have been conducted for this study include the use of neural networks in predicting oil pipeline leak from the pressure sensor data [1]. Research on the relationship between the magnitude of the leakage with pressure by comparing some leakage exponent value [2]. Research on the use of EPANET of modeling water pipe leaks and the SVM method to predict the location and large leakage [3]. Research on the use of the application method of RBF-NN for detection magnitude and location of leakage [4].

In this research, to complement previous studies detect the magnitude and location of leakage has used artificial intelligence methods namely Extreme Learning Machine (ELM). It is the machine learning methods were developed to cover the shortfall in the feedforward neural network, where the ELM enhanced neural network learning speed to get the maximum results with finding nodes give maximum output.

2. Extreme Learning Machine

One of the new methods which offer speeds the learning process, namely Extreme Learning Machine (ELM). The method introduced by Huang Guang-Bin et al, 2006, in a research entitled Extreme learning machine: Theory and applications. ELM utilizing inverse matrix theory in the learning process. The theory used is moore Penrose pseudoinverse. In theory, the process of learning to use the ELM network requires a relatively short time [5]. ELM is a neural network learning algorithm on the model single hidden layer feedforward networks (single-hidden layer feedforward network / SLFN) In general, the ANN models using ELM as the method of their learning can be seen in Figure 1.

When a SLFN- ANN models with n inputs, m neurons in the hidden layer and the activation function g (x). Let X = [x_1, x_2, x_3,..., xn] with xi is the input value on the network, w is a weighting matrix connecting the input layer and the hidden layer then w is a matrix with the size n x m. Determination of the elements of the matrix is done randomly.. Then each input value is processed in the hidden layer using a specific activation function and the value is collected in a matrix H with the order 1 x m (H = [h_1, h_2, h_3, ..., h_m].

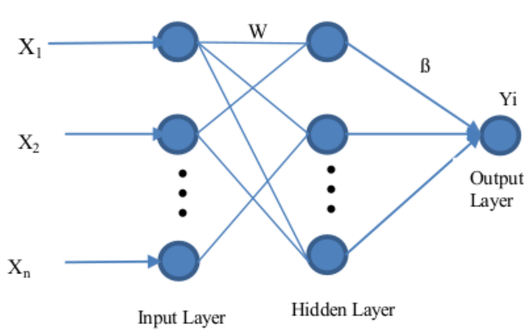

Fig 1. Model JST with learning ELM methods

Moore-Penrose pseudoinverse is used to determine the value of the weights between the hidden layer and output layer. In general, the algorithm of ELM is as follows [6]:

Given a training set ($\mathbf{x}_i$, $\mathbf{y}_i$), $\mathbf{x}_i \in R^{d1}$, $\mathbf{y}_i \in R^{d2}$, an activation function $f : R \rightarrow R$ and the number of hidden nodes H.

1) Randomly assign input weights $\mathbf{w}_i$ and biases b_i, $i \in [1, H]$;
2) Calculate the hidden layer output matrix $\mathbf{H}$;
3) Calculate output weights matrix $= \mathbf{H}^{\dagger}\mathbf{Y}$.

3. Case Study

3.1. The data retrieval

In the data process use the method of Extreme Learning Machine (ELM) to obtain a good prediction results with high accuracy, it requires a lot of training data so that it takes the actual pipe leak data contained in the field as training data. They can be obtained from the simulation results by using the software pipeline that EPANET 2.0, which owns the hydraulic system software used by the Regional Waterwork Company in monitoring pipelines. And the accuracy of the program depends on the number of hidden neurons are used.

In Data Taking Technique, the first step to do is establish the pipe network using EPANET 2.0 software by arranging the input data from the Regional Waterwork Company of Makassar in the form of the magnitude of water debit on the reservoir as the primary source of the water flow in the pipe network, length and diameter. The magnitude of the elevation and demand (the average needs of water on each junction), and the roughness level on each pipe based on the field data in Taman Khayangan Resident Makassar, Indonesia [4].

After establishing the pipe network using EPANET 2.0 software, the next step is creating the leakage simulation by changing the emitter coefficient on the junction which will be set as the leakage point. The emitter is a tool associated to the junction which is the model of the flow passing the nozzle of orifice released to the open air. The function of the emitter on EPANET is as the following [1]:

$$EC = Q / P^{P\,exp} \qquad (1)$$

Where *EC* is the emitter coefficient, *Q* is the water debit, *P* is the fluid pressure, and *P exp* is the pressure exponent. So

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that, the emitter coefficient is the debit of each pressure unit of liter unit per second per meter of the pressure ($L\ s^{-1}\ m^{-1}$). Since the head nozzle and the sprinkler of *P exp* as same as 0,5. The emitter coefficient used for the leakage simulation training is starting from 0.0005 up to 0.01 with the interval of 0.0005. The magnitude of the average pressure in the pipe network is 15.81486172 m. Thus, for 0.0005 of the emitter coefficients will result the leakage of 0.007 L. So that, the size of the simulated leakage is ranging from 0.007 L/s up to 0.14 L/s. For example, the second pipe leakage simulation (pipe 7-8) is set to be 25 sets of leakage case in the junction and 100 sets of leakage case in the pipe. Both of the leaky pipes are made in each leakage spot which has a distant of 4 meters each and the emitter coefficient of 0.0005 – 0.001. Therefore, overall, there are 19.320 data for the size and the location of varied leakages. To detect the leakages happened on the different pipe, it should use the different model. It caused by the pattern of the pressure changes on the junction when the different leakages happen on each pipe. The position of the pipes and junctions on in the pipe network in Taman Khayangan Resident, Makassar can see in figure 3. After taking the data, the ELM system is arranged using the Matlab application.

3.2. The Implementation of Extreme Learning Machine (ELM)

There are several stages to be followed in implementing the method of ELM, Broadly speaking, these measures are divided into three phases:

1) The division of data

The division of data is intended to distinguish the input data is the pressure (pressure) at 44 junctions and the data output (emitter coefficient, and the location of leakage) on the training data and the testing data.

Fig 2. The Pipe Network System in Taman Khayangan Resident Makassar by using the EPANET 2.0 Software.

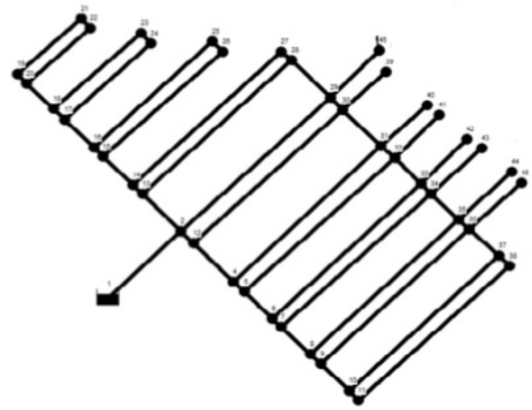

Fig 3. The position of the pipes and junctions on in the pipe network in Taman Khayangan Resident, Makassar.

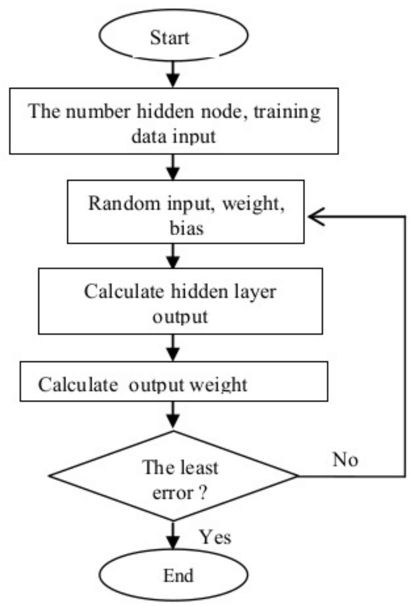

Fig 4. The flowchart of ELM training

2) Training ELM

Before being used to forecast ofl leakage, ELM methods has to go through the training the process in advance to get the input weight (w), biases (b) and the weight output (ß) with the smallest RMSE value. Flowchart ELM training can be seen in Figure 4.

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3) Testing ELM

Once the training process, it will be obtained the input weight, biases and the output weight that will be used to the best predict pipeline leak from the test data.

4. Result and Discussion

After doing the training data on the ELM models, it was obtained test results for the entire pipeline on each model. Here is a sample of the test data leaks is taken randomly The result of the prediction of leakage magnitude and location of leakage can be seen respectively in Figure 5 to 8.

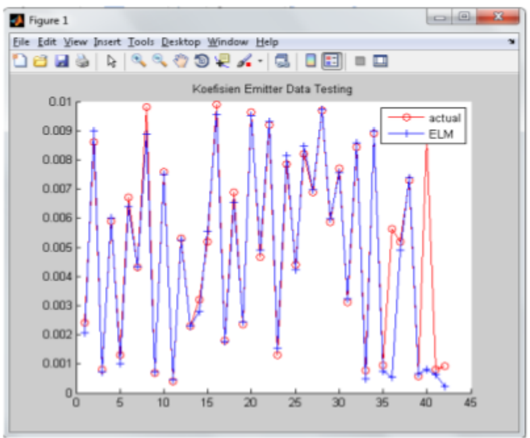

Fig 5 Prediction of magnitude of leakage at pipe 13-28

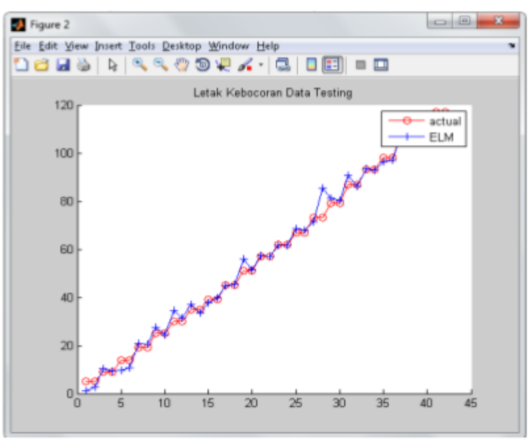

Fig 6. Prediction of location of leakge at pipe 13-28

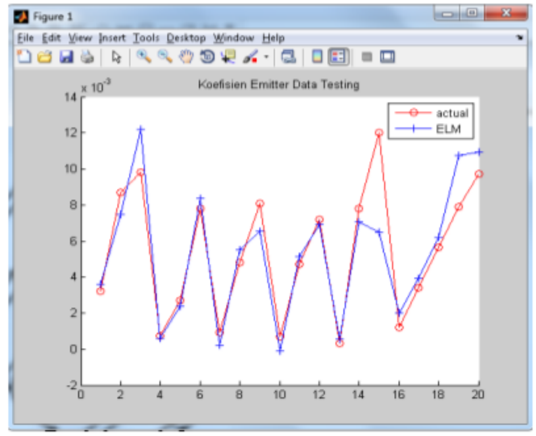

Fig 7. Prediction of magnitude of leakage at pipe 2-13

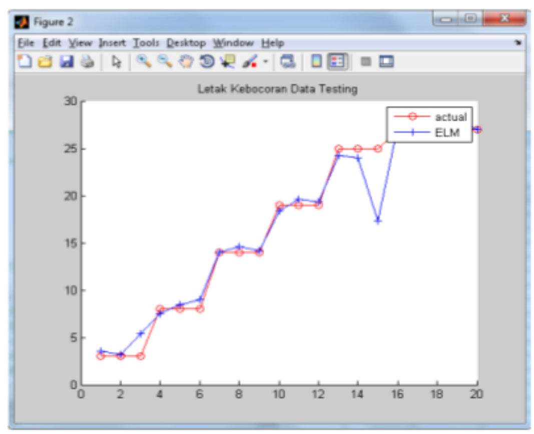

Fig 8. Prediction of location of leakge at pipe 2-13

Validation is the process conducted to see the model reliability in conducting the prediction. The magnitude of error of the prediction results from the established model can be calculated by using the RMSE (Root Mean Square Error) calculation. The magnitude of error showed the magnitude difference between the prediction results and actual data. The lower RMSE value, the more accurate the prediction results. To find the comparison of the performance accuracy of the Extreme Learning Machine (ELM) method prediction can be seen on the Root Mean Square Error (RMSE) value. The RMSE value can be calculated by using SVM with the formulation as follows:

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$$RMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(P-a)^2}}{Pmax-Pmin} \quad (2)$$

Where :

N : The total of the input data
P : Observation value
a : Observation results value
P*max*: The maximum value of the observation data
P*min*: The minimum value of the observation data

The accuracy of prediction of the location of the leak can also be expressed by the formula percentage of accuracy as follows:

$$A = \frac{N_p}{N_t} \ x \ 100\% \quad (3)$$

Where Np is the amount of success prediction and Nt is the total number of observation.

TABLE I. THE PREDICTION RESULTS OF EXTREME LEARNING MACHINES METHOD BASED ON THE RMSE VALUE.

The Pipe Models	Data test from the Random Data	
	Size of Leakage	Location of Leakage
Pipe 1328	0.1564	0.0253
Pipe 213	0.139778	0.07828

Fig 9. The display of the prediction results on GUI

By using the GUI interface, the use of this system will ease the user in detecting the leakage. By using the available buttons, the input of the pressure data that will be tested can be conducted easily and the results display of the program that will be conducted in the form of the leakage location and size will be seen directly. The display of the prediction results on GUI can see in figure 9.

There are two buttons available in this application, the "input data" is used to open the excel file which is a data input pressure of 44 junction and the "prediction" to see the results of a large prediction and location of the leak. Field "Description" will display the predicted results and the map location of the marker will appear in the form of red-yellow dot flashing on the point of leakage.

5. Conclusion

Prediction of magnitude and location of leakage using Extreme Learning Machine (ELM) obtained average yields RMSE = 0.06785 for magnitude of leakage and RMSE = 0.1382 for the location of leakage. The RMSE values indicate that the ELM models created can detect the location and large leaks in pipelines with a fairly accurate result.

The average of the accuracy prediction magnitude and location of leakage is 82.68% of the magnitude of leakage and 88,94 % for the location of leakage.

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