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EVALUATION OF NEURAL NETWORKS FOR PREDICTING NODAL PRESSURE IN WATER DISTRIBUTION NETWORKS

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1. Introduction

An artificial neural network is used to estimate pressure values at different pressure gauges in Block 12 of the supervisory water supply networks of Fukuoka City. The existing operational models of water supply networks which usually contains embedded optimization algorithm required solving the full hydraulic components of different water supply network elements many times which make the short term on-line operation difficult. The aim of this study is to reduce the required computational time for operational model by replacing the existing full hydraulic solver models by an Artificial Neural Network (ANN) model which is developed based on the past recorded telemeters data. In verification for the application case study, the estimated pressure values agree well with the measured ones and the new approach gives acceptable results.

2. Application

A skeletonized figure of Block 12 which is used as case study is shown in **Fig. 1**. In this block, there are 57 nodes, 83 pipes, 20 electric motor valves, 7 flow meters, and 11 pressure gauges. It is noticed from the figure that flow meters are connected to the main inlets and outlets and a valve is connected adjacent to each flow meter in order to control the flow entering or leaving the block. Motor valves are operated by remote control while pressure gauges and flow meters fitted to distribution pipes are monitored. The values of flow rate passing each flow meter, the opening percentage of each motor valve and the pressure intensity at each pressure gauge are recorded every minute. The analyzed data of this study are based on one minute data for all flow meters, pressure gauges, and motor valves for a randomly selected two days (Saturday and Sunday, 9th and 10th of November 2002). The total number of data for each telemeter equal to 2880 (total minutes during those two days).

One of the main objectives of the supervisory control of water supply network in Fukuoka City is to regulate pressure in all the network nodes within a target range (approximately between 24 m and 32 m)[1]. **Fig. 2** shows a box-whisker plot for all the 11 pressure gauges of Block 12 for the above mentioned two days, this figure shows the mean, upper and lower quartiles, upper and lower 5% of events occurrence and maximum and minimum values for all pressure gauges in comparison with the upper and lower regulated target values.

With the ever-increasing complexity of the city-wide distribution pipe network, motor valve operation to regulate pressure and flow came to depend more and more on the experience and skills of operators. For this reason, an improvement of valve operations support functions should be done based on valve operation planning for flow and pressure regulation, and the operation knowledge database which is constructed on the basis of past experience in order to prevent the events of pressure regulation falls outside the target pressure range and also to reduce the effort of investigator operators. The existing operational models which aim to regulate the pressure at selective nodes within a target range required solving the full hydraulic components of different water supply network elements many times which present a significant amount of the total computational time of the operational model[2]. For the case study considered, feed-forward back-propagation ANN was used to predict pressure gauges readings at the different 11 pressure gauges of Block 12 of Fukuoka City water supply network.

The back-propagation ANN is well-known approach for the prediction applications. In this type, the weighted links feed activations from the input layer to the output layer in forward direction. Learning in neural networks comprises adjusting the weights of links. The success of applying such supervised neural networks on any problem depends on training the net with sufficient range of data that spans a broad range of conditions. In this study we used the typical feed-forward back-propagation algorithm, which was presented by Rumelhart and McClelland[3].

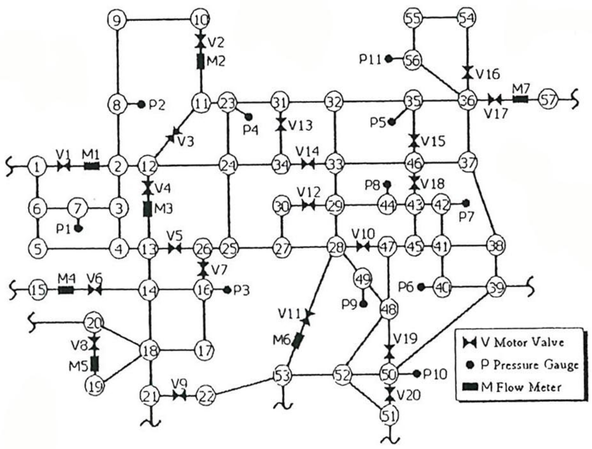

Fig. 1. Block 12 of the Fukuoka City water supply

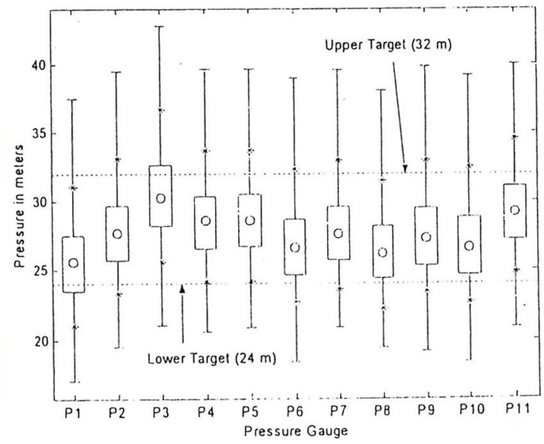

Fig. 2. Box-whisker plots of Block 12 pressure gauges

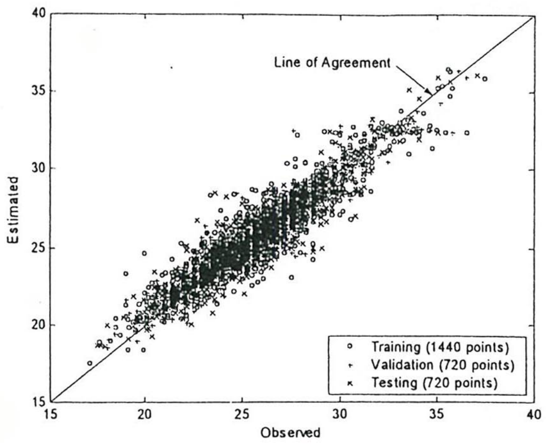

Fig. 3. Comparison between observed and measured pressure values for pressure gauge P1 (lowest mean value)

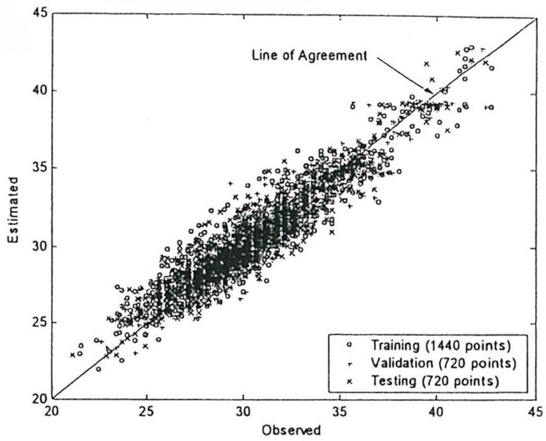

Fig. 4. Comparison between observed and measured pressure values for pressure gauge P3 (highest mean value)

3. Model Development

The number of input and output nodes in the back-propagation algorithm is determined according to the nature of the studied problem. In the proposed model the number of input nodes are set to the total number of flow meters and electric motor valves (27 nodes) while the output nodes number are set to the total number of pressure gauges (11 nodes). Regarding that the dimension of the input vector is large; it is useful in this situation to reduce the dimension of the input vectors. Using one of the most effective procedures for performing this operation (principal component analysis) the total number of input nodes has been reduced from 27 to 7 nodes. The number of hidden layers and hidden nodes which depends on the complexity of the mathematical nature of the problem is determined by trial and error. One hidden layer with 40 nodes is found to be suitable to describe the relationship between the input and output variables. All transfer functions in the hidden and output layer are hyperbolic tangent functions.

Other additional information used in the model formulation is as follows: the mean squared error is used as an error function, batch mode of training is used in which all weights and biases are updated after presentations of all training vectors, the maximum number of feed backs counts is 2000, the initial weights and biases are randomly selected between -1 and 1, learning rate during training processes is 0.01 while the momentum constant is 0.9.

In developing the ANN model, a cross-validation technique is used in which the data set is divided into three subsets; a training set, testing set and validation set. The odd number data are used for training while the even number data are divided to two subsets; one for testing and the other for validation. A data pre-processing has been used because it may have a significant effect on model performance, all original data of input and output vectors of the three previous sets are scaled in the range of the used hyperbolic tangent functions (-0.9 to 0.9).

4. Results and Discussions

Fig. 3 and **Fig.** 4 show scatter plots of the model estimated data versus observed data for pressure gauges P1 (lowest mean value) and P3 (highest mean value), respectively. The plotted results for those two pressure gauges are an example of the results obtained while all remaining pressure gauges show same trend.

In both figures there is good agreement between both estimated and observed data for all model sets, the training set (1440 points), the testing set (720 points) and the validation set (720 points).

The RMSE for the estimated pressure values is relatively acceptable for all pressure gauges; it varies between 1.066 m at pressure gauge P9 and 1.148 m at pressure gauge P3.

It is important to notice that the applicability of the model presented in this study is limited to the water distribution network of Block 12 of Fukuoka City and it is limited also to the upper and lower values of flow meters readings and valve openings used in the training phase of the back-propagation ANN. To generalize this model to make it applicable at any time around the year it should include all the expected extreme values of flow meters values and valves openings that it could occurs. To ensure the generalization we are now performing a model to include a three year data for the same Block of the Fukuoka City water supply network.

5. Conclusions

This study evaluates the potential of applying ANN for predicting nodal pressure at different pressure gauges of Block 12 of the supervisory water supply network of Fukuoka City. Artificial neural network model was able to successfully predict the pressure values at the desired locations which perform a good option to replace the existing hydraulic models which is based on iteration procedures and required long time for computation in operational models. Principal component analysis which has been used to decrease the number of input nodes is a good tool for decreasing the training time of the ANN. ANN model parameters which has been described in the section of model development has a significant effect on the model results, all those parameters have been selected by trial error based on the most recommended values in the literature.

References

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3) Rumelhart, D. E., and McClelland, J.L. (1986). Parallel distributed processing, MIT Press, Cambridge, Mass.