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Application of Hybrid Neural Modeling and Radial Basis Function Neural Network to Estimate Leakage Rate in Water Distribution Network

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Abstract: In this research the ability of a hybrid model of artificial neural network (ANN), feed forward networks (FFN) and recurrent neural networks (RNN), is investigated with genetic algorithm (GA). GA is used in order to determine the optimal structure of ANN (i.e. the number of neurons for each hidden layer). Furthermore, hybrid model's results are compared with radial basis function neural network (RBF). A water supply network located in Kerman, Iran is considered as case study in order to illustrate the efficiency of the modeling procedure. Obtained results apparently show that the ANN-GA models can be used successfully to estimate leakage rate in water distribution networks. In addition, a comparative study of models indicates that the feed forward networks hybrid with GA performed better than the other models.

Key words: Leakage · Water distribution network · Feed forward network · Recurrent neural network · Radial basis function · Genetic algorithm

INTRODUCTION

Leakage is one of the most serious problems in municipal water distribution networks. Limited resources of water special in arid area and the increasing expenses of transport, treatment, pumping, storage and distribution of water, notify the importance of leakage reduction. Also water quality problems could result from pollution at leak points. Due to the direct relation between leakage and pressure, pressure monitoring is a useful and cost effective method for leakage reduction. On the other hand the relationship between pressure changes and the rate of leakage in water supply networks is non-linear and complex. Mathematical hydraulic models can be utilized for modeling the leakage rate in terms of pressure changes. The problems in developing these models are twofold: firstly, understanding of complex concepts related to the field of hydraulic, secondly, wasting a plenty of time for driving a suitable mathematical relation.

In recent years, successful application of soft computing techniques in water distribution networks have been widely published, in the following a short review of these studies is given. Martinez *et al*. [1] used an artificial neural network (ANN) predictor in place of the EPANET model and a dynamic genetic algorithm to optimize the control setting of pumps and valves up to 24h rolling operating horizon, in response to a highly variable demand. Salomons *et al*. [2] described the Haifa-A hydraulic network, the ANN predictor, the GA optimizer and the demand forecasting model that were used. Mounce *et al*. [3] presented the online application of artificial neural network and fuzzy inference systems for detection of leakage in real water distribution system. Nazif *et al*. [4] used a genetic algorithm based optimization model to develop the optimal hourly water level variations in a storage tank for minimizing the leakage level in different seasons. Koppel *et al*. [5] showed that the Levenberg-Marquardt algorithm may successfully be used for calibration of water distribution system model. Rao *et al*. [6] described that the ANN is employed in preference to the hydraulic simulation model within the optimization process. Bowden *et al*. [7] developed general regression neural networks (GRNNs) for forecasted chlorine residuals in the Myponga water distribution system. Mounce *et al*. [8] presents the application of artificial neural network (ANNs) for analysis of data from sensors measuring hydraulic parameters (flow and pressure) of the water flow in treated water distribution systems. Celia *et al*. [9] used ANN models to predict residual chlorine, substrate and biomass

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concentrations in water distribution system. Also Fadaee and Tabatabaei [10] presented a statistical model for decision making in repairing water pipes network. In this study, a new method was proposed to improve the estimating of leakage rate by using genetic algorithm (GA) to optimize the structure of multi-layer feed-forward network (FFN) and recurrent neural networks (RNN) and also compare the results with radial basis function (RBF) model.

MATERIALS AND METHODS

Artificial Neural Networks: Artificial neural networks estimation approach has received tremendous attention of researchers in the last few decades. An interesting property of ANNs is that they often work well even when the training data sets contain noises and measurement errors [11]. Moreover, they have the capability of representing complex behaviors of nonlinear systems [12]. A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights and the activation function [13, 14].

Feed-forward Neural Network Models: One way of characterizing ANNs is based on the direction of information flow and processing, as feed-forward (where the information flows through the nodes from the input to the output side) and recurrent (where the information flows through the nodes in both directions). Among these combinations, the multi-layer feed-forward networks, also known as multi-layer perceptions (MLPs), trained with a back-propagation learning algorithm have been found to provide the best performance with regard to input–output function approximation, such as forecasting. A typical MLP with one hidden layer is shown in Fig. 1 (a). The first Layer connects with the input variables and is called the input layer. The last layer connects to the output variables and is called the output layer. The layer between the input and output layers, is called the hidden layer (there may be more than one hidden layer in an MLP).The processing elements in each layer are called nodes or units. Each of the nodes is connected to the nodes of neighboring layers. The parameters associated with each of these connections are called weights. The architecture of a typical node (in the hidden or output layer) is also shown in Fig. 1 (b). Each node j receives incoming signals from every node i in the previous layer. Associated with each incoming signal x_i is a weight w_{ji}. The effective incoming signal s_j to node j is the weighted sum of all the incoming signals,

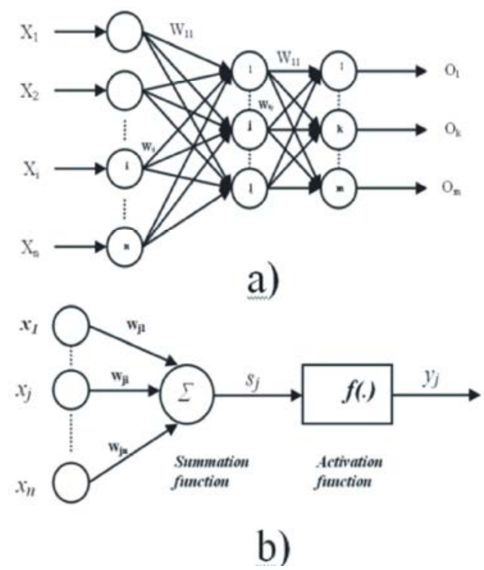

Fig. 1(a): Multi-layer feed forward ANN, (b) a

$$f(s_j) = \frac{1}{1+\exp^{-s_j}} \tag{1}$$

,is passed through the effective incoming signal, s_j non-linear activation function (sometimes called a Transfer function or threshold function) to produce the outgoing signal y_j of the node. The most commonly used function in an MLP trained with back-propagation algorithm is the sigmoid function. The sigmoid function most often used for ANNs is the logistic function [15]:

$$S_j = \sum_{i=0}^{n} w_{ji} x_i \tag{2}$$

Recurrent Neural Network Models: The recurrent neural network (RNN) is another multi-layer architecture that has been used for a variety of applications including control systems and forecasting of dynamic processes. In this section we briefly present a general discussion of RNN.

The RNN architecture, a variation of general feed-forward back-propagation (FFBP) architecture, is used to capture dynamic and highly nonlinear systems by including a feedback mechanism in the architecture. The general RNN architecture uses specialized hidden nodes to introduce feedback to the network. In such a network, the output of these specialized nodes is provided as input to others. Once such feedback connections are allowed, the network topology becomes more connected since any node can be connected to any other node, including to itself. These concepts are well described in [16, 14].

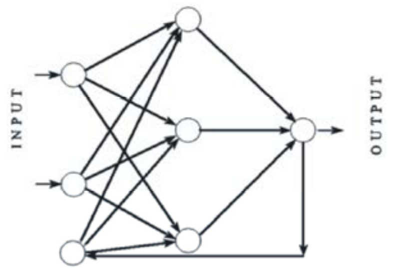

Fig. 2: Typical Recurrent Neural Network

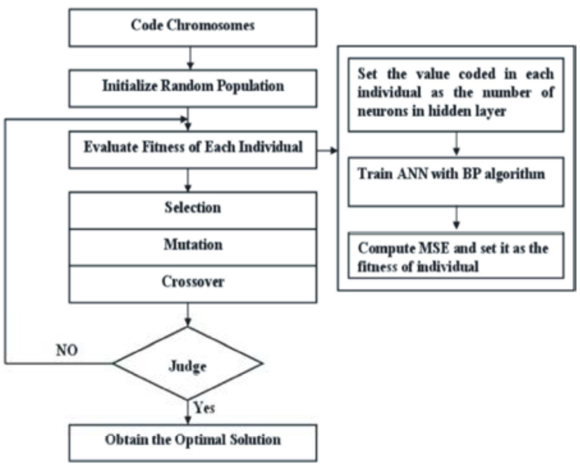

Fig. 3: The flow chart of ANN-GA model.

Training Methodology in RNN: The method of training RNN is similar to that of feed forward network models. The training algorithm is explained with the help of a simple example. A small network which has two input neurons, one hidden layer having three neurons and one output neuron is shown in Fig 2. In addition, a neuron taking input from the output layer and connected to the hidden layer is added as shown. This neuron is the additional neuron in RNN.

Genetic Algorithm (GA): GA optimizes using a search process that emulates natural evolution. On the other hand GA is a global heuristic, stochastic, optimization technique based on evolution theory and genetic principles developed by [17]. Goldberg and Michalewicz discussed the mechanism and robustness of GA in solving nonlinear o ptimization problems [18, 19]. The algorithm begins with a randomly generated population which is consist of chromosomes and applies three kinds of genetic operators: The selection, crossover and mutation operators to find the optimal solutions. The selection operator chooses chromosomes from the current population based on fitness value of the individuals. The crossover operator combines the features of two parent chromosomes to form two similar offspring by swapping corresponding segments of the parents [18]. The mutation operator creates new chromosomes by randomly changing the genes of existing chromosomes. GA can explore the entire design space by the genetic manipulations, it does not easily fall into a certain local minima or maxima.

As this occurs, the GA converges to increasingly better solutions. Improvements in fitness, however, diminish as the population diversity decreases and the population converges toward a good solution. Stopping criteria such as “100 generations without improvement” and minimum population diversity are often used to terminate the algorithm when improvements are sufficiently small and infrequent. These concepts are well described in [20, 18]. Therefore, GA is an aggressive search technique that quickly converges to find the optimal solution in a large solution domain.

ANN–GA Model Scheme: In this research, a multi-layered feed-forward neural network (FFN) and recurrent neural network (RNN) with a back propagation algorithm are adopted. Although the back propagation algorithm is successful, it has some disadvantages. The algorithm is not guaranteed to find global minimum of error space and the convergence tends to be extremely slow. In addition, the selection of the learning factor and inertial factor affects the convergence of the BP neural network which is usually determined by experience. In present research, the number of neurons in the hidden layer is determined using the genetic algorithm. The number of hidden layers and the number of nodes in each layer depends on the complexity of the patterns and the nature of the problem to be solved. The use of a single hidden layer is sufficient to approximate to any continuous function as closely as requested [21, 22] and studies also showed that having more than two layers may not result in significant performance improvements [23]. Thus, in our study, a two-layer ANN is utilized (Fig. 1). The number of neurons in the input and output layers are given by the number of input and output variables of network. The number of neurons in hidden layer is obtained by GA. In this study, an ANN with one hidden layer is employed. The number of neurons in this layer is determined by GA. The optimization process flow chart of the ANN-GA model is shown in Fig.3. The sigmoid function was used in each node of the hidden layer and output layer as the transfer function.

Number of neurons in hidden layer is the only information that is coded in a chromosome in GA. After that, the GA is run and in its fitness assignment past, an ANN which the number of its hidden layer neuron is determined by coded chromosome is trained via ANN. Then the MSE of this trained ANN is set as the fitness values. The GA will generate many of individual values will be set to MSE. This process is depicted in Figure 3.

Radial Basis Function Networks: Radial basis function (RBF) networks are attracting a great deal of interest due to their structural simplicity and training efficiency [24]. Like an MLP trained by the back-propagation, the RBF network is a universal approximator, that is, given a network with enough hidden neurons, it can approximate any continuous function with arbitrary accuracy [25, 26]. RBF networks are usually orders of magnitude faster than back-propagation in addition to avoiding the local minima problem. However, after training, they are generally slower to use, requiring more computation to perform function approximation than back-propagation. The mapping produced by the RBF network has the form of a weighted sum over nonlinear functions. A schematic diagram of an RBF net work is shown in Fig. 4. Basically, it consists of three layers. An input layer with n inputs, one hidden layer with m neurons and an output layer with k output units. Input vectors x propagate to the hidden neurons where each neuron computes a hyperspherical function of x. The output of the RBF network is represented as a linear summation of the basis functions in the form of

$$y_k(x^p) = \sum_{j=1}^{m} w_{kj}\phi_j(x^p) \tag{3}$$

Where $\phi j(x^p)$ is a radially symmetric function.

RBF networks perform a specific nonlinear input–output mapping by using a set of examples named training data set. One major difference between MLP and RBF is that RBF utilize a local learning strategy vs. MLP global learning and this leads to a higher rate of accuracy and faster training of RBF [27]. A RBF neural network can compute a decision function from a given input. In this work, the RBF neural network model with one hidden layer, three inputs and one output (leakage rate) was designed for estimation leakage rate in water distribution network. The algorithm is performed by using commands in MATLAB software which is ‘newrb’.

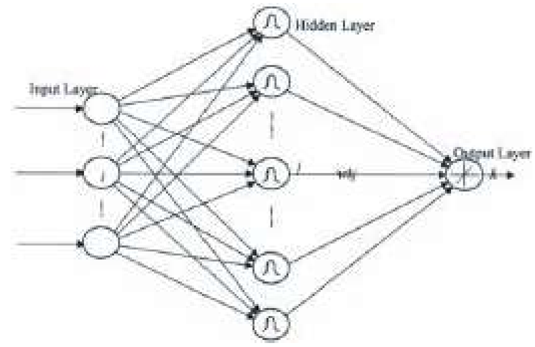

Fig. 4: A radial basis functions neural network.

Case Study: Nowadays statistical based methods are being developed for detailed leakage assessment. A minimum nightly flow method is used to obtain leakage statistical information related to pressure. In order to do so, the existing flow in an isolated system (a system in which its input and output is controlled and is isolated from any other surrounding systems) is measured at the time of night with minimum demand known as minimum nightly flow method. Minimum nightly flow method consists of two factors as follows 1- normal nightly consumption 2-leakage. The leakage can be calculated by subtracting the determined normal nightly consumption from the minimum nightly flow. Kerman (one of Iranian provinces) is located in a dry region with relatively low rainfall amounts. The only source of drinking water supply in this province is practically limited through groundwater resources. Since the networks of this province are too old, pipe network leakage is the main reason of fresh water loss. Therefore, case study (located in Kerman) was used in order to examine the efficiency and applicability of the proposed method in estimating water leakages as shown in Fig 5.

Case study is focused on a loop system which is located in the north of Kerman province as shown in Fig 5. Number of network pipes are 133 that have been designed for a population of 4500 person. Three pressure sensors are installed on the network that their locations are shown on the network in Fig.5 by S1, S2 and S3 letters. Other nodes are depicted by dots on Fig5. Also, 250 random fractures in different zones of water distribution network are created and then the changes of pressure are recorded. Data consist of 200 samples in four columns. The first three columns are pressure values measured in sensors 1, 2 and 3 respectively. The values in these columns are fed as inputs to the hybrid models and RBF model. The fourth column is the target output and

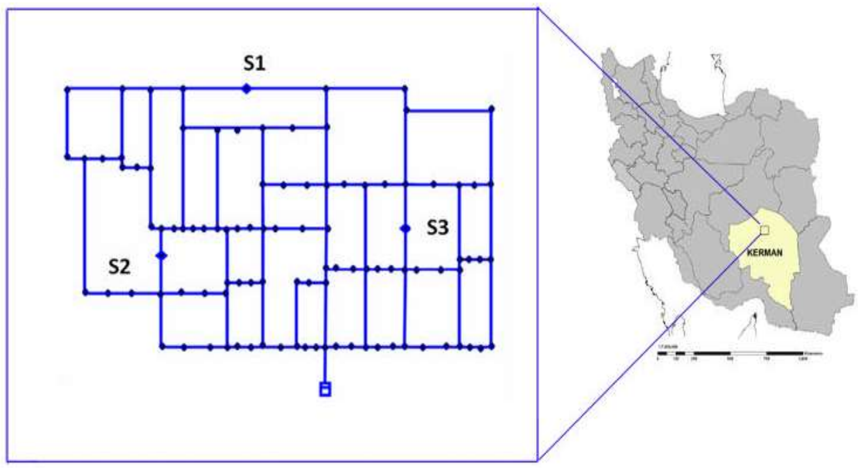

Fig. 5: The location of water distribution system in Kerman province

Table 1: The statistical parameters of recorded data

Data set	Unit	Xmean	Sx	Csx	Xmax	Xmin
Pressure head in Sensor 1	m	35.639	3.761	-0.49	40.35	24.79
Pressure head in Sensor 2	m	52.598	3.779	-0.51	57.32	41.34
Pressure head in Sensor 3	m	67.851	3.518	-0.45	72.29	58.18
Leakage rate	Lit/sec	2.29	1.16	-0.14	5	0

the models must predict the values in this column.80 percent of the data is used for training and 20 percent is used for test. The statistic characteristics of each recorded data are given in Table 1. In the table the X_{mean}, S_x, C_{sx}, X_{max} and X_{min} respectively denote the mean, standard deviation, skewness coefficient, maximum and minimum of recorded data.

Parameter Setup: Population size and generation numbers are set to 100. The tournament selection is used as selection method in GA, two point crossover and an uniform mutation are consider for reproduction Crossover rate and mutation probability are set to 0.7 and 0.03 respectively. Learning rate in BP algorithm is set to 0.02 and 50 epochs are considered for training the ANNs.

RESULT AND DISCUSSION

In this work two hybrid models (FFN-GA and RNN-GA) and RBF neural network were also used in order to estimate leakage rate in water distribution network. Three different types of standard statistical fitness criterion to evaluate the performance of the models were considered. These criteria were correlation coefficients (R^2), Root Mean Square error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE). The three performance evaluation criteria are based on the following equations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(L_i^o - L_i^e)^2}{n}} \tag{10}$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|L_i^o - L_i^e\right|}{L_i^o + L_i^e}\times 100 \tag{11}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(L_i^o - \overline{L}_i^o)(L_i^e - \overline{L}_i^e)}{\sqrt{\left[\sum_{i=1}^{n}(L_i^o - \overline{L}_i^o)^2\right]\left[\sum_{i=1}^{n}(L_i^e - \overline{L}_i^e)^2\right]}}\right)^2 \tag{12}$$

Where, L_i^0 is the observed leakage rate and L_i^0 is the estimated leakage rate with artificial intelligence (AI) models.

RMSE=0, SMAPE=0 and R^2=1 shows a perfect fit. Table 3 represents the resulted fitness statistics of testing and training steps for considered models. In the theory of system identification and modeling, a good model is an accurate and simple model for training data [28]. The simplicity of obtained model by means of training data results in a good generalization of model when unseen data are presented in to model (i.e. a good performance on test data) [28].

Table 2: Error analysis of leakage estimation in test and train period.

Set			Training			Testing		
Model	No. ofinputs	No. of hidden neuron	RMSE	SMAPE	R2	RMSE	SMAPE	R2
FFN-GA	3	7	0.188	0.465	0.996	0.592	1.955	0.995
RNN-GA	3	6	0.306	0.887	0.995	0.636	2.528	0.994
RBF	3	175	0.071	0.174	0.999	1.252	3.495	0.98

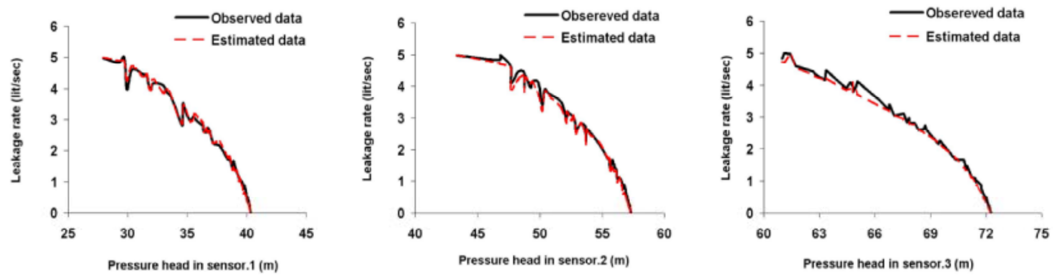

Fig. 6: Observed and estimated of values leakage rate for the test period using by FFN-GA model.

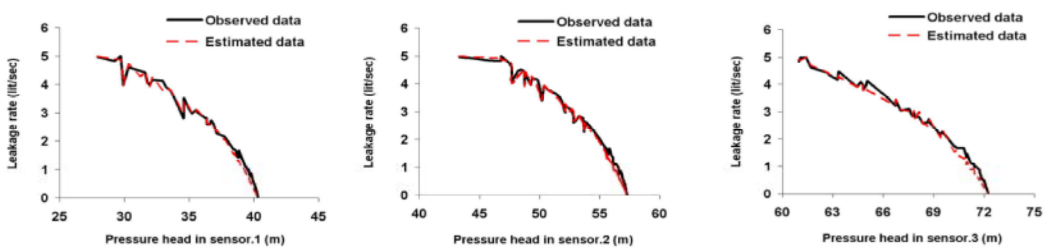

Fig. 7: Observed and estimated values of leakage rate for the test period using by RNN-GA model.

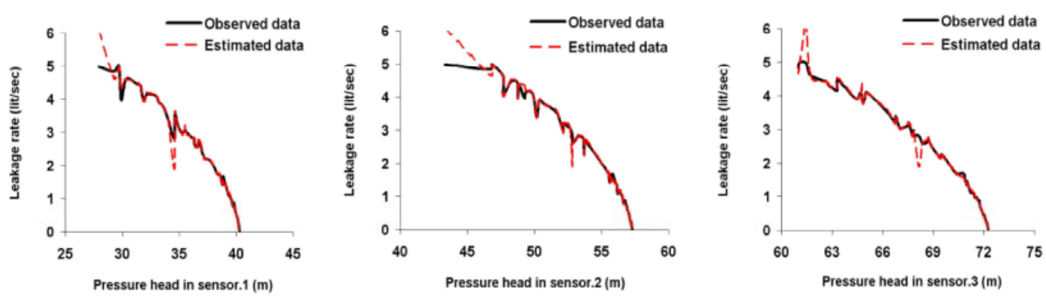

Fig. 8: Observed and estimated values of leakage rate for the test period using by RBF model.

In addition to the Table (2) which indicates the overall accuracy and simplicity of obtained hybrid models and RBF model on train and test data, some graphs are presented in the following for more illustrations. Regarding to the case study, these graphs depict the pressure head measured in each sensor versus the leakage rate for both actual and predicted leakage on test data. These figures are given in the following in order to visualizing the prediction accuracy. Figures (6-8) plot the leakage rate versus the values of pressure measured by sensor one, two and three respectively. In these figures the outputs of obtained ANN models are indicated by dashed lines and are compared with actual values of leakage rate (bold lines).

Information given in Table (2) as well as Figures (6-8) apparently shows the success and efficiently of our proposed algorithm for finding accurate and simple ANN models. Performance measures apparently show that the FFN-GA model is the best model.

CONCLUSIONS

Water leakage results in losses of supply pressure and capital investment. It also has adverse effects on water transfer capability, water treatment and also other elements in distribution process. It is therefore necessary to estimate leakage rate at water distribution network as a function of pressure. Owing to the importance of this problem, a new hybrid algorithm is introduced in this study for the sake of estimating water leakage in terms of measured pressures at multiple positions of the network. In this work, artificial neural networks coupled with a genetic algorithm were developed and used for estimating leakage rate. The number of neurons in the hidden layer was determined using the GA algorithm for two types of ANNs (FFN and RNN). Radial basis function neural network (RBF) was also used to estimate leakage rate and results are compared with our proposed method. A water distribution network in Kerman province (Kerman, Iran) is considered as case study. This network is used and the pressure and leakage rate are measured in some points of network by means of three sensors. After that, these measured data are used as training and test data. The study showed that genetic algorithm could find the optimal architecture of the neural network of the back-propagation algorithm. Further, the artificial neural network model based genetic algorithm was tested and the results indicated that excellent agreement between the estimations and the experimental data is obtained. The FFN-GA model was found to perform the best result for estimating leakage rate. Simulation results confirm the applicability of our proposed method in terms of producing compact ANN models for estimating the water leakage accurately.

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