Urban Water Demand Forecasting Using Artificial Neural Network Model: Case Study of Daegu City

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Abstract

This paper employs a relatively new technique of Artificial Neural Network (ANN) to forecast water demand of Daegu city. The ANN model used in this study is a single hidden layer hierarchy model. About seventeen sets of historical water demand records and the values of their socioeconomic impact factors are used to train the model. Also other regression and time serious models are investigated for comparison purpose. The results present the ANN model can better perform the issue of urban water demand forecasting, and obtain the correlation coefficient of R^2 with a value of 0.987 and the relative difference less than 4.4% for this study.

Key words: Urban Water Demand Forecasting, Artificial Neural Network, Daegu City

1. Introduction

Since entering 21 century, a series of phenomena have appeared under the rapid development of economies and societies in all of the world. These phenomena like the increasing of urban population due to many people moving to the cites in search for an improved living life, and the rapid expanding of urbanization and industrialization, criticise the current urban water supply systems. In order to tackle the increasing of urban water demand, most countries apply an urban water demand forecasting model for primarily predicting the amount of urban water demand, so that generating an efficient and reasonable plan for better managing and designing the existing water systems. The methods reported in previous literatures on predicting urban water demand include quota method, time series analysis techniques (e.g., trend method, autoregressive method, multi-linear regression method), system dynamic method, artificial neural network (ANN) and gray algorithm. The quota method is a very common and conventional method used for simply and quickly predicting. Due to lack of considerations on most factors which are sensitive to the urban water demand, the quota method is limited in further realistic modeling. The regressive method has been successively used in urban water demand forecasting. Maidment et al.

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(1985) developed a time series forecasting model for short-time urban water demand prediction. Zhou et al. (2000) and Gato et al. (2003) adopted the methodology based on time series analysis for predicting water demand. Recently, most studies on prediction modeling are focusing on the use of evolutionary algorithms based on computer programming technology. Ashu Jain et al. (2001) developed and compared six different ANN models with several time series models by applying to the city of Kanpur, India. Zhang Xuefei et al. (2005) developed a backpropagation ANN model for forecasting the water demand of the city of Tangshan, China. Both the studies showed an best result by the ANN algorithm.

The present paper is intended to develop a simple backpropagation ANN model for predicting water demand of the Daegu city with the socioeconomic variables such as population and gross regional domestic production (GRDP). The autoregressive model and gray model are also presented in this study for comparison of the modeling results with the ANN model.

2. Methodology

2.1 Autoregressive model (AR)

The autoregressive model (AR) is a simply linear regression model attempt to predicts an output of a system only based on one or more previous outputs. The AR model used in this research is formulated as,

$$x_t = \delta + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + A_t \tag{2.1}$$

where x_t is the time series, p is the order of the AR model, A_t is white noise process, $\varphi_1, \cdots, \varphi_p$ are the parameters of the model, δ is a constant and defined as equation 2.2.

$$\delta = (1 - \sum_{i=1}^{p} \varphi_i)\mu \tag{2.2}$$

with μ denoting the process mean.

2.2 Gray model (GM)

The theory of Gray system was firstly discussed by Deng, Julong in 1982 (Deng, 2002). The gray system is defined as a hybrid system, with one part of known information and the other part of unknown information. One of commonly used gray models $GM(1,1)$ is introduced in the following processes.

- Generate new accumulated dataset

Given the original dataset of $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$, the new dataset is represented as $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n))$, that is for the kth data,

$$x^{(1)}(k) = \sum_{t=1}^{k} x^{(0)}(t) \tag{2.3}$$

- Apply one order differential equation

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u \tag{2.4}$$

where, a, u, are the parameters. According to the method of minimum squares, the value of a and u are determined by,

$$(a, u)^T = (B^T B)^{-1} B^T X_n \tag{2.5}$$

where,

$$B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] & , & 1 \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] & , & 1 \\ \cdots & \cdots & \cdots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)], & & 1 \end{bmatrix}; \; X_n = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(2) \\ \vdots \\ X^{(0)}(n) \end{bmatrix}$$

- Solve the equation 2.4 using Laplace transform and inverse transform methods. The result is,

$$\widehat{x^{(1)}}(k+1) = (x^{(0)}(1) - \frac{u}{a})e^{-ak} + \frac{u}{a} \tag{2.6}$$

- Then Restore the problem,

$$\widehat{x^{(0)}}(k+1) = \widehat{x^{(1)}}(k+1) - \widehat{x^{(1)}}(k) \tag{2.7}$$

2.3 ANN model

Artificial Neural Networks (ANNs) are mathematical models of theorized mind and brain activity which attempt to exploit the massively parallel local processing and distributed storage properties believed to exist in the human brain (Zurada, 1992). A basic ANN model consists of three layers as shown in Fig 2.1. The input layer consists of input dataset from external environment which should be normalized between 0 and 1. The hidden layers receive and perform the transferred weighted inputs from the input layer or previous hidden layer, and then pass the output to next hidden layer or output layer. The output layer receives the output from hidden layers and then sends to user.

A most commonly used ANN model is based on the back propagation (BP) algorithm as shown in Fig 2.2. In a BP-ANN model, the actual model output is obtained based on an initially randomized network weights and compared with the desired output, then the computed error is back propagated through the network and the weights are updated. The process of feed-forward calculations and error back propagation is repeated until an acceptable level of convergence is reached. This whole process is known as training of the ANN model. As shown in Fig 2.1, the model has m number of input nodes, viz. $x_1, x_2, \cdots, x_m$, n number of output nodes, viz. $O = [y_1, y_2, \cdots, y_n]$. The calculation processes is discussed in the following.

- Feed-forward networks

Using sigmoid function as defined in equation 2.8, the inputs are converted to output.

$$O_k = \frac{1}{1 + e^{-(I_k + \theta_k)}} \tag{2.8}$$

where, O_j is output to node j, θ_k represents a bias or threshold term that influences the horizontal offset of the function, I_k represents the input to node k in hidden layer, can be expressed as $I_k = \sum w_j O_j$, here w_j is the weight. Given the desired output D_j for node j, then the compute error δ_j is computed using equation 2.9.

$$\delta_j = O_j(1 - O_j)(D_j - O_j) \tag{2.9}$$

• Recurrent or feedback networks

Update the weights using generalized rule according to the following equations,

$$w_j(t+1) = w_j(t) + \Delta w_j(t) \quad (2.10)$$

$$\Delta w_j(t) = \eta \delta_j O_j + \alpha \Delta w_j(t-1) \quad (2.11)$$

where $w_j(t+1)$ is the value of a weight at iteration $t+1$, $\Delta w_j(t)$ is the change in the value of a weight at iteration t, η is the learning coefficient, α is the momentum correction factor, δ_j is the error signal, and O_j is the output from the output node j, t is an index representing iteration. The values of the learning coefficient and the momentum correction factor normally range between 0 and 1.

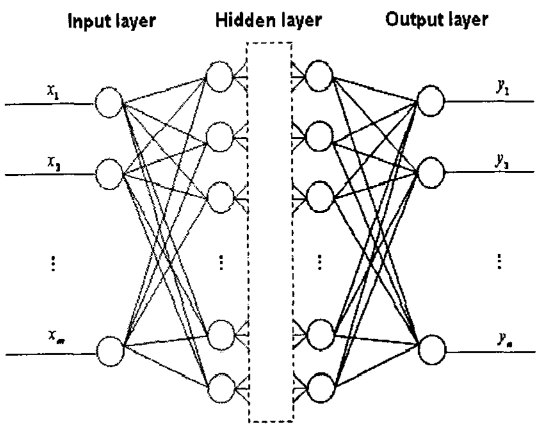

Fig 2.1 Structure of a Basic ANN

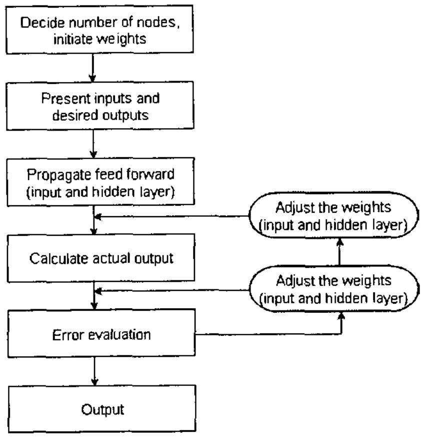

Fig 2.2 Flow chart of the back propagation learning algorithm

3. Models application and Results analysis

The above three models are applied to Daegu city, which is the third largest city in Korea. The data used for modeling and validation are a series of historical records from 1985 to 2001 on yearly population, gross regional domestic production (GRDP) and relative city water demand, which are derived from the National Water Management Information System (WaMIS). The data from 1997 to 2001 as listed in Table 3.1 are used for testing models. The results are illustrated in Fig 3.1. Also a comparison of simulated water demand by the ANN model and the observed water demand is illustrated in Fig 3.2. The results present a better prediction by the ANN model with the correlation coefficient R^2 of value 0.987.

Table 3.1 Testing dataset for ANN model and Time series model

Year	GRDP (mil. won)	Population	Observed (m^3)	Simulated (m^3)
1997	18,992,791	2,466,548	709,916.7	692,756.2
1998	17,621,591	2,477,990	683,374.9	696,720.2
1999	19,228,636	2,492,524	679,492.8	689,685.8
2000	20,776,260	2,516,984	688,060.3	684,728.9
2001	21,720,600	2,520,151	676,853.1	683,254.1

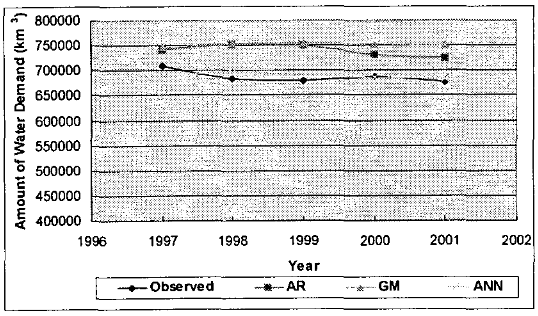

Fig 3.1 Results comparison of ANN model and Time serious models

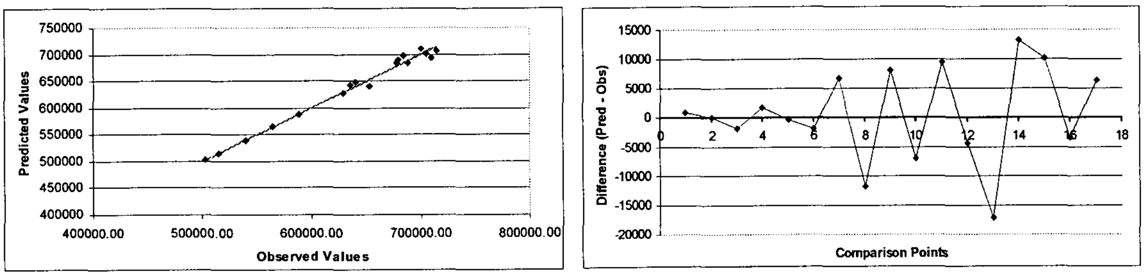

Fig 3.2 Comparison of predicted by ANN model and observed water demand (1985-2001)

4. Conclusions

The study presents that the ANN algorithm is more reliable and convenient for urban water demand forecasting comparing to conventional regressive models.

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