A Water Demand Forecasting Model using BPNN
for Residential Building

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Abstract

This paper presents a residential water demand forecasting model using a back propagation neural network (BPNN) in the context of residential buildings in Korea. The water demand of a building demonstrates a highly complex and non-linear phenomenon reflecting such features as geographic and climatic and special types of buildings.
We describe the impact of several potential determinant factors affecting water use in residential buildings in four different provinces in Korea. Empirical data sets consisting of water consumption retrieved from multiple residential buildings in Korea were evaluated to verify the performance evaluation.
Our results show that the proposed model can successfully predict estimated outputs through the BPNN. The model we propose can used in decision making for the residential water management policy in Korea through the optimal estimation of residential water consumption.

Keywords: Water Demand Forecasting Model, Residential Water Use, BPNN, Machine Learning, Residential Building

1 Introduction

Water demand forecasting influences various factors, including geographic,
climatic, population, socio economic and environmental factors. In particular, potential factors affecting water consumption related to size, shape and complexity of the buildings or the type of water supply infrastructures must not be underestimated.

Water demand forecast modeling is crucial for designing water planning systems and managing water resources at the city or national level. It is also necessary for making reliable demand forecasting in management and creating the most benefit in terms of water conservation. Water conservation is efficient and economical as well as significant in protecting the environment. In Korea, reducing water use by 10% saved 2,883 thousand tons of water in the year (2011), and it saves 30 billion Won a year of total water production (report from the Ministry of the Environment).

Approximately 25% of the total water use in Korea is from domestic and residential water consumption, which indicates that at least one fourth of the total water use comes from building sites. Residential water consumption occupies roughly 66.4% of the total water supply, which means that the building sector can have the most influence on improving water use efficiency [1].

Accurate forecasting of future demand for water by appropriate methodology is necessary for the operation and management of the municipal water supply to provide better planning of national or regional water policies. This study analyzes the unique features of the residential buildings regarding water consumption, and we propose a water demand forecasting model that estimates the amount of water use considering various residential building types in Korea. This paper is an extension of work published in [2].

2 Research Background

Water demand prediction modeling is a big issue in water management and policy in the residential sector in terms of environmental economics and preservation of our water resources. Research groups have studied residential water prediction modeling, which analyzes the main features affecting residential water consumption regarding the impact of price, income, population, inter-annual climate variability, housing types and household composition of residential consumption [2-4].

Most studies have used top-down or bottom-up approaches. Top-down approaches use macroscopic exploration at a regional or national level over a long-term scale such as annual estimations.

Romano [5] analyzed relevant studies on water demand in European countries and derived the determinants which influence water consumption. He introduced a residential water demand model for Italian provinces in the period 2007–2009, which relied on econometric components, such as tariffs and income, as well as many other factors, including population characteristics and density, the presence of immigrants or tourists and household features.
A water demand forecasting model using BPNN

Howe [6] econometrically explored the impact of the influence and effectiveness of water pricing in the United States and Canada according to the type of water service. Schleich [7] studied the influence of economic (prices and income), environmental and social determinants (household size, the effects of population age, the share of wells, housing patterns, meteorological information) for the per capita demand for water in about 600 water supply areas in Germany from the perspective of econometric analysis.

On the other hand, bottom-up methods deal with a microscopic scale, inferring regional and national levels from the estimated water demand of a representative set of individual houses over a relatively short-term scale, such as daily or monthly estimations. This study mainly focused on a bottom-up approach on a residential building scale with monthly estimations, evaluating the impact of the water use of residential buildings in relation to national water use levels.

Zhang [8] presented a residential water demand model for urban household units through both empirical investigations from surveys and analytical studies of Beijing and Tianjin in China. Höglund [9] examined household water use and the effects of a water tax in Sweden. Jorgensen [10] investigated individual level variables that affect household water use taking into account dwelling types, location, and income in addition to individual motivations and behaviors associated with household water consumption in South Australia. Blokker [11] developed a water demand end-use model in the Netherlands based on statistical information of users and water outlets with respect to behavior patterns with a small time scale and small spatial scale.

Forecasting water demands in buildings mainly consider annual water usage characteristics from simple simulations using simple regression techniques [12-13] to very complicated models. Recently new predictive modeling using nonlinear estimation methods, including Artificial Neural Network (ANN) based models, have also been used in various forecasting areas, such as prediction outcomes for carbon emission [14, 15], stock market [16], and energy consumption [1, 17, 18].

We investigated the relationship of morphological and climatological variables with monthly water demand through a case study. We initially analyzed potential elements affecting water demand in apartment buildings and climate elements in relation to the empirical water consumption and then devised a Back Propagation Neural Network (BPNN) model, with any response of a nonlinear pattern through the training and learning system, and explored the features.

3 Back-Propagation Neural Network (BPNN)

Artificial neural networks can be classified into several categories based on supervised and unsupervised learning methods and feed-forward and feedback recall architectures.
This study adopts the Back Propagation Neural Network (BPNN), one of the most novel supervised learning and multilayer perceptrons, where a hidden layer exists, feed-forward neural network architecture proposed by [19].

Back Propagation is the most employed in classification and regression to resolve complex non-linear issues [20-21] and has been utilized in training neural network models in conjunction with an optimization method such as gradient descent [22]. In the BPNN, the learning process was derived from the presentation of the entire training set during the network.

The neural network produces results, and this output can be compared with the expected results. When an error is detected, the weighting values related to neurons of the entire network are regulated to reduce the errors. The error is then propagated back to the neural network, which causes the system to regulate the weight for the target system through minimizing criterion equivalents to the differences between the actual outputs and the desired outputs.

Through the training of the entire neural network the same set of data is repeated until some criterion is met, with the connection weights being continually refined [23]. The architecture the BPNN is described in Figure 1.

![The architecture of a BPNN](image)

**Figure 1.** The architecture of a BPNN

### 4 Water Demand Prediction Method

Through an extensive review of the models discussed so far, we examined the previous studies to determine the relevant factors affecting water consumption levels before we designed an appropriate neural network model.
We analyzed the various factors related to residential buildings and their environment as input datasets for the BPNN. Then, we devised a BPNN model capable of modeling extremely complex nonlinear patterns through a training and learning system with the carefully investigated features.

We verified the diverse elements constituting apartment buildings as input datasets for the BPNN, which is the most relevant supervised learning neural network based model according to the empirical water use data. Then, we used the BPNN model to analyze the complex nonlinear patterns accurately through a training and learning system encompassing carefully investigated factors.

We analyzed the empirical data to show how those factors affect the water usage of apartment complexes and weather information that affected the changing water consumption patterns.

Data obtained from other sources to estimate water demand included climate variables, geometric variables, and the types of residential buildings. Monthly averaged water consumption data for 2012 and 2014 were used in this case study. In addition, we selected residential complexes located in four different provinces, Choongnam, Gangwon, Gyeongnam, and Gyeonggi provinces in Korea.

In accordance with water use, we explored the significant differences with 95% confidence interval for the calculated mean data. Table 1 describes the information on the selected residential buildings.

Table 1 Information of Selected Residential Buildings (Residential Complex)

<table>
<thead>
<tr>
<th>Subject</th>
<th>Selected Residential Buildings (residential complex)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selected Province</td>
<td></td>
</tr>
<tr>
<td>No. of Complexes</td>
<td>Choongnam, Gangwon, Gyeongnam, Gyeonggi</td>
</tr>
<tr>
<td></td>
<td>3 2 5 8</td>
</tr>
<tr>
<td>No. of Apartment Complexes</td>
<td>18</td>
</tr>
<tr>
<td>Total num. of buildings</td>
<td>183</td>
</tr>
<tr>
<td>Heating Type</td>
<td>Individual Heating</td>
</tr>
</tbody>
</table>

The variables used in this study are classified into three broad categories: climate variables, geometric variables, and the factors of the buildings, details of which are discussed later.

The geometric factors include the latitude and longitude of each region. The climate factors include months of the year, average monthly dry bulb temperature and the relative humidity. The morphological factors (for buildings) include volume size and number of buildings. These factors generated a total of 20 selected input parameters as described in (1).

\[ I_{BPNN} = [C_{Month}[1], \cdots + C_{Month}[12], C_{Temp}, C_{Humd}, C_{Hdd},
G_{Latitude}, R_{N\text{.building}}, R_{N\text{.households}}, R_{G\text{.area}}, R_{M\text{.area}}] \]

\[ O_{BPNN} = [Water\ Consumption] \]

where \( I_{BPNN} \) denotes the input vector and \( O_{BPNN} \) represents output vector of the BPNN forecasting model.

The range of the dataset used in this case study included 12 months for 18 apartment complexes which included 183 buildings. The raw data of the \( I_{BPNN} \) consisted of 20 x 216 datasets that defined 20 attributes for 216 different cases that included ‘1-12 coded month of year’, ‘relative-temperature’, ‘relative humidity’, ‘latitude’, ‘heating degree days’, ‘number of buildings’, ‘number of households’, ‘gross area’, and ‘maintenance area’, while the \( O_{BPNN} \) of the raw data was 1 x 216 matrices for the residential water use that was to be forecasted.
The sample training data we used consisted of a 21 × 168 matrix, and the sample test data had a 20 x 48 matrix.

To perform the estimation process, all input and output data were linearly normalized to be within the range [0, 1] to avoid the masking effect because all the inputs and outputs had different ranges [1, 2]. In this study we used a BPNN model with only one hidden layer, but it is possible to have more complex neural network models that have two or more hidden layers to optimize the proposed model of the BPNN to derive the relationship among the various variables.

In addition, the hyperbolic tangent described in (2) was applied as the activation function of the neurons in the hidden layer of the proposed model.

\[
tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]

The network was operated with the training data set and the stopping criterion for the training process was when either the training goal was met or the number of the epoch encounters was 1,000. The training goal was met when the sum of squared error became less than 0.06, and the learning rate was 0.01.

To evaluate the performance for the prediction accuracy of the models, we used two distinct error related statistical indicators, the mean absolute percentage error (MAPE) and the root mean square error (RMSE) in this study [1, 38, 39].

<table>
<thead>
<tr>
<th>Error Indicators</th>
<th>Yearly water consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAPE (%)</td>
<td>19.6</td>
</tr>
<tr>
<td>RMSE</td>
<td>98,110(m³/yr)</td>
</tr>
</tbody>
</table>

The statistical indicators representing the prediction performance shown in Table 4 show that the differences between the forecasted water use and the actual values are rather small. The RMSE of each case is also quite small regarding the scale of annual water use for each residential complex. The results confirm a significantly high accuracy of the prediction, which indicates the proposed model is reasonably reliable. This demonstrates that the proposed BPNN based water demand modeling is a reliable approach for Korea.

5 Conclusion

This study introduced a BPNN based water demand forecasting model that considered the extraction of potential factors affecting water use of residential complexes in Korea.
Estimation of water use for residential buildings in Korea is a significant issue in supporting stable water supplies since approximately at least one fourth of the total water use comes from the building sector, and residential water use accounts for roughly seven tenths of the total water supply.

Such a model can support reliable water supply management that considers the needs of customers and the local community can be used to design water infrastructure appropriately, such as reservoir supply and distribution facilities.

Extensive reviews for residential water demand models confirm that the selection of potential factors affecting water consumption are crucial in water use estimation and determining the accuracy of prediction models. We hope that future research will concentrate on retrieving potential parameters that affect residential water use to overcome any limitations of the present research.

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