Neural Network Application for Geothermal Heat Pump Electrical Load Prediction

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지열 히트펌프 전기부하 예측을 위한 신경망 적용 방법

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Abstract

신경망방법은 공학, 경영 그리고 정보기술과 같이 다양한 분야에서 널리 사용되어지고 있다. 신경망방법은 기본적으로 예측, 제어, 식별과 같은 기능을 가지고 있는데, 본 논문에서는 신경망방법을 이용하여 C와 모델 T의 히트펌프 전기부하를 예측하였다. 부하예측은 시스템을 더욱 효율적으로, 적절하게 만들기 위해 필요하다. 본 논문에서 사용된 히트펌프는 지열 히트펌프 시스템이다. 이 지열 히트 퓨프는 퓨프의 바다에 담긴 저온수와 근처의 땅온수를 이용하게 되어, 해양 폐쇄형을 위한 냉각 분리기와 같이 satisfaction을 얻을 수 있다. 이 신경망방법은 신경망 학습 순서를 통해 부하 예측을 위해 히트펌프의 성능 데이터를 필요로 한다. 이 부하 예측 인공지능방법으로 외기 온도변 변화를 통해 히트펌프 부하 예측이 가능해질 수 있다.

Keywords : Neural Network(신경망), Geothermal Heat Pump(지열 히트 퓨프), Electrical Power Consumption(전력 소비량), Outdoor Temperature(외기온도)

Nomenclature

COP : Coefficient of performance
E : Cost function
EER : Energy efficiency ratio
f  : activation function

I  : Input value of neural network
k : Number of iteration (epoch)
O_d : The jth component of the desired output
S_j : The output of jth neuron from the last hidden layer

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$W_i$ : Value of weight  
$y$ : Output value of neural network  
$y_d$ : The $j^{th}$ component of the ANN output  
$\eta$ : Learning rate

1. Introduction

Geothermal heat pump (GHP) or ground source heat pump (GSHP) is appropriate device to keep temperature. Ground can keep temperature more consistent than others, due to the ability in absorbing 46% heat energy inside of it and its buffering characteristics. Moreover, the heat pump operates using the same cycle as refrigerator. This can be seen at Fig.1. The significant difference between a ground source heat pump and a refrigerator is that the ground source heat pump is meant to run in both directions. When in cooling mode, the earth connection to refrigerant heat exchanger becomes the condenser, and the refrigerant-to-air heat exchanger becomes the evaporator\(^1\).

![Refrigeration cycle in heating mode](image)

Load prediction is needed for making planning, strategies, and decision. It can not change what will happen in the future that come from nature, but it can help to prepare facing it. In Geothermal heat pump (GHP) field, a load prediction can be used to get information about electrical load in the future depending upon the outdoor temperature. The value of GHP thermal load very depends on weather condition and it will also effect the value of electrical load which will be consumed. The predictor can not change the weather condition, but it can be the guidance for the decision maker to decide how much electrical source should be provided for GHP system. Jan Kreider\(^2\) developed the artificial neural network (ANN) model and this paper utilizes his model to predict electrical load predictor of a GHP based on a real model data.

2. ANN modeling

An artificial neural network(ANN) is a mathematical or computational model that is inspired by the structure and functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach for computation. In most cases ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex

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\(^1\) Clean Energy Project Analysis: RETScreen Engineering & Cases Textbook Ground-Source Heat Pump Project Analysis Chapter, Ministry of Natural Resources Canada 2001-2005, pp. 11, 17, 37

relationships between inputs and outputs or to find patterns in data. ANN is built by some neural layers and each layer consists of several nodes (neurons) which have the calculation function. Simple model neuron can be seen in Fig. 2.

\[ E = \frac{1}{2} \sum_j (O_d - y_d)^2 \]  \hspace{1cm} (2)

Where \( O_d \) is the \( j \)th component of the desired output, while \( y_d \) is the \( j \)th component of the ANN output. To minimize the value of error, the ANN weights are trained according to the Eq.3.

\[ W(k+1) = W(k) - \eta \frac{\partial E}{\partial W} \]  \hspace{1cm} (3)

At the output layer, the gradient of cost function to weight, Eq.4

\[ \frac{\partial E}{\partial W_{th}} = -\sum_d (O_d - y_d) \frac{\partial y_d}{\partial W_{th}} \]  \hspace{1cm} (4)

Where \( W_{th} \) is the weight that connects the \( d \)th neuron from output layer with the \( j \)th neuron from the last hidden layer. For the hidden layer, the gradient equation is, Eq.5

\[ \frac{\partial E}{\partial W_{ji}} = -\sum_d (O_d - y_d) \frac{\partial y_d}{\partial W_{ji}} \frac{\partial S_j}{\partial W_{ji}} \]  \hspace{1cm} (5)

\( W_{ji} \) is the weight that connects the \( j \)th neuron from the last hidden layer with \( i \)th neuron from the behind hidden layer and \( S_j \) is the output of \( j \)th neuron from the last hidden layer\(^3\).

3. ANN Predictor Design

The ANN predictor is designed to have some inputs and outputs. These inputs will be processed with ANN calculation, and then generate 2 actual outputs. These actual outputs will be compared with the desired outputs to generate errors which will be used in back propagation calculation to improve the weights. The block diagram of ANN design can be seen at Fig. 3.

![Fig. 3 Block diagram of neural network predictor](image)

Moreover, it uses sigmoid as activation function. Eq. 6

\[ f(x) = \frac{1}{1 + e^{-x}} \]  

(6)

The result of sigmoid calculation is always between 0 and 1, therefore that results must be multiplied with the maximum value of each parameter. The maximum value can be found in rows of learning data.

The predictor in this paper is only effective in certainty conditions as described in the following paragraph. The prediction is calculated in heating mode and cooling mode separately; outside temperature is assumed in the range of -1.1°C to 15.6°C for heating case and in the range of 21.1°C to 32.2°C for cooling case. On the other hand, comfort temperature is assumed in the range of 15.6°C to 21.1°C. These value ranges are taken as the assumption due to the data availability in performance data of Climate Master Tranquility 27 model 026 full load which is water-to-air type as can be seen in the Table 20, so they can be
Table 2. Performance and Specifications of Climate Master Heat Pump

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Cooling 30°C</td>
<td>Heating 20°C</td>
<td>Cooling 15°C</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Capacity Watts</td>
<td>EER</td>
<td>Capacity Watts</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Full</td>
<td>7.415</td>
<td>4.7</td>
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<td>Part</td>
<td>5.66</td>
<td>5.4</td>
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<tr>
<td></td>
<td></td>
<td>Full</td>
<td>10.61</td>
<td>4.6</td>
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<td>Part</td>
<td>7.679</td>
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<tr>
<td></td>
<td></td>
<td>Full</td>
<td>14.18</td>
<td>4.6</td>
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<td>Part</td>
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<tr>
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<td>Full</td>
<td>20.15</td>
<td>4.2</td>
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<tr>
<td></td>
<td></td>
<td>Part</td>
<td>15.47</td>
<td>4.7</td>
</tr>
</tbody>
</table>

well interpolated to make heat pump model.

4. ANN learning

The data for ANN learning are basically from demand data and supply data. In this case, demand data contain building heating load and building cooling load. And supply data contain geothermal heat pump electrical load in heating mode and cooling mode. Typical values for building heating load range from 20 to 120 W/m². Cooling loads generally vary from 50 W/m² for buildings in cool climates with little internal gains to 200 W/m² or more for commercial buildings in hot climates with high internal gains\(^4\). In this paper building heating load is assumed between 27 W/m² and 110 W/m², beside that, cooling load is assumed between 50 W/m² and 130 W/m². Its graph can be seen in Fig 5.

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\(^4\) Ground Source Heat Pump Climate Master Tranquility 27 Manual, p8

The demand data above can be resolved in conflicting zone between heating and cooling load demand. To resolve it, the GHP project model assumes that both equation fall to 0 in the conflicting region resulting the graph below Fig. 6.

Therefore, the outside temperature data between 15.6 °C and 21.1°C are not used in neural network calculation. The GHP is assumed not operated in that range of temperature. To get the information about the heating capacity, cooling capacity, and electricity load that are supplied and needed by geothermal heat pump, it can use the table of Climate Master Tranquility 27 model 026 full load which is provided by manufacturer. It is the function of entering water temperature as input. There is no entering water temperature data, so they can be got by the graph below, as described in Fig. 7 taken from RETScreen, GSHP project analysis. Fig.7 can also be written on the equation form as mentioned below:

\[ T_e = T_{\text{min}} + \left( \frac{T_{\text{ext, max}} - T_{\text{cw, min}}}{T_{\text{cw, min}} - T_{\text{d, heat}}} \right) (T_{\text{d, i}} - T_{\text{d, heat}}) \]  

(7)

In this paper, \( T_{\text{min}} \), \( T_{\text{cw, min}} \) in winter, \( T_{\text{cw, max}} \) in summer. \( T_{\text{cw, max}} \) in winter, \( T_{\text{cw, max}} \) in summer are assumed as 0, -1.1°C, 21.1°C, 15.6°C, 32.2°C respectively.

To comply the heating and cooling demand as Fig. 7 describes, the heat pump needs the electrical supply. The value of electrical supply depends on the value of heating and cooling that will be supplied by Fig. 8. Its value can also be found by using table of Climate Master Tranquility 27 model 026 full load, resulting:

\[ \text{Electricity Supply (Heating)} \]

\[ \text{Electricity Supply (Cooling)} \]

After knowing all data, either inputs or outputs, the ANN can be trained separately in heating case and cooling case by using LabVIEW. Heating mode is assumed happened along 5 months, from November until March, cooling mode is happened along 4 months, from July until October, and resolved conflicting zone is happened along 3 months, from April until June. Training for heating mode uses 3,600 epochs and for cooling mode uses 2,880 epochs. Beside that, to know the validity of the ANN predictor, it uses root mean square error (RMSE):

\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (y(n) - y'(n))^2} \]  

(8)
Resulting these graphs below:

**Fig. 9** Electrical load prediction data comparing with actual data (Heating mode)

**Fig. 10** RMSE of electrical load prediction data (Heating mode)

**Fig. 11** Electrical load prediction data comparing with actual data (Cooling mode)

**Fig. 12** RMSE of electrical load prediction data (Cooling mode)

Fig. 9 and Fig. 11 show the electrical load prediction data comparing with actual data in heating and cooling mode. As can be seen that the blue lines, which represent the electrical load at 24 hours ahead generated by the ANN predictor, are able to approach the red lines, which also represent the electrical load at the same time as the blue one generated by LabVIEW simulation based on Fig. 8. Moreover, the RMSE values on Fig. 10 and Fig. 12 are relatively small which are 0.001 and 0.002. RMSE indicates the difference average between prediction and actual data. This means that the predictor can work properly.

For example, the prediction is taken at 12:00 am. in November 18. By that time, it will be known the electrical load prediction data 24 hours ahead which is at 12:00 am. in November 19. November 18 equals to 7,762 hours of year. And it is assumed that the output temperature at that time is 1.9°C and the thermal load is 9.5 kWt. Then, these inputs are calculated by neural To validate the prediction result above, it can be done by using the electrical supply versus outside temperature graph as shown in Fig. 6. Table 2 is the prediction input data of Nov. 18 and Table 3 is the load prediction results of the Nov. 19 using ANN.

**Table 2** The example of input data prediction

<table>
<thead>
<tr>
<th>Input parameter (12am in November 18)</th>
<th>Hour of Year (h)</th>
<th>Outside Temp. (°C)</th>
<th>Thermal Load (kWt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>7,762</td>
<td>1.9</td>
<td>9.5</td>
</tr>
</tbody>
</table>

**Table 3** The example of output data prediction

<table>
<thead>
<tr>
<th>Output parameter (12am in November 19)</th>
<th>Electrical Power Consumption 24 hours ahead (kWe)</th>
<th>Thermal Load (kWt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>2.33</td>
<td>3.93</td>
</tr>
</tbody>
</table>
6. Acknowledgment

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7. References