[논문] 한국태양에너지학회 논문집
Journal of the Korean Solar Energy Society

Vol. 32, No. 3, 2012
ISSN 1598-6411

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 분양에서 널리 사용되어지고 있다. 신경망방법은 기본적으로 예측, 제어, 식별과 같은 기능을 가지고 있는데, 본 논문에서는 신경망방법을 이용하여 C사의 모델 T의 히트펌프 전기부하를 예측하였다. 부하예측은 시스템을 더욱 효율적이고, 적절하게 만들기 위해 필요하다. 본 논문에서 사용된 히트펌프는 지열원 히트 펌프 시스템이다. 이 지열 히트 펌프의 부하는 사전에 미리 예측되어진 외기온도 및 건물 열부하에 따라 측정 학습된 전력 소비량으로 겨울에는 난방, 여름에는 냉방에 대한 전력 부하를 예측할 수 있다. 이 신경망방법은 신경망 학습 순서를 통해 부하 예측을 위해 히트펌프의 성능데이터를 필요로 한다. 이 부하 예측 인공지능망 방법으로 외기 온도별 건물 통합형 지열 히트 펌프 부하가 예측되어질 수 있다.

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

Nomenclature

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

Submit date : 2012. 2. 8, Judgment date : 2012. 2. 12, Publication decide date : 2012. 5. 22
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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
η : 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].

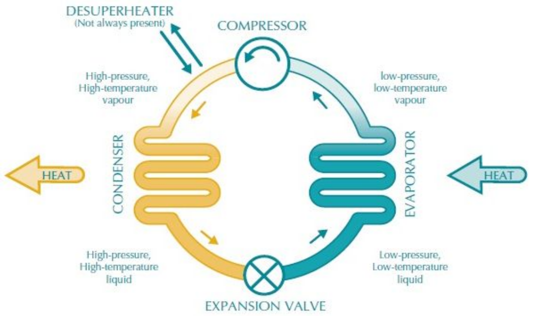

Fig. 1 Refrigeration cycle in heating mode

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

1) Clean Energy Project Analysis: RETScreen Engineering & Cases Textbook Ground-Source Heat Pump Project Analysis Chapter, Minister of Natural Resources Canada; 2001-2005, pp.11,47,57

2) Kreider, K.F., and J.S. Haberl. Predicting hourly building energy use: The great energy predictor shootout - Overview and discussion of result, 1994. ASHRAE Transactions 100(2), pp 1104 - 1118, 1994.

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.

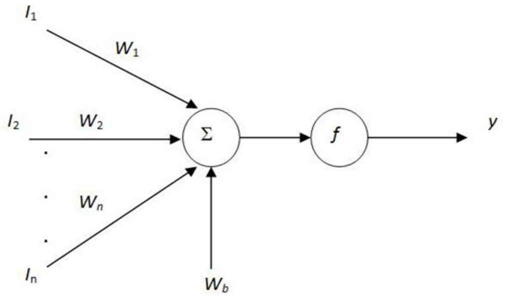

Fig. 2 A neuron model

W_1 states the value of weights $W_1, W_2, \cdots W_n$. On the other hand, I_i states the value of inputs $I_1, I_2, \cdots I_n$ f is activation function, has a role as trigger output of the neuron, meanwhile the w_b is the bias. It is necessary to adjust the value result from the activation function f. This model can be expressed by other form, Eq.1

$$y = f\left(\sum_{i=1}^{n} W_i I_i + W_b\right) \tag{1}$$

Weights are the parameters of the ANN. Their value can be updated at every iteration. Updating the value of weights is the core of the ANN learning process. This ANN learning process uses back propagation learning algorithm. The cost function that is often used is the sum of squared errors (SSE), stated by Eq. 2

$$E = \frac{1}{2}\sum_{d}(O_d - y_d)^2 \tag{2}$$

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

$$W(k+1) = W(k) - \eta\frac{\partial E}{\partial W} \tag{3}$$

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

$$\frac{\partial E}{\partial W^o_{th}} = -\sum_{d}(O_d - y_d)\frac{\partial y_d}{\partial W^o_{th}} \tag{4}$$

Where W^o_{dj} is the weight that connects the dth neuron from output layer with the jth neuron from the last hidden layer. For the hidden layer, the gradient equation is, Eq.5

$$\begin{aligned}\frac{\partial E}{\partial W^o_{jt}} &= -\sum_{d}(O_d - y_d)\frac{\partial y_d}{\partial W^h_{jt}} \\ &= -\sum_{d}(O_d - y_d)f'(s_j)\frac{\partial S_j}{\partial W^h_{jt}}\end{aligned} \tag{5}$$

W^h_{jt} is the weight that connects the jth neuron from the last hidden layer with ith neuron from the behind hidden layer and S_j is the output of jth neuron from the last hidden layer[3].

3) Anindito, S., Hadisupadmo, S., Samsi, A., Design and Implementation of Water Level and Temperature Controller by Using Artificial Neural Network of Mini-Plant Process, Final Year Project - Physics Engineering - Bandung Institute of Technology, 2009, pp.12-13

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.

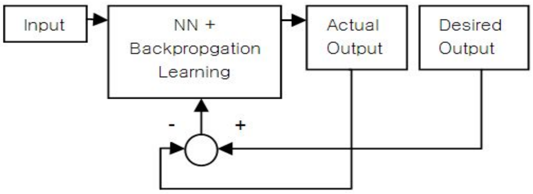

Fig. 3 Block diagram of neural network predictor

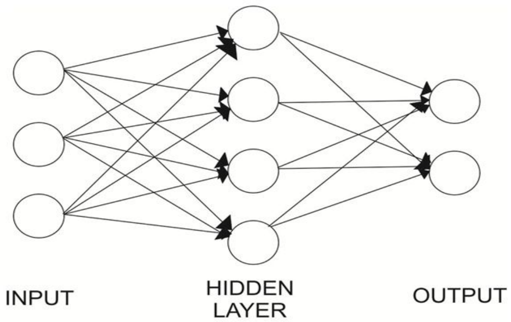

Fig. 4 The structure of neural network predictor

Fig. 4 shows the structure of ANN predictor. The ANN predictor has 3 inputs which are hour of year(h), outside temperature(°C), Thermal load(kWt) and 2 outputs which are electrical power consumption 24 hours ahead(kWe) and COP 24 hours ahead. The parameter of electrical power consumption 24 hours ahead is the point of this paper. Table 1 is the parameter that is predicted with this neural network. Besides that, this ANN predictor uses 1 hidden layer with 4 nodes in side.

Table 1. Parameters of neural network

Parameters	Role
Hour of Year(h)	Input
Outside Temp(°C)	Input
Thermal Load(kWt)	Input
Electrical Power Consumption 24 hours ahead(kWe)	Output
COP/EER 24 hours ahead	Output

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

$$f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

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 2[4], so they can be

Table 2. Performance and Specifications of Climate Master Heat Pump

Model	Capacity Modulation	Water Loop Heat Pump				Ground Water Heat Pump				Ground Loop Heat Pump			
		Cooling 30°C		Heating 20°C		Cooling 15°C		Heating 10°C		Cooling Full Load 25°C Part Load 20°C		Heating Full Load 0°C Part Load 5°C	
		Capacity Watts	EER W/W	Capacity Watts	COP	Capacity Watts	EER W/W	Capacity Watts	COP	Capacity Watts	EER W/W	Capacity Watts	COP
TT026	Full	7,415	4.7	9,027	5.3	8,470	7.2	7,532	4.8	7,796	5.4	5,803	4.0
	Part	5,686	5.4	6,565	6.1	6,506	9.0	5,451	5.1	6,243	7.6	4,836	4.6
TT038	Full	10,610	4.6	13,130	5.3	12,075	6.7	10,756	4.7	11,196	5.3	8,499	4.0
	Part	7,679	5.4	9,027	6.3	8,851	9.2	7,268	5.1	8,470	7.9	6,477	4.5
TT049	Full	14,185	4.6	17,556	5.2	16,002	6.6	14,156	4.7	14,830	5.2	10,991	4.0
	Part	10,580	5.3	12,984	6.2	11,928	8.4	10,375	5.1	11,606	7.3	9,144	4.6
TT064	Full	18,025	4.4	21,190	5.0	20,106	6.4	17,468	4.4	18,992	5.1	14,068	3.9
	Part	13,159	5.2	14,977	5.7	15,211	8.7	12,251	4.7	14,596	7.4	10,991	4.3
TT072	Full	20,135	4.2	25,967	4.9	22,597	5.8	20,574	4.3	20,985	4.7	15,856	3.6
	Part	15,475	4.7	19,109	5.1	17,526	7.2	15,152	4.3	16,911	6.3	13,306	3.9

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[5]. 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.

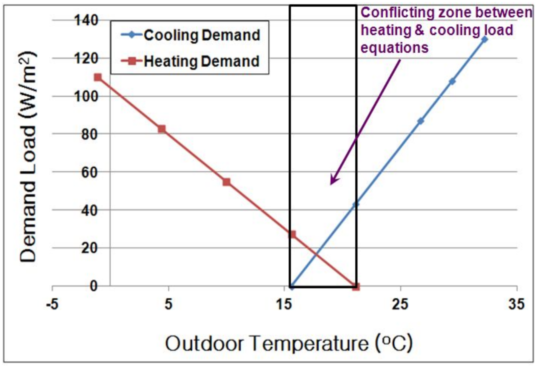

Fig. 5 Building demand load vs outside temperature

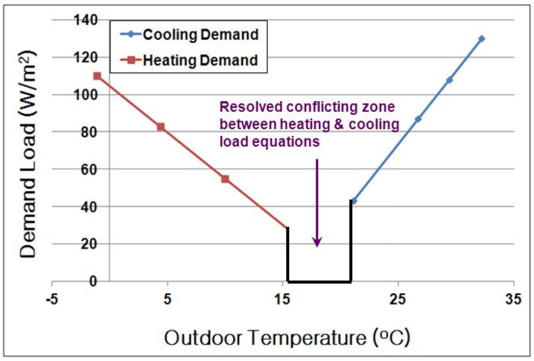

Fig. 6 Building demand load vs. outside temperature with resolved in conflicting zone

4) Ground Source Heat Pump Climate Master Tranquility 27 Manual, p.61

5) http://www.iklimnet.com/expert_hvac/cooling_load.html

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 :

$$T_w = T_{\min} + \left(\frac{T_{ewt,\max} - T_{ewt,\min}}{T_{d,cool} - T_{d,heat}}\right)(T_{bin,i} - T_{d,heat}) \quad (7)$$

In this paper, T_{min}, $T_{ewt,min}$ in winter, $T_{ewt,min}$ in summer, $T_{ewt,max}$ in winter, $T_{ewt,max}$ 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:

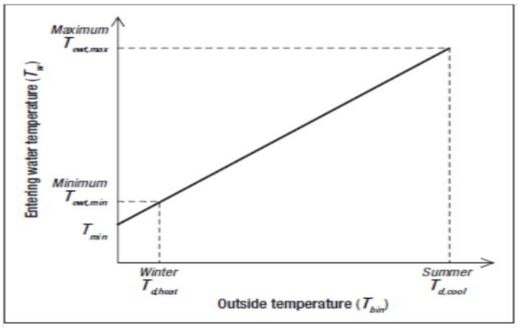

Fig. 7 The entering water temperature vs. outside temperature

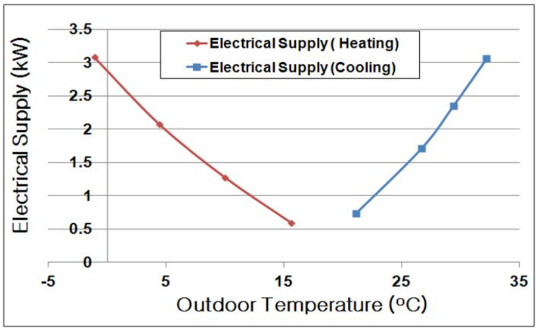

Fig. 8 Electrical supply in heating and cooling mode

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):

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{n}(y(n) - y'(n))^2} \quad (8)$$

Resulting these graphs below:

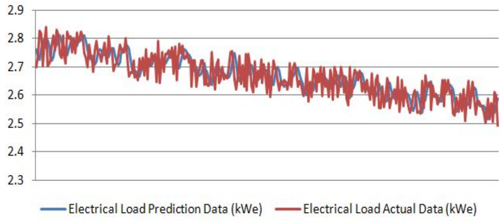

Fig. 9 Electrical load prediction data comparing with actual data(Heating mode)

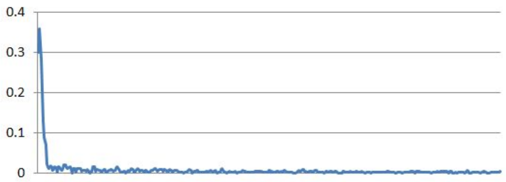

Fig. 10 RMSE of electrical load prediction data (Heating mode)

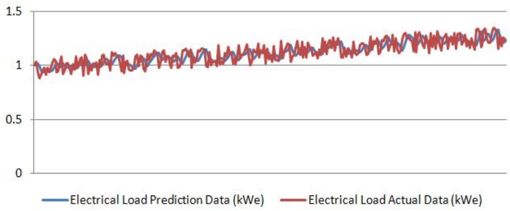

Fig. 11 Electrical load prediction data comparing with actual data (Cooling mode)

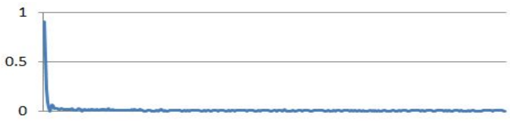

Fig. 12 RMSE of electrical load prediction data (Cooling mode)

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 7,752 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. Fig. 13 is the graph of prediction correlation results between outside temperature and electrical supply.

Table 2. The example of input data prediction

Input parameter (12am in November 18)	Hour of Year (h)	Outside Temp. (°C)	Thermal Load (kWt)
Value	7752	1.9	9.5

Table 3. The example of output data prediction

Output parameter (12am in November 19)	Electrical Power Consumption 24 hours ahead(kWe)	Thermal Load (kWt)
Value	2.53	3.93

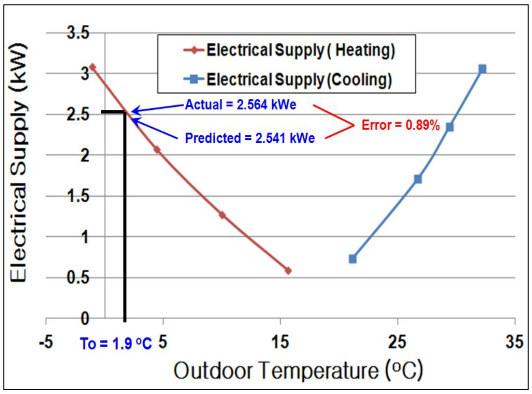

Fig. 13 The example of correlation between outside temperature and electrical supply.

5. Conclusion

In order to supply electricity properly from the source, it is necessary to know the electricity demand of heat pump in the future. Learning characteristic of past data is the one way to generate the predictor. The neural network can be implemented as the predictor of electrical load. It works by learning the data of inputs and outputs to get the proper weights, then it would be known the transfer function between inputs which are present-data and outputs which are future-data. As can be seen in Fig 9, Fig 11, and Fig 13, the neural network predictor could work properly with small error relatively. To make this simulation better in the next research, the input and output parameters should be added in the neural network learning such as month of year, day of month, day of week, high temperature outside, low temperature outside, underground temperature, etc. so that the model will be more similar with the real system.

6. Acknowledgment

This work was supported by the International Cooperation of the Korea Institute of Energy Technology Evaluation & Planning (KETEP) grant funded by the Korea Government Ministry of Knowledge Economy. (No. 2010T100100422)

7. References

1. Kreider, K.F., and J.S. Haberl. Predicting hourly building energy use: The great energy predictor shootout – Overview and discussion of result, 1994. ASHRAE Transactions 100(2), pp 1104 – 1118.
2. Anindito, S., Hadisupadmo, S., Samsi, A., Design and Implementation of Water Level and Temperature Controller by Using Artificial Neural Network of Mini-Plant Process, Final Year Project – Physics Engineering – Bandung Institute of Technology, 2009.
3. Climate Master Tranquility 27 Manual
4. Clean Energy Project Analysis: RETScreen Engineering & Cases Textbook Ground-Source Heat Pump Project Analysis Chapter, Minister of Natural Resources Canada; 2001-2005
5. M.Anstett., J.F. Kreider., Application of Neural Networking Models to Predict Energy Use. ASHRAE Transactions.
6. Kreider, K.F., and X.A. Wang. Improved artificial networks for commercial building energy use prediction. Proceedings of the ASME Annual Solar Engineering Meeting, 1992, Maui, HI, vol. 1, pp. 361-366.
7. Han H. S., Ground Source Heat Pump Heating/Cooling System, Hallymwon, 2004.