2017 International Conference on Computer Network, Electronic and Automation (ICCNEA 2017)

Prediction of the Heat Load in Central Heating Systems Using GA-BP Algorithm

Bingqing Guo
China Electric Power Research Institute
Beijing, China
E-mail: bqguo@ epri.sgcc.com.cn

Jin Xu
Key Laboratory of Thermo-Fluid Science and Engineering, Ministry of Education,
Xi’an Jiaotong University,
Xi’an, China
E-mail: xujin@stu.xjtu.edu.cn

Ling Cheng
China Electric Power Research Institute
Beijing, China
E-mail: chengling@epri.sgcc.com.cn

Lei Chen
Key Laboratory of Thermo-Fluid Science and Engineering, Ministry of Education,
Xi’an Jiaotong University,
Xi’an, China
E-mail: chenlei@mail.xjtu.edu.cn

***Abstract*—This paper presented the research on heat load prediction method of central heating system. The combined simulation data at Xi'an in January was used as the samples for training and predicting. This paper selected the daily average outdoor wind speed, the daily average outdoor temperature, date type, sunshine duration as input variables and the heating load value as output variable. After preprocessing of the historical data, the BP neural network algorithm and the GA-BP algorithm were employed to predict and verify heat load respectively. Based on the analysis of prediction results, it showed that the error between the predicted data and the actual value using the BP algorithm is large (maximum:-39.8%) and not suitable for heating load prediction while the error between the predicted data and the actual value using the GA-BP algorithm is small (maximum:-16.6%) and within the acceptable range. This paper provided a feasible method for heating load prediction.**

Keywords-Central heating; Heat load; BP network; GA-BP network; Heating network

I. INTRODUCTION

Global warming is one of the most important issues to handle in the energy sector, due to the high CO2 emissions from fossil fuel based power plants. The central heating sector can play a significant role in reducing the emissions [1], [2] and [3]. Central heating systems (CHS) are based on simple idea of central production of heat and further distribution of produced heat to final consumers [4], and. Primary energy use for central heat production is dependent not only on the availability of technology and on the considered environmental and social costs but also on the scale of central heat production. Every CHS comprises of three basic elements: heat source, distribution network and consumers, which are in most cases indirectly (through heating substations) connected to distribution network. To improve the efficiency of CHS, heat pumps were integrated in some models. The development of CHS is gaining more and more interest, but, in some case the space available for the integration is limited and the use of decentralized systems is necessary in order to improve efficiency of CHS and. Analysis was shown that regulation of the central-heating sector is necessary in principle, particular in terms of pricing. In order to be competitive with individual heating systems, CHS must use one of the five suitable strategic local energy resources: useful waste heat from thermal power stations (cogeneration); heat obtained from refuse incineration; useful waste heat from industrial processes; natural geothermal heat sources and fuels difficult to manage, such as wood waste, peat, straw, or olive stones and have advanced control which will lower operation and distribution costs. Models for the prediction of the temperature at critical points of central heating systems are paramount for heat suppliers to make optimal decisions on the water temperature at the supply point. Control of central heating systems is complex task and comprises of four different control sub-systems:

1) Heat demand control
2) Flow control
3) Differential pressure control and
4) Supply temperature control.

The performance of the CHS controller was characterized by an economic cost function based on predefined operation ranges. Temperature fault detection in CHS has changed from being slow and expensive to becoming fast and inexpensive. This is a basic condition for more efficient central heating systems in the future. The developed model, which manages detailed calculation of water flows, temperatures and heat losses in CH pipes, enables robust and accurate CH network state estimation. The central heating system for an building with many floors was analyzed and it was determined that under prescribed total mass flow rate, the mass flow rate of a floor increases with the increase in its heat load, while those of the other floors decrease and the temperature of supply water increases. A controlled case, for one real thermal plant in the central heating system for the purpose of predicting the heat supply was shown that the model-based controller successfully regulates the outlet temperature of the boiler, and the total amount of heat duty has been well reduced due to the constraints on inputs considered in the control algorithm. Precise prediction of heat demand is crucial for optimizing CHS. In a central heating system, errors and deviations in customer substations propagates through the network to the heat supply plants. Based on the defined building types, the average absolute deviation of the predicted heat load was about 4–8% .The concept introduced a mass flow control model optimizing the primary and secondary water streams to achieve to achieve better results. The central heating mode not only improves the quality of life of the people, but also reduces the pollution to the environment, at the same time; it also improves the energy utilization rate and saves energy. There is a great significance to conduct research on the heat load prediction of central heating. Based on the quick and accurate prediction of heat load, making the heating system achieve fine management and improve the economy, efficiency and reliability of the central heating network to a great extent, also achieve the purpose of energy saving and environmental protection.

As early as 1984, Werner [5] in Sweden selected multiple central heating systems to be tested. The results showed the influence of outdoor temperature on the heat load of was about 60%. The heat loss of pipe could make the heat load increased by 5%-8%. Natural wind can make the heat load increase from 1% to 4%. The heat gain from solar radiation can reduce heat load from 1% to 5%. Living hot water consumption is different on working day and weekend and the average value of total heat load of 30%.

Arvastson [6] established a prediction model of the heat load based on the outdoor temperature. Erik Dotzauer [7] established a heat load prediction model based on user behavior. Peder Bacher [8] studied the prediction of thermal load at single building space. Therefore, they selected sixteen houses in Denmark Sandburg town as the object and an adaptive linear time series model using time series method. The study found great influence of the change of behavior patterns and weather forecast residents estimated on the uncertainty of the load. Also the influence of solar radiation was the largest. These factors lead to the heat load forecast deviation.

Vladimir D. Stevanovic [9] studied the prediction of the heat load in central heating system. They established a mathematical model in the complex system of heating pipe network. The model was based on the solution and carried out by hydraulic pressure and fluid velocity of high order accurate numerical prediction of the transient energy equation. It was found that the outside air temperature, the wind speed, the intensity of solar radiation, and the opening and closing state of the heating system may influence the value of heat load in the central heating system.

Krzysztof [10] modified the outdoor temperature through the intensity of solar radiation and natural wind speed, and focused on the study of the effects of these two factors on the heating load. The test selected the Poland Warsaw area. The results showed that the effect of natural wind on heating load was much weaker than the sun the effects of radiation and the solar radiation was the main factor affecting the heat load.

Because the method of artificial neural network prediction of nonlinear load has great advantages, so the artificial neural network forecasting method was also popular in the field of heating. Mattias B. Oohlsson[11], William J. stevenson[12] and Bradley P. Feuston [13] used the method of artificial neural network to predict the heat load of a large-scale construction of the United States. They selected temperature, sunshine, wind speed, time as input variables, which also marks the research of artificial neural network has begun to enter the field of heating. This paper is going to study on heat load prediction method of central heating system.

II. SELECTING THE INPUT AND OUTPUT VARIABLES

According to the BP neural network algorithm based genetic algorithm, the establishment of heating load forecasting model. To determine the input variables and output variables, the prediction model is trained on historical data. The trained model is used to predict the future load, it will need historical data as input variables, and the method of BP neural network optimized by genetic algorithm based on the mature training (GA-BP) model to predict, the output variable is the load forecasting the required value. This section applies the method to establish the central heating heat load prediction model. The input and output variables required respectively from the selection, pretreatment and analysis normalized.

Input variables are the original data or processed samples which directly affect the results of prediction. So selecting the right input variables is extremely important. The more practical and comprehensive of the input variables, the precision of the simulation neural network computing is higher. In this paper, the prediction of heat load is obtained by using the data of date, weather and history of the heat load.

The input variables of the heating system are the flow of water, supply-water temperature, return-water temperature, inlet pressure, outlet pressure and so on. The external conditions are outdoor wind speed, outdoor temperature, weather conditions and solar irradiation time. In the aspect of time, weekday and the day or night also matters. In the selection of input variables that affect the heating load, the degree of difficulty of data acquisition, and the fluctuation of the data itself need to be considered.

After simplifying the input variables, the daily average outdoor wind speed, the daily average outdoor temperature, date type and sunshine duration are determined as input variables.

The output variables of the central heating system are selected according to the different operation mode of the system. Main control operation modes are: (1) operation temperature is the major control parameter; (2) the pressure difference between supply and return water is the major control parameter. For the temperature parameter based system, the heating load value is selected as output variable. For the pressure difference parameters based system, the pressure difference is selected. This paper selects the heating load of the day as the output variable of the neural network.

III. CASE STUDY ON LOAD PREDICTION OF CENTRAL HEATING SYSTEM

Based on the above analysis, the daily average wind speed, the daily average temperature, sunshine duration and the date type are the input variables and the heat load of the day is the output variable. First, the DeST is used to calculate the heating load of the whole heating season in Xi'an and the results is showed in Table 1. The data in Table 1 is the input and output variables of the network.

TABLE I. SAMPLE DATA

Date	*Wind speed (m/s)*	*Temp-eratu-re(℃)*	*Sunsh-ine dura-ion (h)*	*Date type*	*Heat load (kW)*
1	0.4	2.12	7.1	0.7	32540
2	1.9	-1.69	6.5	0.7	43280
3	0.7	0.91	6.8	0.7	35620
4	0.6	1.57	6.9	0.4	33480
5	2.9	-2.25	6.4	0.4	45820
6	2.6	-2.24	6.5	0.4	45180
7	3.6	-2.98	5.8	0.4	48800
8	4.7	-3.25	3.6	0.4	51980
9	3.3	-2.82	6.2	0.4	47800
10	2.5	-2.02	6.5	0.4	44540
11	3.8	-3.01	4.3	0.4	49540
12	5.6	-3.45	2.7	0.8	55160
13	0.9	0.65	6.7	0.8	36760
14	3.1	-2.62	6.4	0.4	46960
15	2.4	-1.78	6.5	0.4	43860
16	3.2	-2.76	6.2	0.4	47480
17	0.5	1.78	6.9	0.4	32860
18	1.8	-1.08	6.5	0.4	41260
19	1.4	-0.38	6.6	0.8	39840
20	1	0.53	6.7	0.8	37200
21	1.1	-0.23	6.7	0.4	38120
22	1.2	-0.26	6.7	0.4	38380
23	1.5	-0.94	6.6	0.4	40360
24	3	-2.38	6.4	0.4	46280
25	1.9	-1.38	6.5	0.4	42060
26	0.3	2.55	7.2	0.8	31660
27	0.1	4.45	7.4	0.8	27420
28	0.4	1.91	7	0.4	32380
29	0.7	1.33	6.8	0.4	34180
30	0.1	5.9	7.5	0.4	23500
31	0.3	2.93	7.4	0.4	30060

In this paper, we use the data of the first 21 days of January shown in Table 1. as the training sample and the data of the following 10 days as the prediction samples. Then the data based on the training data and the date in the prediction samples was predicted and compared.

A Prediction of BP

The settings for the BP neural network are as follows: the layers of network structure are 3; input nodes are 4, hidden nodes are 15 and output node is 1, namely the structure of 4-15-1 network. Its main parameters are: learning efficiency: 0.1, the momentum factor: 0.65, the maximum number of training: 2000, square error of network training: 10-5. The results of the perdition of BP neural network and the actual load, absolute error, relative error of the results are shown in Fig. 1, Fig. 2 and Fig. 3.

It can be found from Fig. 1, 2 and 3 that the algorithm of BP neural network can predict the trend of heat load and its change characteristics, but the error between the actual value and the prediction load is large. The relative error range is from -39.8% to 6.5%. Only the prediction errors of two days of are less than 15% and cannot meet the actual needs. In order to improve the precise, we adopted the GA-BP algorithm.

B Prediction of GA-BP Algorithm

The main parameters of the training process of network connection weights in the optimization using Genetic algorithm are: population size is 100 N; maximum generation equals 60; neural network training times is 100; the momentum factor is 11; the maximum square error is 10-5. Through repeated training and learning algorithm, the weights optimized by genetic algorithm are revised using BP neural network algorithm. In the training of BP neural network, the number of BP neural network layers is 3; the number of input nodes is 4; the number of nodes in implicit layer is 15 and the number of the node in output layer is 1; the learning efficiency is 0.2, the momentum factor is 652; the maximum number of training network is 2000, the maximum square error is 10-5.

The results of the perdition of GA-BP neural network and the actual load, absolute error, relative error of the results are shown in Fig. 4, Fig. 5 and Fig. 6.

It can be seen that the predicted heating load curve using genetic algorithm and BP neural network algorithm is basically close to the real value, the relative error range is from -16.6% to -4.0%. So we can say that the GA-BP algorithm is superior to single BP algorithm from the prediction results.

IV. CONCLUSION

The method of GA-BP network optimizes the network weights and threshold and reduces the possibility of the training of BP neural network sunk into the local minimum, which improves the learning performance of the whole network. At the same time GA-BP also accelerates the training speed of the network and improves the learning efficiency. So using the GA-BP network provides a better method for heating load prediction.

ACKNOWLEDGMENT

This work was financially supported by the State Grid technology project “Research on the electric heating

planning and optimizing oepration of non municipal central heating district" (YD71-16-009).

REFERENCES

[1] D. Böttger, M. Götz, N. Lehr, Hendrik Kondziellaa, Thomas Bruckner Potential of the power-to-heat technology in district heating grids in Germany. Energy Procedia, 46 (2014), pp. 246–253.

[2] M.A. Ancona, M. Bianchi, L. Branchini, F. Melino District heating network design and analysis. Energy Procedia, 45 (2014), pp. 1225–1234.

[3] A. Gebremedhin. Optimal utilization of heat demand in district heating system—a case study. Renewable Sustainable Energy Rev, 30 (2014), pp. 230–236.

[4] L. Di Luciaa, K. Ericssona. Low-carbon district heating in Sweden—examining a successful energy transition. Energy Res Soc Sci, 4 (2014), pp. 10–20.

[5] S.Werner, The heat load in district healing system. Swenden: Chalmers University of Technology, 1984

[6] L.Arvastson, Stochastic modeling and operational optimization in district heating systems. Lund University, 2001

[7] E.Dotzauer, "Simple model for prediction of loads in district-heating systems," Applied Energy, vol. 73, 2008, pp. 277-284, doi

[8] Bacher P, Madsen H, Nielsen HA. "Online short-term heat load forecasting for single family houses," Proc. 39th Annual Conference of the IEEE Industrial Electronics Society, IEEE Press,, 2013,pp.5741-5746

[9] Stevanovic VD, Zivkovic B, Prica S, et al. Prediction of thermal transients in district heating systems. Energy Conversion and Management, 2014, 50(9): 2167-2173

[10] Wojdyga K. An influence of weather conditions on heat demand in district heating systems. Energy and Buildings, 2015, 40(11): 2009-2014

[11] Ohlsson MB, Peterson CO, Pi H, et al. Predicting System Loads with Artificial Neural Networks--Methods and Results from" The Great Energy Predictor Shootout". ASHRAE Transactions-American Society of Heating Refrigerating Airconditioning Engin, 1994, 100(2): 1063-1074

[12] Stevenson WJ. Using artificial neural nets to predict building energy parameters]. ASHRAE Transactions., 2014, 100(3): 1076-1087

[13] Feuston BP, Thurtell JH. Generalized nonlinear regression with ensemble of neural nets: the great energy predictor shoot out. ASHRAE Transactions, 2012, (5): 1068-1080

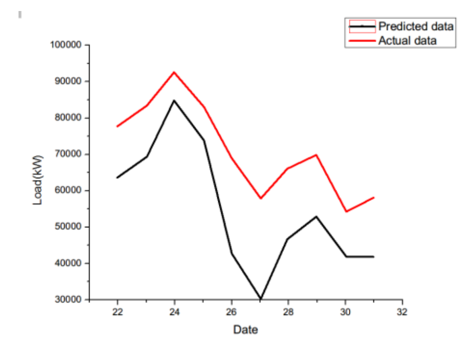

Figure 1. Predicted load by BP network and actual load

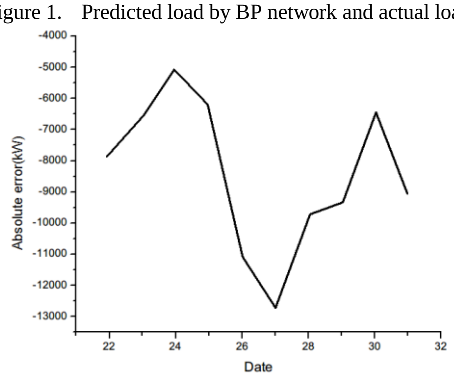

Figure 2. Absolute error of BP network

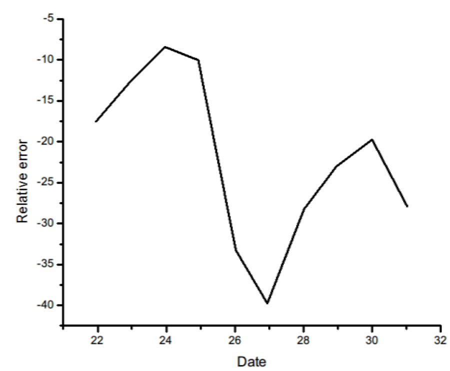

Figure 3. Relative error of BP network

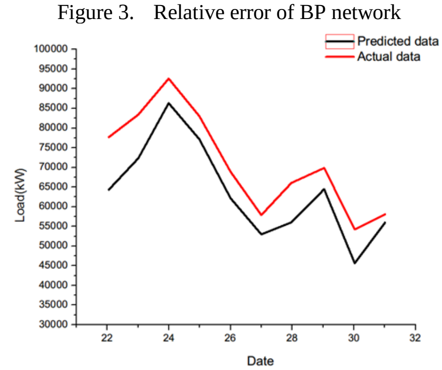

Figure 4. Predicted load by GA-BP network and actual load

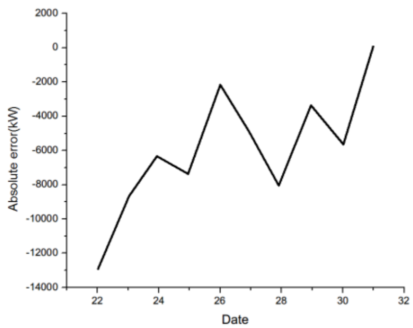

Figure 5. Absolute error of GA-BP network

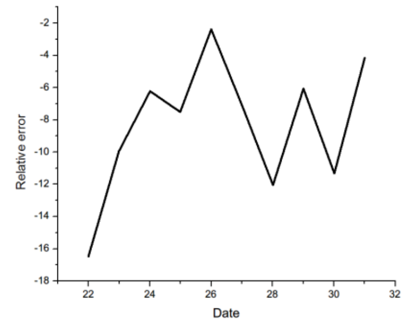

Figure 6. Relative error of GA-BP network