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Analysis of Key Factors in Heat Demand Prediction with Neural Networks

Jiyang Xie[a], Hailong Li[b]*, Zhanyu Ma[a]†, Qie Sun[c]‡, Fredrik Wallin[b], Zhongwei Si[d], Jun Guo[a]

[a]*Pattern Recognition and Intelligent Systems Lab., Beijing University of Posts and Telecommunications, China*
[b]*School of Business, Society and Engineering, Mälardalen University, Sweden*
[c]*Institute of Thermal Science and Technology, Shandong University, China*
[d] *Key Laboratory of Universal Wireless Communications, Ministry of Education, Beijing University of Posts and Telecommunications, China*

Abstract

The development of heat metering has promoted the development of statistic models for the prediction of heat demand, due to the large amount of available data, or big data. Weather data have been commonly used as input in such statistic models. In order to understand the impacts of direct solar radiance and wind speed on the model performance comprehensively, a model based on Elman neural networks (ENN) was adopted, of which the results can help heat producers to optimize their production and thus mitigate costs. Compared with the measured heat demand, the introduction of wind speed and direct solar radiation has opposite impacts on the performance of ENN and the inclusion of wind speed can improve the prediction accuracy of ENN. However, ENN cannot benefit from the introduction of both wind speed and direct solar radiation simultaneously.

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Keywords: District heating, data processing, prediction, heat demand, CHP plant

1. Background

* Corresponding author. Hailong Li, Tel.: +46 21 10 31 59. Responsibility: characterizing the operation of districting systems.
E-mail address: hailong.li@mdh.se
† Corresponding author. Zhanyu Ma, Tel.: +86 10 6228 3059. Responsibility: mathematical simulation.
E-mail address: mazhanyu@bupt.edu.cn
‡ Corresponding author. Qie Sun, Tel.: +86 531 8839 9000. Responsibility: patterns of heat demand.
E-mail address: qie@sdu.edu.cn

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Even though district heating (DH) has been considered as the most efficient, environment friendly and cost-effective method for supplying heat to buildings, it is under big pressures that require to further improve efficiency, reduce the operating cost and raise the profitability. Generally, a large potential of energy and cost savings can be obtained by reducing the peak loads of a district heating network. An important option is to adjust the heat supply according to the demand. However, heat demand, especially the peak load, is very difficult to predict because of the changes in weather such as wind and solar radiation [1].

In general, there are two types of models used for predicting the heat demand: physical models, which calculate the heat loss based on the principle of heat transfer; and statistic models, which correlate the demand to some factors, such as weather data, based on large amount of metering data. Evolving technologies about smart meters and smart energy network open up new opportunities, allowing energy companies to do things in a better way or do things they never could before, such as better understanding customer segmentation and behavior, shaping customer usage patterns, improving the reliability, optimizing unit commitment and more [2,3]. Hence, with the development of heat metering, the statistic models attract more and more attention in the prediction procedure, due to its higher accuracy by reflecting the sociological parameters such as consumer behaviors. For example, Artificial Neural Network (ANN) models, one type of statistic models, have been used to predict the heat demand and shown the ability to produce accurate predictions [4].

As aforementioned, weather conditions like wind speed and solar radiation may heavily affect DH loads. Previous works [5-7] have studied the influence of solar radiance and wind speed on the heat demand in buildings. However, there have not many studies comprehensively comparing the effects of wind speed and solar radiation on heat demand. Therefore, this work aims to quantitatively investigate the impacts of both solar radiance and wind speed on heat demand, using a model based on Elman neural networks (ENN), which is an effective method for predicting heat demand under various weather conditions [6,7]. The paper contributes to the academic field by performing the simulation from the production side, rather than the consumption, and the results can thus be directly used to help heat producers optimize their production and thus mitigate costs.

Nomenclature	
ENN	Elman Neural Network
ANN	Artificial Neural Network
DH	District Heating

2. Model description

2.1. Elman neural network

Elman neural network [8,9], initially proposed for speech processing problem in 1990 by J. L. Elman, is a global feed forward local recurrent neural network. An ENN generally comprises four levels: the input, the hidden, the context, and the output layers. The structures of input, hidden, output layers are similar to normal feedforward neural network. The role of context layer nodes is to store the output values of the hidden layer nodes, which is equivalent to the time delay operator or the state feedback [10-12]. The model of Elman neural network is represented as follows [13]:

$$x(k) = f(w^2 u(k-1) + w^1 x_c(k)) \quad (1)$$

$$x_c(k) = x(k-1) \quad (2)$$

$$y(k) = g(w^3 x(k)) \quad (3)$$

where w^1 is the connection weight matrix between the context layer and the hidden layer, w^2 is the connection weight matrix between the input layer and the hidden layer, w^3 is the connection weight matrix between the hidden layer and the output layer, $u(k)$ is the input of the model, $x_c(k)\ and\ x(k)$ are the output of context layer and hidden layer, respectively, $y(k)$ is the output of output layer. $f(\cdot)$ and $g(\cdot)$ are transfer functions.

The mean absolute percentage error (MAPE), which is defined as

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - y_{pi}|}{y_i} \quad (4)$$

is used as indicator when evaluating the prediction performance.

2.2. Data description

Hourly measured data during the period 2008-2009 were collected from a utility company, including heat demand, ambient temperature, direct solar radiance, and wind speed. To evaluate the effect of direct solar radiance and the wind speed, respectively, four data sets were created for ENN training, which details are listed in Table. 1. Corresponding to those four sets, the data from October 2008 to January 2009 (four months) were used for model training and those from February 2009 to March 2009 were used for model validation.

Table 1. Data set description

	Heat demand data	Ambient temperature	Direct solar radiance	Wind speed
Data set A	√	√	×	×
Data set B	√	√	√	×
Data set C	√	√	×	√
Data set D	√	√	√	√

2.3. Algorithm steps

Data in consecutive 24 hours are combined to create a super-vector. A time step of 4 hours is chosen to update the super- vector. For example, the first super- vector contains the data from 1st to 24th hours and the second super- vector contains the data from 5th to 28th hours. During the training procedure, 123 super-vectors from October 1st to January 31st were used as the training sets and applied to trained model. In the test step, heat demands for the next 24 hours were predicted based on the heat demand in the past 24 hours and the ambient temperature, the direct solar radiance the wind speed data in the next 24 hours. The training steps of the Elman neural network are as follows [14]:

$$\begin{cases} \Delta w_{ij}^3 = \eta_3 \delta_i^0 x_j(k)\ i = 1,2,\cdots,m; j = 1,2,\cdots,n \\ \Delta w_{jq}^2 = \eta_2 \delta_j^h u_q(k-1)\ j = 1,2,\cdots,n; q = 1,2,\cdots,r \\ \Delta w_{jl}^1 = \eta_1 \sum_{i=1}^{m}(\delta_i^0 w_{ij}^3)\frac{\partial x_j(k)}{\partial w_{jl}^1}\ j = 1,2,\cdots,n; l = 1,2,\cdots,n \end{cases} \quad (5)$$

$$\delta_i^0 = (y_{d,i}(k) - y_i(k))g'_i(\cdot) \quad (6)$$

$$\delta_j^h = \sum_{i=1}^{m}(\delta_i^0 w_{ij}^3)f'_i(\cdot) \quad (7)$$

$$\frac{\partial x_j(k)}{\partial w_{jl}^1} = {f'}_i(\cdot)x_l(k-1) + \alpha \frac{\partial x_j(k-1)}{\partial w_{jl}^1} \; \mathrm{j} = 1,2,\cdots,\mathrm{n}; l = 1,2,\cdots,\mathrm{n}, \quad (8)$$

where $\eta_{1,}\eta_2\eta_3$ are the training steps of w^1, w^2, w^3, respectively, m is number of the output layer nodes, n is number of the hidden layer nodes, r is number of the input layer nodes.

In the test step, the predicted heat demand is calculated as

$$\mathrm{y(k)} = \mathrm{g}(w^3\mathrm{f}(w^2\mathrm{u(k-1)} + w^1\mathrm{x(k-1)})). \quad (9)$$

3. Results

ENN trained by using data set A, data set B, data set C, and data set D, was named as ENN-A, ENN-B, ENN-C, and ENN-D. Correspondingly, the inputs for ENN-A, ENN-B, ENN-C and ENN-D are $T_{ambient}$, $T_{ambient}$ + Direct solar radiation, $T_{ambient}$ + Wind speed, and $T_{ambient}$ + Direct solar radiation + Wind speed, respectively. The heat demand for the period February - March 2009 was predicted by using ENN models. The results were compared with the measured data. Results are displayed in Fig 1 and the corresponding MAPE are listed in Table 2. In general, all models can reflect the change of heat demand and predict the heat demand with MAPE less than 10%, of which ENN-C shows the best accuracy, with MAPE=6.95%. However, big discrepancies can also be observed, as illustrated in the zoom-in part of Fig 1. For example, in Subfigure A, the deviation between the predicted heat demand and the measured demand is about 40 MWh for the point at the 741th hour (13%); and in Subfigure B the deviation is about -80 MWh for the point at the 388th hour (-26%).

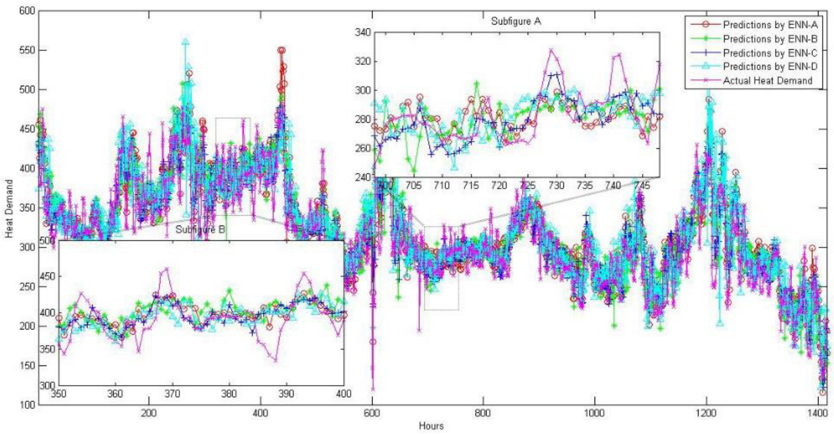

Fig. 1. Dynamic heat demand, predicted and measured results (in MWh)

According to MAPE (Table 2), the introduction of wind speed and direct solar radiation has opposite impacts on the performance of ENN that the inclusion of wind speed can improve the prediction accuracy of ENN. It implies that wind speed is a more important parameter than direct solar radiation. Meanwhile, it is also interesting to see that the introduction of both wind speed and direct solar radiation simultaneously cannot improve the model accuracy, which is even worse than ENN-B. This indicates that, simply combination of wind speech and solar radiation cannot help in improving prediction accuracy.

Table 2. The mean absolute percentage error (MAPE) of different models

Model	MAPE
ENN-A	7.22%
ENN-B	8.53%
ENN-C	6.95%
ENN-D	9.16%

Some advanced methods are required to investigate how to combine different factors for the purpose of improving prediction performance.

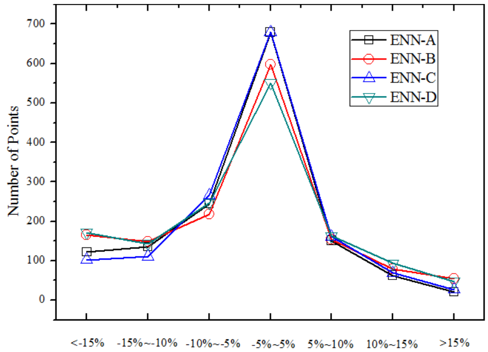

Fig 2 Distribution of absolute percentage errors

Fig 2 shows the distribution of absolute percentage errors. For the best one, ENN-C, the error of most of the points (>78%) is between -5%~5%. However, it is worth to note that there are more points which heat demand was under-estimated than those which heat demand was over-estimated.

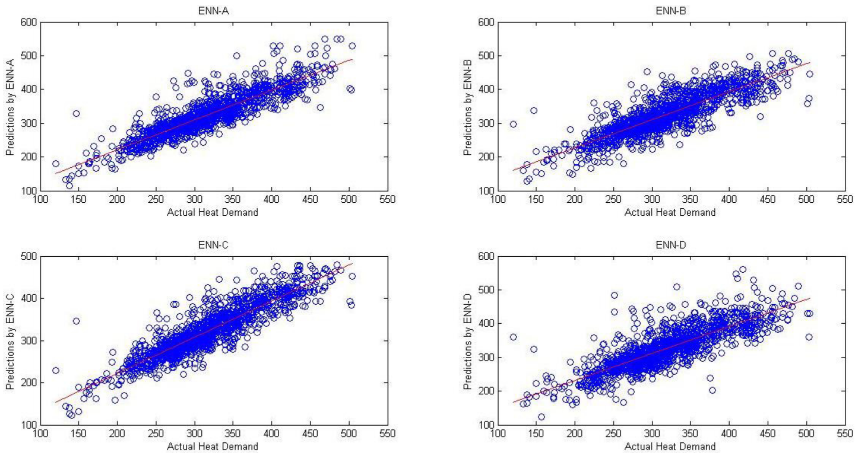

Fig. 3. Predicted heat demand vs. measured heat demand (in MWh)

Fig 3 shows the deviation between the predicted and measured results at different heat demands.

Compared to ENN-A, when introducing direct solar radiation (ENN-B), the deviations become bigger at lower heat demands comparatively; meanwhile, introducing wind speed (ENN-C), the deviations become smaller at higher heat demands. However, when introducing both direct solar radiation and wind speed, the deviations become larger at both low and high heat demands.

4. Conclusions

In this paper, the impacts of wind speed and direct solar radiance on the prediction of heat demand have been investigated. A statistic model based Elman neural network (ENN) was adopted. Measured data collected at a utility company producing heat and power were used for model training and validation. Results show that the introduction of wind speed and direct solar radiation has opposite impacts on the performance of ENN and the inclusion of wind speed can improve the prediction accuracy of ENN. However, ENN cannot benefit from the introduction of both wind speed and direct solar radiation simultaneously.

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