Simulation and Prediction of Thermal Energy Demand

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Abstract: - This paper presents the development and exploitation of two mathematical models based on statistical methods and artificial neural networks for analyzing and predicting the thermal power of buildings connected to a substation supplied by a district heating system. Both models are able to accurately capture the non-liner dynamics of thermal power demand that depends on very different technical and subjective human factors. The two models are compared taking into account the correlation coefficient R as a performance criteria and are validated by evaluating the accuracy of the approximation for other experimental data than those used in modeling stage. Predicted and experimental values for each model are well matched and highlight the success of applying statistic and neural networks models in predicting thermal power demand of buildings.

Key-Words: - district heating systems, thermal request, prediction, neural networks, regression analysis

1 Introduction

The built environment accounts for carbon dioxide emissions, hence buildings are critically important to climate change. District heating produces significantly lower emissions and greenhouse effects, compared to alternatives. Even when a large plant supplying district heating is using the same fuel as small decentralised boilers, air quality in the immediate proximity is still enhanced, due to better pollution control technologies [1].

Actually, 144 district heating companies operate in Romania. Implementation of national strategies regarding district heating production and distribution is in progress. Financial support for numerous projects concerning rehabilitation and modernization of thermo energetic domain generated important investments. The recommended measures of the national program "District heating 2006 - 2009 quality and efficiency" require institutional, technological, social, market and financial decisions that will reduce the consumption of primary energy sources with 10 millions Gcal per year.

One major area of saving energy and resulting financial expenditure is the ability to predict the thermal power consumption of buildings, in order to match supply to demand. Buildings are microcosms of complexity derived from the interaction between form and fabric, service plant, control systems, occupants, climate. Consequently, the forecast of the building thermal energy is a difficult task.

The objective of this work is to develop and analyze methodologies able to predict thermal load trend of buildings. The paper presents soft computing methods created for prognosis of daily space heating consumption using statistic and neural network models. Such models allow evaluating the heat load dynamics of users connected to a substation, a very important requirement for a saving energy management. Validation of the methods was performed by comparing the modeling results with acquired data via a monitoring system from the District Heating Company of the city of Iasi (Romania).

2 Methodology for buildings thermal request simulation

There will always be discrepancies between heat demand and heat supply with important consequences on wasted energy. Ideally, district heating companies have to match thermal requests with production, but without any information about the evolution in time of the heat demand, this is practically impossible. The problem is quite complicated, mainly because it involves objective and subjective factors.

Theoretically, space thermal power demand of a building depends on climate characteristics, indoor air temperature and construction characteristics such as structural materials type, orientation, height, volume, external and internal area of walls, floor, roof, windows and doors etc. In the design stage, this is the only method to apply. The human factor generated by the different preferences on thermal comfort, the daily schedule of the inhabitants, the ability to pay the bills, can not be taken into consideration. Unfortunately, subjective factors can not be neglected, owing to their importance.

In Romania, unlike the other European countries, more then 50% of the apartments that were initially supplied from district heating systems are disconnected now and the process continues. The district heating companies supply thermal energy to blocks of flats with a lot of apartments that use other forms of energy, mainly gas for individual heating systems, and sometimes apartments without any heat sources. Accurate prediction of hourly space heating consumption profile by using only climatic parameters and construction characteristics will be a huge and in vain effort. Simulation models of thermal power dynamics of buildings based both on subjective and objective factors are the only to be considered satisfactorily.

Essentially, simulation involves four steps: problem analysis, model creation, numerical simulation, results analysis. Two models are presented in this paper: a statistical one and a neural network one.

The statistical model (SM) for predicting the heat load Q of buildings is nonlinear, according to the equation

$$Q = k_1 + k_2 T_O + k_3 \left(T_i - T_O\right) V^{\frac{4}{3}} + k_4 T_{sP} + k_5 T_{aO} + k_6 \left(q_a\right)^{\frac{4}{5}} \quad , \tag{1}$$

where T_O, T_i are the outdoor and the indoor temperatures.

Some terms of the statistical model were determined by using thermal resistance method based on the energy balance, similar with the terms used by R. Yao and K. Steemers [2] for their simulation model of load profile for space heating. For instance, the first two terms illustrate the heat transfer Q_C through the building envelope calculated with the equation (2) that includes transmission losses through the area denoted S of walls, ceiling, glass, roof and transmission loss through the floor Q_F,

$$Q_C = \sum m_1 S \frac{T_i - T_o}{R_o} + Q_F \quad , \tag{2}$$

where R_0 is the thermal resistance.

The third term represents the heat losses corresponding to the cold air infiltration through the building, namely

$$Q_V = m_2 \left(T_i - T_O\right) V^{4/3} , \tag{3}$$

where V is the wind velocity.

The dynamic of the heat load is also influenced by T_{sP} , the supply temperature at the exit of the substation. Another extra term $k_5 T_{aO}$ depends on the previous average outdoor temperature T_{aO} and was also used by B. Bohm et all [3] in a simulation model for dynamic modeling of district heat consumers. The term $k_6 \left(q_a\right)^{\frac{4}{5}}$ proposed in this paper, indicates that the previous average fluid flow rate q_a has a direct effect on the heat load. A justification of this assertion is the observation that the heat transfer through the distribution pipes and radiators depends on the convection correlation $Nu = f\left(Re^{4/5}\right)$, therefore the heat load Q depends on the fluid velocity, in other words on the fluid flow rate .

The constants k_1, k_2, …k_6 are characterisic for every building and may be estimated by regression analysis using the nlinfit function from Statistics Toolbox of MATLAB.

As an alternative to the statistical modeling of District Heating Systems, the neural network modeling was chosen because this methodology is an alternative to modeling physical and non-physical system with scientific or mathematical basis.

Neural networks (NNs) perform computation in a very different way than conventional computers. Neural networks are built from a large number of very simple processing elements, neurons that individually deal with pieces of a big problem. A processing element (called neuron) simply multiplies an input by a set of weights, and nonlinearly transforms the result into an output value. The power of neural computation comes from the massive interconnection among the neurons and from the adaptive nature of the parameters (weights) that interconnect them.

The neural networks architecture which is most frequently used in data fitting and non linear approximation consists of three layers: the input layer, the hidden layer and the output layer. In the input layer, each neuron corresponds to an input parameter and in the output layer there is a neuron for each output parameter. In hidden layer, the number of neurons may vary. For neurons from hidden and output layers, the activation function and learning rule are chosen.

Multilayer feed forward neural networks offer a generous framework for modeling non linear phenomena. The neural network operates as a nonlinear mapping, parameterized by the weights and biases of its layers, which can be adjusted so as to fit experimental data, but without any physical meaning for the identified parameters.

As in the case of statistical modeling, the outdoor temperature, the wind velocity, the fluid flow rate, the supply temperature at the exit of the substation, the average previous temperature were chosen as inputs and this means that NNs has 5 neurons in the input layer. The output layer has only one neuron corresponding to the desired values of thermal power.

Some different NNs topologies were studied: feedforward networks typically trained with static backpropagation or generalized feedforward networks with one or two hidden layers and different numbers of neurons, sigmoidian or tanhsigmoid activation functions, different learning rules and number of epochs used for training the NNs. For each topology, the error criteria MSE (Mean Squared Error), NMSE (Normalised Mean Square Error), AIC (Akaike's information criterion) and MDL (Rissanen's minimum description length) were performed in order to evaluate general performance of the NNs. After that study case, a feedforward NN with backpropagation, one hidden layer with 27 neurons, tanhsigmoid activation function was chosen and than trained for 3000 epochs.

The accuracy of the statistical and the neural network methods was appreciated by calculating the correlation coefficient (R). When R=1 there is a perfect correlation between measured and calculated values, but when R=0 there is no correlation.

3 Numerical Simulation

Two buildings denoted A and B, connected at the Iasi District Heating Company were chosen for the analysis of the models. The full access to the database of the consumers connected to the substation allowed to view the records for each parameter supervised. Values of the following parameters were acquired in the period 1st- 31st December 2006 with a sample rate of 5 minutes:

- climate parameters such as outdoor temperature and wind velocity;
- parameters at the entrance of the building such as fluid flow rate, supply temperature, return temperature;
- parameters at the exit of the substation such as supply temperature.

Based on the analysis of the measurements, data from six representative days were selected for the development of the statistical model. The coefficients k_1, k_2, …k_6 from the eq. (1) calculated by regression are presented in Table 1, for each building. Measured values and calculated heat load with eq. 1 for building B is presented in Fig. 1. The thin line represents the measured data and the points represent the data obtained with the mathematical model.

Table 1. Parameters of the statistical model.

	A	**B**
$\mathbf{k_1}$	-26.0198	-24.2840
$\mathbf{k_2}$	-2.2271	-0.4998
$\mathbf{k_3}$	-0.0031	-0.0025
$\mathbf{k_4}$	0.9807	1.0983
$\mathbf{k_5}$	1.6341	0.3400
$\mathbf{k_6}$	0.1314	0.2510

While the daily forecast simulation does not match the measurements very well, the model pursues with accuracy the graph of the measured data. It should be noted that in the case B, the dispersion of the measured data is lower than in the case A. This observation is underlined by the values of the correlation coefficient: R=0.9516 for the building B compared with R=0.9127 for the building A (Table 2). The outdoor temperature of the representative days varies from -6^0C to $+11^0$C. Maybe better results could be obtained by using different models for different domains of outdoor temperature.

Table 2. Correlation coefficients for the statistical modeling

	Building A	Building B
R for model	0.9127	0.9516
% error	7.42	4.78
R - test for 2nd Dec	0.6440	0.8169
R - test for 14th Dec	0.7675	0.8936

The SMs were tested using experimental data for other days not considered initially and the correlation coefficients are presented in Table 2. For building A, R values are less than those for building B as it was expected due to the % error high value of the model in the case of building A.

Therefore, the statistical model can not be used to predict with high accuracy the thermal power request for any building and any conditions. Anyway, the statistical model performance is acceptable and recommended for a saving energy management of the DHS.

The results obtained after training NNs for the two buildings are good enough and the performance information criteria are very closely MSE<0.008, R>0.93, AIC<-120 and MDL< -130. The RMSE criteria of the NNs training for the two building are plotted in Fig. 3.

Once the NNs has been trained, the weights are then frozen, the testing set is fed into the network and the network output is compared with the desired output in order to validate the NNs performance. The R coefficients for NNs training and testing are presented in Table 3.

For building B, the variations in time of experimental data and NNs model output are presented in Fig. 2.

The graphs presented in Figs 1 and 2 are very similar and this fact is in concordance with the very good values for correlation coefficient (R>0.95), denoting a perfect match between experimental and calculated values.

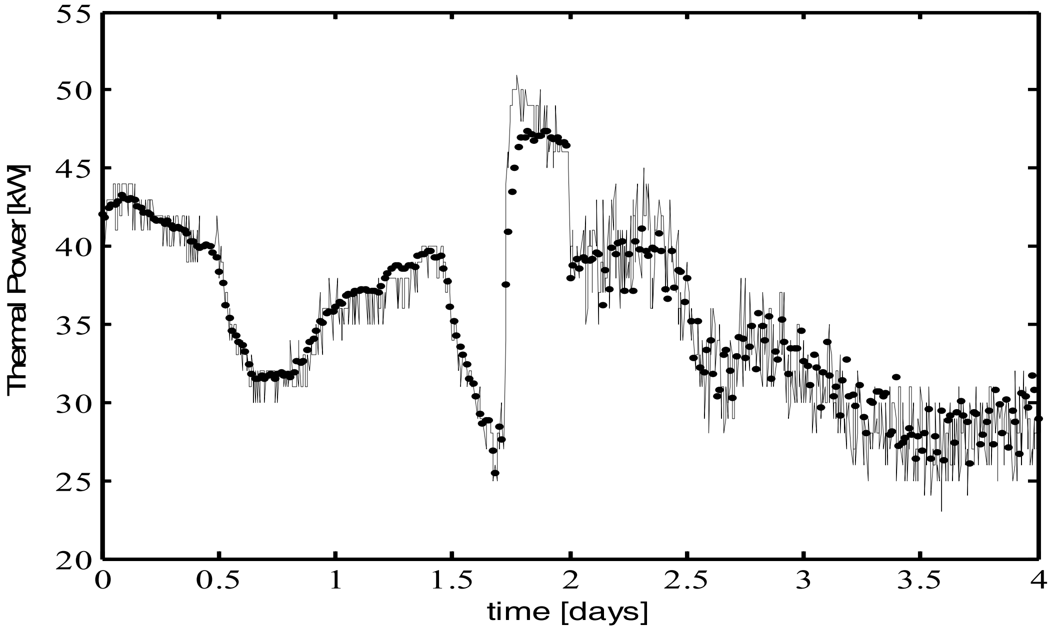

Fig. 1. Calculated values (♦) using statistical model and experimental data (—) for building B.

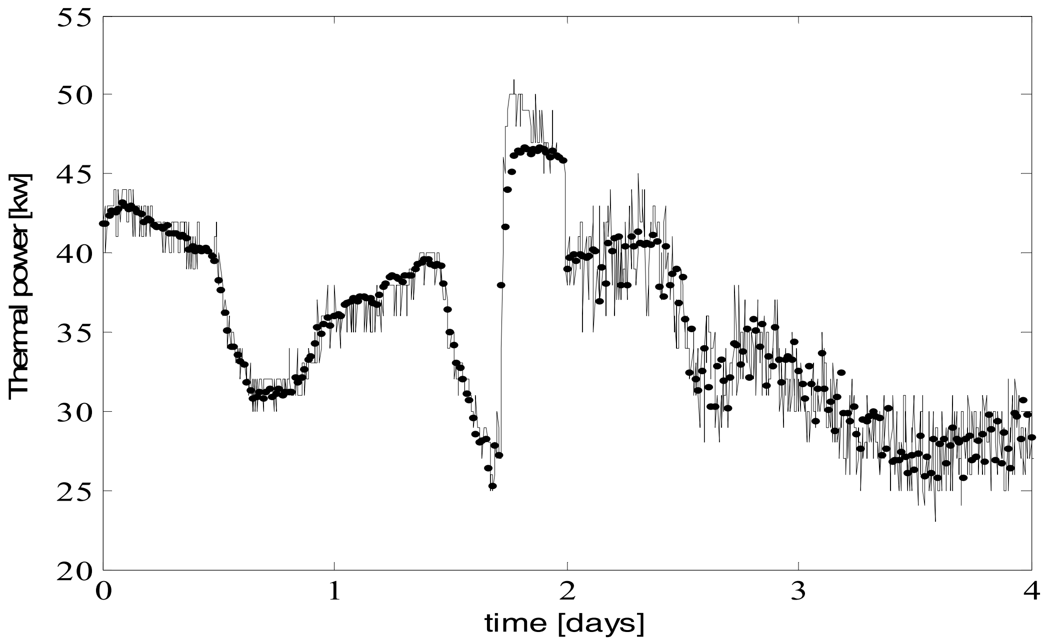

Fig. 2. The output of the trained NN (♦) and experimental data (—) for building B.

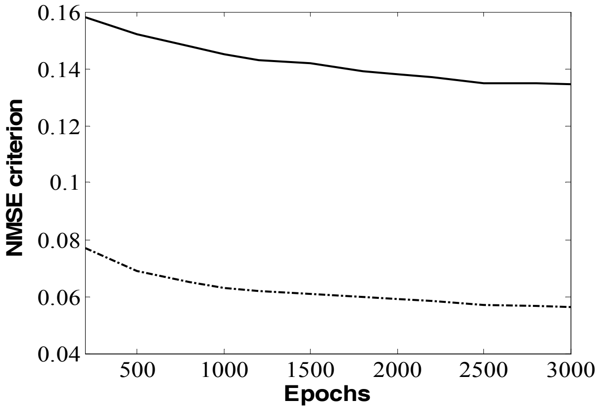

Fig. 3. The RMSE criterion of the NNs training: (—) for building A and (–·) for building B.

Table 3 Correlation coefficients for NNs modeling

	A	B
R for training	0.93	0.97
% err for training	4.87	3.68
R - test for 2nd Dec	0.87	0.88
R - test for 14th Dec	0.83	0.92

For building A, on the 2nd of December, the experimental and the predicted values in the test process of the two models are presented in Fig. 4.

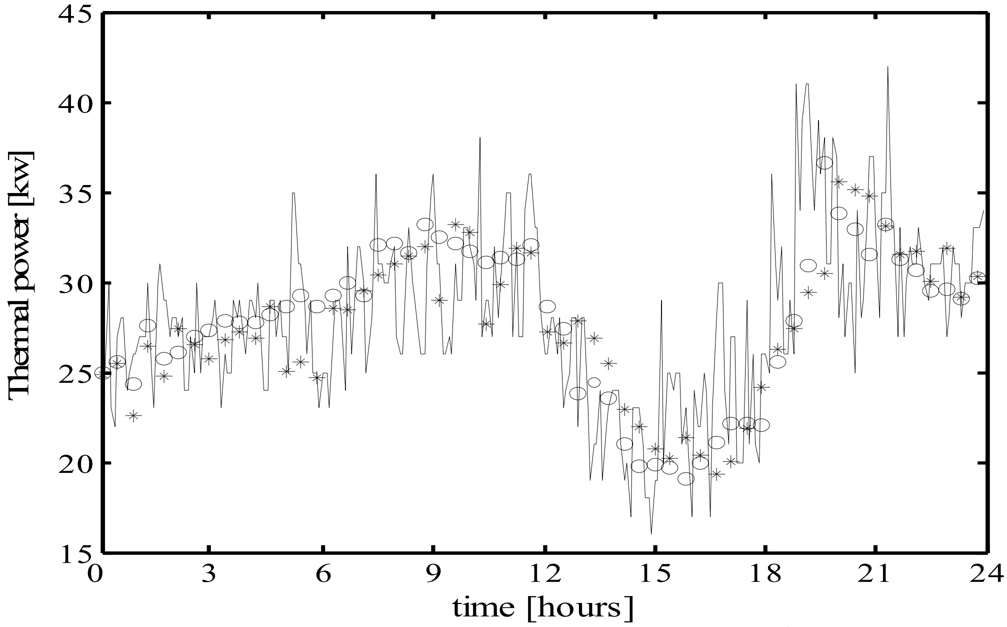

Fig. 4. The prediction with NNs (o), SM (*) and experimental data (—), 2nd Dec. 2006, building A.

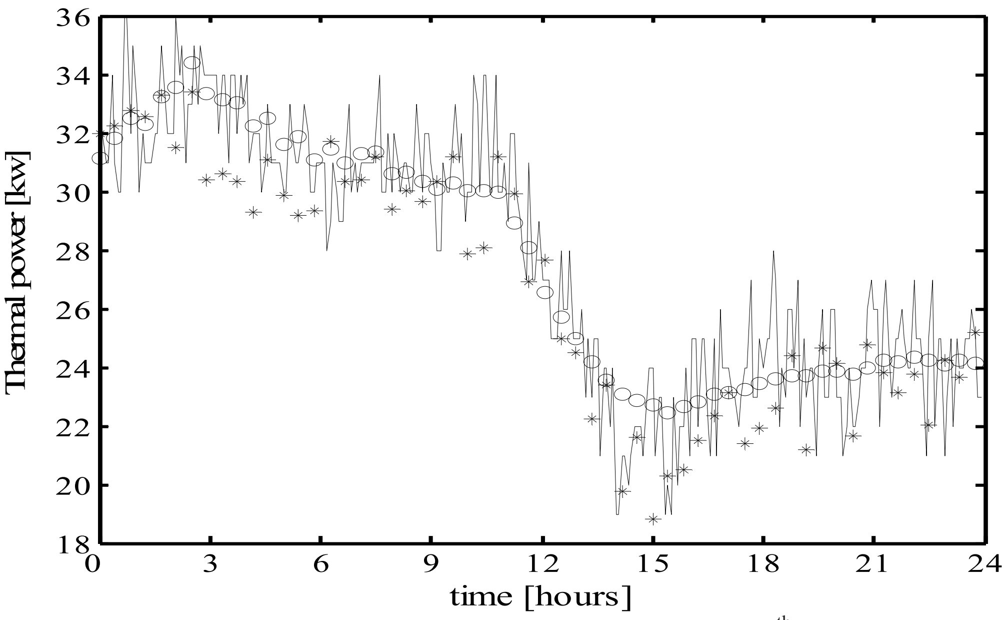

Fig. 5. The prediction with NNs (o), SM (*) and experimental data (—), 14th Dec. 2006, building B.

It can be easily seen a better correlation between measurement and predicted values for the NNs model. For SM, the dispersion between predicted and experimental data is great as it was expected, because the value of R is only 0.76.

Figure 5 shows the plots of predicted and experimental values for building B, obtaining by testing statistical and NNs model for the 14^{th} of December. In this case the best predictions were obtained.

The comparative approach for the two models highlights the superiority of NNs models vs. statistical ones in prediction of thermal power request. But the usefulness of SM couldn't be neglected, as very good results were obtained with such a model in some conditions and for some consumers. It might take into account that some unsatisfactory results could come from inherent data acquisition errors with the framework of monitoring system. The studies carried out might be extended to others buildings and other periods of time with large variations of outdoor temperature and wind velocity, because the period for which experimental data were available, was characterized by very mild weather.

4 Conclusions

The aim of this paper is to develop a methodology for predicting the thermal power demand of buildings in any conditions. The technical and human factors that influence the heating system are very different and that is why no one analytical mathematical model may be considered for this purpose. For this reason, two models describing the dynamic of thermal power request are proposed and validated – a statistical one and an artificial neural networks one.

The development of the two models is based on a series of representative experimental data selected from the database of a global monitoring system designed and implemented for supervising the behavior of the DHS of Iasi (Romania). Accuracy of the computer simulation, as shown by the agreement between the modeling and experimental test results, depends on the accuracy of acquiring the values of the following parameters: outdoor temperature, wind velocity, supply temperature at the exit of the substation and at the entrance of each building supply fluid flow rate, temperature and return temperature. The data for six different days, covering a wide range of values, were chosen for training the NNs and for determining the coefficients from eq. (1) using statistical methods. The proposed models were studied for two buildings.

Both models led to good correlation coefficients ($R>0.9$) for the six days initially considered. The comparison of the two models shows that NNs model is better, because R values are higher for both buildings. In the case of NNs models, for both buildings, the error is less than 5%, denoting that errors introduced by data processing in models construction do not exceed the inherent errors resulted from data acquisition.

The validity of NNs models was verified with very good results using experimental data for other days not considered initially. The statistical model describes well enough the dynamic of thermal load for any building studied but offers poor results regarding the prediction for different data collections.

Considering all above, it could be summarized that NNs models represent a very powerful and useful tool for prediction of the thermal power request if predictions for outdoor temperature, wind velocity and supply temperature at the exit of the substation are available. NNs models allow a unified approach that represents the background for optimization and a global prediction for the whole thermal power request of a substation from a DHS supplying a group of monitored buildings.

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