METHODS FOR SIMULATING HEAT CONSUMPTION

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One major area of saving energy and resulting financial expenditure is the ability to simulate the heat consumption of buildings, in order to match supply to demand. This work presents development and exploitation of two mathematical models based on statistical methods and artificial neural networks for analyzing and predicting the heat consumption of buildings connected to a district heating system. The 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.

Keywords: district heating network, simulation model, prognosis.

1. Introduction

Projects promoting energy efficiency at all levels of European society would save at least 20% of its present energy consumption in a cost effective manner, equivalent to EUR 60 billion per year. Documents regarding saving energy policy stipulate that if 1 Euro is invested for increasing the energy efficiency, then a decrease of 1.26 Euro for acquisition of primary resources is realized. The amount of the annual heat delivered through district heating systems all over the world is about 11EJ [1]. Modernization leads to highly efficient utilization of the primary energy, considerable energy savings giving lower heat supply costs and improvement of environmental by reduction of emissions [2-4].

Usually, in East European countries such as Romania, operation of most district heating systems is based only on a simple mapping between the outside temperature and the supply temperature of the network, a wasting energy procedure. The aim of this paper is to develop and analyze soft computing methods created for simulation of space heating energy consumption of buildings using statistic and artificial neural networks models with a saving energy procedure in view. The model validation was done by comparing the modeling

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results with collected data via a monitoring system from the District Heating Company of the city of Iasi (Romania).

2. Analysis of models

Werner S. [5] did one of the first studies on space heating modeling using acquired data. His model takes into account temperature-dependent heat-losses due to transmission and ventilation, transient heat transmission, solar gain, wind induced air infiltration

$$Q = k_1 + k_2 T_\mathrm{O} + k_3 \left(T_\mathrm{i} - T_\mathrm{O}\right) V + k_4 R . \tag{1}$$

Regression analysis was used to find out model coefficients, where average daily indoor temperature T_i, outdoor temperature T_O, wind velocity V and solar radiation R represent the dependent variables.

The basic idea is to study a model depending on input parameters found by energy characteristic analysis. The model described by the equation

$$Q = k_1 + k_2 T_\mathrm{O} + k_3 \left(T_\mathrm{i} - T_\mathrm{O}\right) V^{\frac{4}{3}} + k_4 R + k_5 T_\mathrm{O24h} + k_6 T_\mathrm{S} + k_7 q_{24h}^{\frac{4}{5}} , \tag{2}$$

where T_O24h - outdoor temperature 24 hours ago, T_S -supply temperature at the exit of the substation, q_{24h} - fluid flow rate 24 hours ago, is partially based on classical engineering equations and partially on statistical analysis of experimental data.

The set of constants $k_1, \ldots k_4$ corresponding to equation (1) presented in table 1 and k_1, $k_2, \ldots k_7$ corresponding to equation (2) presented in table 2 were estimated using the function *nlinfit* from Statistics Toolbox MATLAB. This function finds the parameters that minimize the sum of the squared differences between the observed responses and their fitted values. It uses the Gauss-Newton algorithm with Levenberg-Marquardt modifications for global convergence.

Correlation coefficients R calculated for five buildings denoted A, B, ..E using equation (1) and (2) are also presented in table 1 and 2. It may be noticed that the influence of the operating conditions taken into account in the equation (2) increase significantly the values correlation coefficient R for all buildings. Therefore, this is the best option for the heat consumption simulation. The good match between measured and calculated values of heat consumption can be also noticed in figure 1.

Table 1

Eq. 1	A	B	C	D	E
R	0.8218	0.8638	0.8616	0.8358	0.8674
k_1	45.4329	26.8239	36.2123	31.3757	32.4778
k_2	-1.9328	-1.0505	-1.2906	-1.0243	-1.3102
k_3	0.0069	0.0256	0.0234	0.0153	0.0112
k_4	0.0150	-0.0007	-0.0030	0.0052	-0.0049

Table 2

Eq. 2	A	B	C	D	E
R	0.9823	0.9456	0.9432	0.9771	0.9172
k_1	33.5635	-7.2424	-12.7024	-19.8611	-1.9277
k_2	-0.1117	-0.3191	-0.3607	-0.0605	-0.5748
k_3	-0.0068	0.0037	0.0019	0.0005	0.0002
k_4	0.0049	-0.0023	-0.0042	0.0012	-0.0063
k_5	-0.1932	-0.2724	-0.2971	-0.1196	-0.2548
k_6	1.3667	0.5828	0.8500	0.9550	0.5809
k_7	0.0785	0.6253	0.0536	-0.0246	0.0542

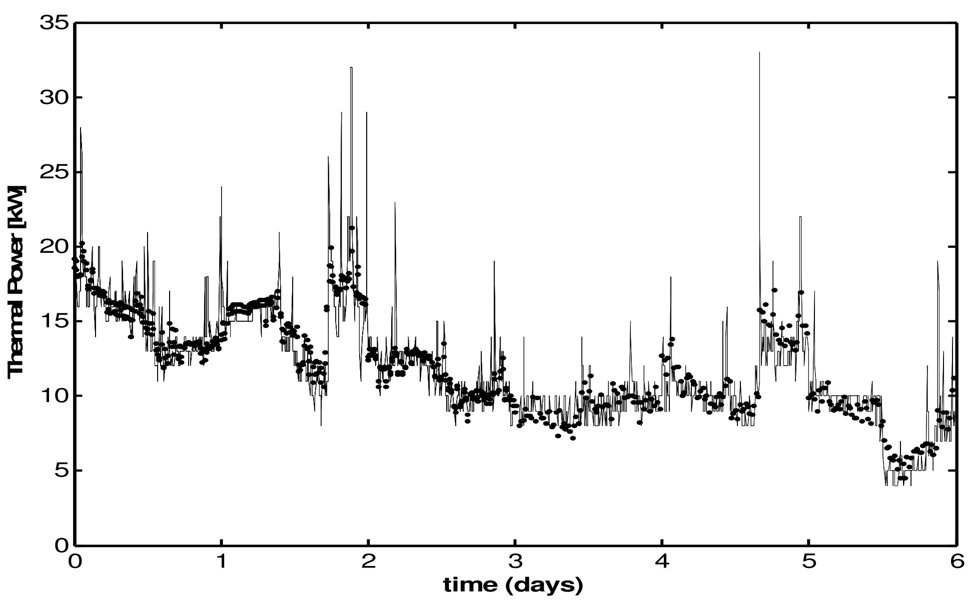

Fig. 1. Measured (−) and calculated (•) values of heat consumption.

An other method may be taken into consideration for heat consumption modeling: the neural network method [6]. Neural networks are built from a large number of very simple processing elements, neurons that individually deal with pieces of a big problem. The neural networks architecture consists of three layers: input layer, hidden layer and 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. In the studied case 6 neurons are chosen in the input layer and one single neuron in the output layer. Training results obtained using the input parameters from eq. 2 are presented in table 3.

Table 3

NN	**A**	**B**	**C**	**D**	**E**
Training results	R =0.984	R = 0.94	R = 0.91	R = 0.95	R = 0.92

It may be noticed the correlation coefficient values are very close to those obtained by the statistic modelling using eq.2.

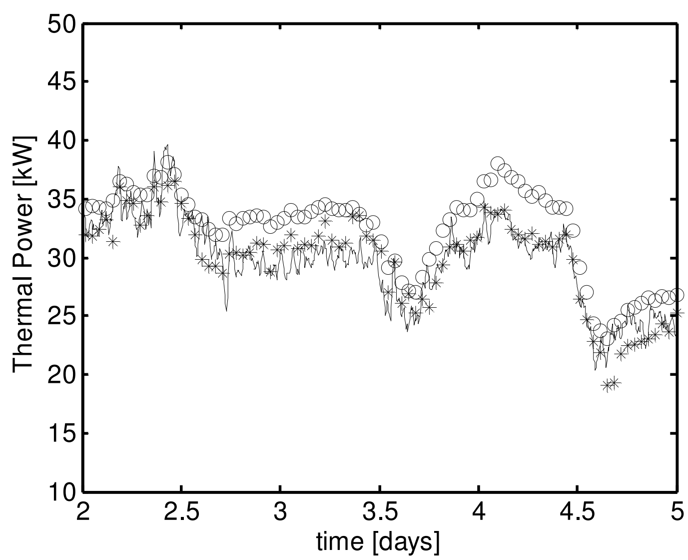

Fig. 2. Simulation models eq. 1 (o), eq.2 (*) and experimental data (—).

Concluding, both statistical and neural network methods can be used for simulation and prognosis of space heat consumption of buildings. In fig. 2, the models are compared with experimental data, for building A and the results underline the superiority of the proposed model compared with the model based only on weather input data (eq. 1).

3. Conclusions

The aim of this paper is to develop a methodology for simulating and predicting the heat consumption of buildings. Two models describing the dynamic of heat load are proposed and validated – a statistical one and an artificial neural networks one. Identification of input parameters was made by analysis of energy characteristics. It was pointed out that using as input parameters outdoor temperature, wind velocity, solar radiation, supply temperature, previous fluid flow rate, previous outdoor temperature, very good results are obtained.

The development of the two proposed 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 district heating system. The data covering a wide range of values, were chosen for training the NNs and for determining the coefficients from eq. (1) and (2) using statistical methods. Both models led to good correlation coefficients ($R>0.9$), but the statistical model described by the equation (2) is recommended due to its simplicity.

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