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SIMULATION OF SPACE HEAT DEMAND

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Abstract – **This paper develops and analysis soft computing methods created for simulation and prognosis of space heating energy consumption of buildings using statistic models based on acquired data. The validation was done by comparing the modeling results with collected data via a monitoring system from the District Heating Company of the city of Iasi (Romania).**

Keywords: *district heating systems, 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]. District heating systems represent well-known technologies and long time practice in Europe and 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], [3], [4].

Usually, 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 and prognosis of space heating energy consumption of buildings using statistic and artificial neural networks models based on acquired data. The validation was done by comparing the modeling results with collected data via a monitoring system from the District Heating Company of the city of Iasi (Romania).

2. BASIC MODELS

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 request. Buildings are microcosms of complexity derived from the interaction between form and fabric, service plant, control systems, occupants, climate. The attempts to model the heat loads may be classified in two categories: one based on the thermal causes for heat demand, the other based on the analysis of the acquired heat load data collected by a monitoring system.

The most significant parameters to be taking into consideration as thermal causes for the heat demand are: heat losses through building envelope by transmission, heat losses by natural and forced ventilation and infiltration, solar heat gain through windows and passive solar installations, internal gain by electrical apparatus, inhabitants, etc [5], [6]. Softwares based on a detailed description of the building such as DOE-2 , EnergyPlus , ESP-r, IDA,TRNSYS, Bsim2000, BLAST, BDA and many others have already been developed [7], [8], [9]. One of the problems is that building energy tools use detailed calculation procedures that require a large amount of input parameters for a detailed description of the building. Detailed level of information required by these programs requires that the user have a high level of knowledge and training and this may be considered an other problem. Practically, this type of software is useful only for building's design.

The second category of methods, based on the analysis of the heat load data is more appropriate in power engineering. During the last years many district heating systems have got monitoring systems, therefore this type of methods can be applied for an efficient thermal power plants operation.

Actually, due to its simplicity the degree-day method is the common one for prognosis in long term planning, in Romania. A similar method, the degree hour method is often used in mid-term and short-term simulation. Considering that shorter is the period of forecasting higher accuracy is necessary, the procedure for modeling the heat demands must depend on terms of planning. As complementary input parameters to the outdoor temperature, literature mentions various amounts such as the seasonal operation hours and timetable of the heating service distribution [10] or the social behavior of the consumers [11]. Detailed researches on the behavioral factors that influence the heat load demand according to people's occupancy pattern, age, number of persons per household are presented by Yao R. and Steemers K. [12] .

Multiregression analysis, time series analysis [13] and neural networks methods [14] are more complex procedures for determination of space heating models. For instance, one of the first studies on this topic done by Werner S., proposes a statistical model regression model based on indoor temperature, outdoor temperature, wind velocity and solar gain [15].

The statistical model presented in this paper uses for prediction two types of input parameters: forecast data and historical data. The prognosis input data are the climate characteristics available from a meteorological station and the previous data collected by a monitoring system working into a substation. The model is partially based on classical engineering equations and partially on statistical analysis of experimental data.

$$Q = k_1 + k_2 T_o + k_3 \left(T_i - T_o\right) V^{\frac{4}{3}} + k_4 T_{24h} + k_5 q_{1h}^{\frac{4}{5}} + k_6 T_{t1h} + k_7 P_S \tag{1}$$

where

Q - thermal power

$k_1,...k_7$ - coefficients calculated by regression analysis

T_0 - outdoor temperature

T_i - indoor temperature

V - wind velocity

T_{24h} - outdoor temperature 24 hours ago

q_{1h} - fluid flow rate 1 hour ago

T_{1h} - supply temperature 1 hour ago

P_S - solar radiation

It has to be underlined that the methodology to identify the input parameters is crucial. The outdoor temperature, indoor temperature, wind velocity and solar gain represent thermal causes for heat demand found in most simulation models. If only these parameters are used, the correlation factor is up to 0.85. It is a good value, but it can be improved. A detailed energy characteristic analysis was made and outdoor temperature 24 hours ago, fluid flow rate 1 hour ago, supply temperature 1 hour ago were found as significant input parameters.

3. MODEL'S ANALYSIS

The first step to develop a statistical model is data acquisition. Then the identification of the most important input parameters is necessary, after that calculation of the parameters' coefficients and finally the new model must be compared to well known models or experimental data.

k_1	-20.4267
k_2	-0.3781
k_3	-0.0035
k_4	-0.1582
k_5	0.0879
k_6	1.1163
k_7	0.0021

Table 1. Parameters' coefficients

In order to validate the model corresponding to equation (1) studies on experimental data acquired during two months were developed on 20 buildings. The series of coefficients $k_1 \ldots k_6$, characteristic for every building were calculated by regression analysis using the Statistics Toolbox from MATLAB [16]. In table 1 the values of the coefficients calculated for a chosen building are presented as an exemple.

E	Degree-hour method	Statistical method
1 January	62.5934	4.2697
2 January	57.0087	3.2904
3 January	0.9116	1.0290
4 January	1.3999	4.0124
5 January	26.9362	6.3632
6 January	6.5780	0.0395
7 January	10.9035	2.0172
8 January	11.6569	0.8266
9 January	4.7686	2.0152
10 January	15.1291	2.9504
11 January	0.4090	0.9813
12 January	7.0645	0.7491
13 January	12.1791	1.2046
14 January	41.3267	3.0235
15 January	8.8508	0.5917
16 January	15.5540	3.0155
17 January	13.3163	2.0832
18 January	9.4765	0.4916
19 January	45.5432	3.0770
20 January	9.9013	3.4191
21 January	3.7058	3.2541
22 January	3.1856	5.2115
23 January	10.7937	3.0845
24 January	16.0300	1.4112
25 January	23.4208	2.6675
26 January	26.8461	4.2354
27 January	9.2941	2.921
28 January	2.2929	4.6621
29 January	26.3875	3.1980
30 January	20.0866	2.8592
31 January	17.9863	6.3704

Table 2: Relative error values

The coefficients of the model presented in table 1 were used for prediction of thermal power demand in others days than the ones chosen for the simulation model. Values of the relative error parameter E comparing measured and calculated forecast values of the average daily thermal power were calculated by two methods: the classical degree hour method and the proposed statistical model. The results are presented in table 2.

From table 2 it may be observed that the values of the predicted thermal power are better if the statistical model from the equation (1) is used. The comparison between the relative error coefficients calculated both by the degree hour method and by the statistical model shows that predictions of thermal power demand with the statistical model are recommended.

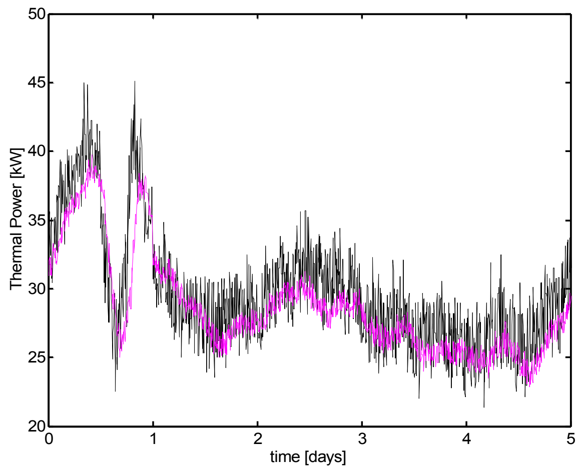

Figure 1. Simulation model

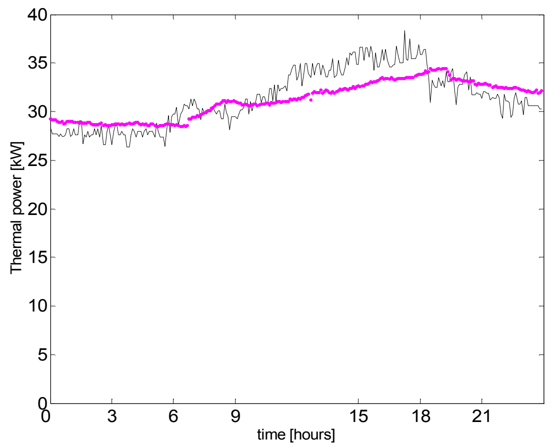

Figure 2. Calculated and measured values during a day

Figure 1 presents measured and calculation values for the simulation model during five days. It may be observed that the statistical model matches very well with the experimental data. In fact, the correlation coefficient for the model which uses measured data during 35 representative days is R=0,967 a very high value. Figure 2 presents a prognosis done with the statistical model described by the equation (1).

4. CONCLUSIONS

The paper develops a methodology for predicting the space thermal power demand of buildings. The technical and human factors that influence the heating system are very different and that is why no analytical mathematical model may be considered for this purpose. For this reason, an original statistical model is proposed and validated.

The development of the model is based on a series of representative experimental data selected from the database of a global monitoring system designed and implemented for supervising the behaviour of the district heating system.

Statistical models allow a unified approach that represents the background for optimization and global prediction for the thermal power request of a substation from a district heating system supplying a group of monitored buildings.

An alternative to the statistical modelling is the neural network modelling [17]. Sometimes this is the best solution. But the usefulness of statistical model could not be neglected, as very good results were obtained with such a model in some conditions and for some consumers.

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