Simulation of Consumption in District Heating Systems

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Abstract: - District heating companies from Europe had an annual turnover (2005) of 19.5 billion Euro and supplies heat to more than 100 million people. District heating contributes to higher energy efficiency, greater security of supply and lower carbon dioxide emissions. There is a need to strengthen the competitiveness of this technology. Important differences between Eastern and Western district heating systems exist not only regarding the level of modern equipment, but also in the conception of design and operating.

In most Western European countries, the entire district heating system is demand driven, using control equipment at four independent levels: two at the customer and two managed by the district heating operator. Each building usually has separately regulated systems for supplying heat to the radiators (space heating), to the domestic hot water system and to the ventilation system. The main advantage of this concept is that customers establish the space heat demands by means of thermostatic valves, at the first level of the heat demand control, without the risk that the District Heating Company delivers more or less heat than necessary.

In most Eastern European countries, the mentality is different: the District Heating Company evaluates the quantity of heat for each building and delivers it through a distribution network to substations. A number of 20-30 buildings, usually blocks of flats, are connected to the substation and must share the quantity of heat delivered. Only few consumers can adjust the quantity of consumed heat, using thermostatic valves, and the others are forced to receive the rest.

One major area of energy savings and the resulting financial expenditure is the ability to predict the heat consumption in order to match the energy supply. Some methods for simulation and prognosis of space heating and domestic warm water heating are presented in this study. The influence of input parameters proposed to be taking into consideration for the simulation of the heat demand of buildings connected to a district heating system is analyzed. The differences between software for prognosis of heat demand appropriate for production driven systems and software appropriate for demand driven systems are pointed out.

Key-Words: - district heating systems, heat spacing, domestic warm water, time series models, autoregressive model, simulation, prediction.

1 Introduction

According to the "Ecoheatcool" study, if European district heating sales were doubled the results would be: higher energy efficiency, as the primary energy supply would be reduced by 2.14EJ/year, equivalent to the whole energy balance of Sweden; reducing of import dependency by 4.45EJ/year corresponding to 5.5% of all European primary energy supply, equivalent to the whole energy balance of Poland; lower carbon dioxide emissions corresponding to 9.3% of the total CO2 emissions from fuel combustion, equivalent to the total fuel combustion in France [1].

In district systems, an important source of saving energy is production according to demand in real-time terms, a very complex task. SCADA systems are monitoring most district heating systems from Western European countries and some are implemented in Romania, too. This study tries to identify methods for prognosis of future space heating and domestic warm water heat demand.

According to Professor Sven Werner [2], the heat produced by Swedish district heating systems is shaped in the following way: 60% for space heating, 30% for domestic hot-water preparation, 6-8% by distribution losses, the rest representing loads that are dependent on the day of the week [3].

There are computer programs such as CONDOR, EcNetz, RNET, SYSTEM RORNET, TERMIS, BoFiT, ANSYS, DH SIM appropriate for space heating load prediction [4]. Interesting models for medium-term and short-term simulation using seasonal operation hours, timetable of the heating service distribution [5], social behavior of the consumers [6,7] were studied. Artificial neural networks represent an alternative. The approach used by Ian Beausoleil-Morrison and Moncef Krarti used a multilayer feedforward neural network with the back-propagation learning algorithm [8] and leads to very good results.

Even if domestic warm water is used within a house for bath/shower, wash hand basin, dish washing, clothes washing, studies about the thermal energy consumed for preparing it are only a few [7]. The energy used for heating domestic warm water depends on the human behaviour most of all, a factor that is difficult to control. Usually, prediction means an average value for the monthly/daily fluid flow rates per person to be taken into consideration. It is not enough for a real-time operation of a district heating system. At least hourly heat load profiles are needed.

This work develops methodologies able to predict dynamic heat demand for space heating and domestic warm water preparation in district heating systems, using time-series analysis. Validation of the methods was performed by comparing the modelling results with acquired data via a monitoring system from the District Heating Company of the city of Iasi (Romania).

2 Theoretical basis

Time-series is a sequence of data points measured typically at successive times. Time-series analysis comprises methods that allow several goals: the detailed and concise description of the specific time-series which is analyzed, the identification of a simulation mathematical model, the prediction of output values using early data as input values. A time series model will generally reflect the fact that observations close together in time will be more closely related than observations further apart. Values in a series for a given time will be expressed as deriving in some way from past values [9].

When modeling variations in the level of a process, there are three broad classes of practical importance: the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearly on previous data and are treated in more details in the articles autoregressive moving average models (ARMA), autoregressive moving integrated moving average (ARIMA), and autoregressive fractionally integrated moving average (ARFIMA).

3 Simulation of space heating demand

A physical-mathematical modeling was used for space heating simulation, a more appropriate approach compared to black box models as time-series models are. The models were developed with different input parameters for simulation models of space heating demand. Model parameters were estimated using a least-squares optimization method. The founded model parameters minimize the sum of the squared differences between the observed responses and their fitted values. The Gauss-Newton algorithm with Levenberg-Marquardt modifications for global convergence was used. In figure 1, variations of space heating demand data collected every 5 minutes during 30 winter days may be observed. Obviously, climate parameters are the most important, especially the outdoor temperature. The classic degree-day model uses only this parameter as input data for prognosis. The main purpose of the study is to identify which others parameters should be taking into consideration having in view particularities of production driven district heating systems.

The multiple correlation coefficient R and the residual mean square RMS were calculated for different models in order to find by multiregression analysis the best one. The Statistics Toolbox from MATLAB was used for the numerical simulation using every 5 minutes data acquired from a building during 30 winter days. The representative days for model simulation must be selected with a wide range variation of climatic parameters: outdoor temperature, wind velocity and solar radiation. The days used in this study cover as large variations of values as possible during winter time in Romania: outdoor temperature $-14.89^0C \div +13.49^0C$, wind velocity $0 \div 9$ m/s, solar radiation $0 \div 340$ [W/m^2].

The results obtained for 6 statistical models, are presented in Table I.

Model M1 takes into consideration only the outdoor temperature, as the degree day method does. Models M2 take into consideration supplementary input data illustrating the influence of climate: the wind velocity and the solar radiation. These are the only parameters used in software from Western European countries, and they are enough because all the links between the consumer and power plant are controlled by automation devices [10].

If only climatic parameters are used, as in model

M3, the correlation factor is 0.8401. Existing software for control driven systems would lead to such values if they were implemented in production driven district heating systems, where the human behavior is much more important than climate parameters.

In production driven systems the situation is different. Usually people turn on or reduce the heat at the same hours, when they are not at home, even if it is a colder day than the previous one. The influence of operating conditions in production driven district heating systems is taken into account in models M4, M5, M6, by means of the mass fluid flow rate at a previous time and the supply temperature in the network T_S. Exponent 4/5 was established after finding different values for different buildings, all around 0.8 by regression analysis.

The fluid flow rate one day before and the supply temperature one hour before seem to be very important input parameters for simulation of heat demand in installations suffering from a lack of control systems. Therefore, model M6 has the higher correlation coefficient R=0.9823 and the lowest RMS=4.3548. A higher correlation factor is difficult to obtain even if extra input parameters are tested, since the sensitivity of the measuring equipment is 1%.

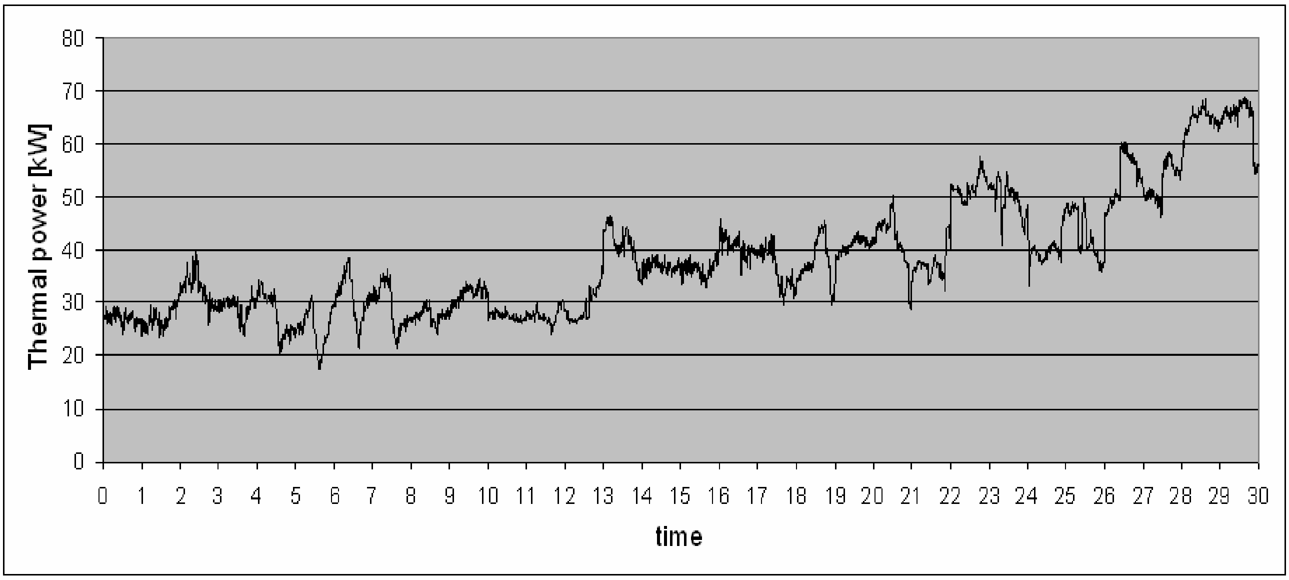

Figure 1. Experimental data collected during a month.

Table I. Statistical results for simulation

Model	Model's equation	R	RMS
M1	$Q = k_1 + k_2 T_O$	0.8116	42.4298
M2	$Q = k_1 + k_2 T_O + k_3 (T_i - T_O) V - k_4 S$	0.8216	40.4050
M3	$Q = k_1 + k_2 T_O + k_3 (T_i - T_O) V - k_4 S + k_5 T_{O24h}$	0.8401	36.5778
M4	$Q = k_1 + k_2 T_O + k_3 (T_i - T_O) V^{\frac{4}{3}} - k_4 S + k_5 T_{O24h} + k_6 \dot{m}_{24h}^{4/5}$	0.9211	18.8535
M5	$Q = k_1 + k_2 T_O + k_3 (T_i - T_O) V^{\frac{4}{3}} - k_4 S + k_5 T_{O24h} + k_6 T_S$	0.9503	12.0576
M6	$Q = k_1 + k_2 T_O + k_3 (T_i - T_O) V^{\frac{4}{3}} - k_4 S + k_5 T_{O24h} + k_6 T_S + k_7 \dot{m}_{24h}^{4/5}$	0.9823	4.3548

Q - heat load demand, T_O - outdoor temperature, T_i - indoor temperature, V - wind velocity, S - solar radiation, T_{O24h} - outdoor temperature measured 24h earlier, T_S - supply temperature in the network one hour earlier, $\dot{m}_{24h}^{4/5}$ mass fluid flow rate 24h earlier.

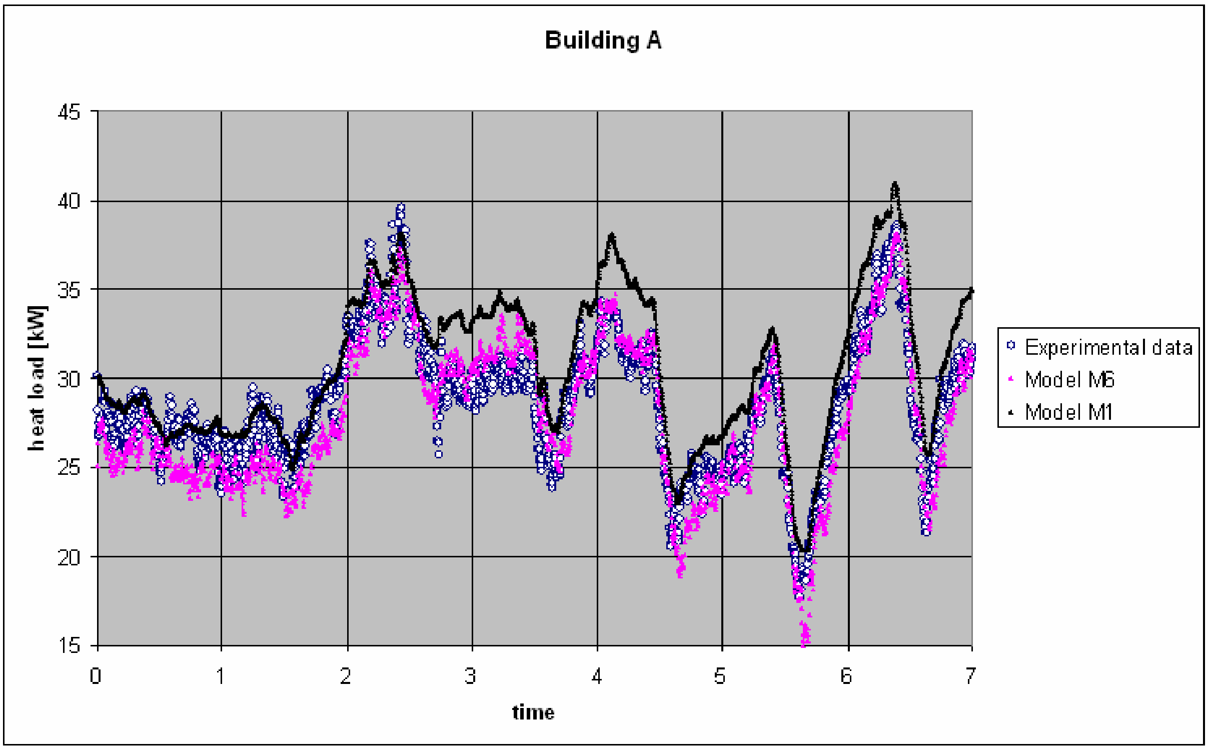

Figure 2. Experimental data and simulation models M1 and M6.

Table II. Results of prognosis using M6.

Statistical coefficients	Day 1	Day 2	Day 3
R	0.8077	0.7168	0.9384
RMS	6.1046	5.7481	4.1816

In Figure 2, a comparison between the outputs of the statistical simulation models M1 and M6 is presented. A better graph trend for model M6 may be observed compared to M1 and this fact is in agreement with the correlation coefficients presented in Table 1. The good trend of model M6 indicates that the proposed mathematical model can be successfully used to predict heat load since the values obtained by simulation are well matched with the measured data. The comparative study carried out for large variations of the input parameters, emphasized that the model M2 leaded to acceptable results only for mild weather, but not during very cold days when the heat demand is high. Moreover, when the climate conditions change significantly during a short period, as it often happens in Romania, the accuracy of model M2 is weak. The results indicate that the proposed model M6 is better than the classic degree-hour model or others models based only on climate data.

Once the best model is adopted, next step is the prognosis. The model output will be calculated in order to predict heat demand for the same studied buildings but for further days with others values of the input parameters: forecast climate characteristics available from a meteorological station and previous data collected by the monitoring system working into the substation.

As is may be observed in table II, if model M6 is used for predictions the results are good. Concluding, model M6 is appropriate for prognosis as space heating demand in production driven systems.

4 Simulation of domestic warm water demand

In order to find a dynamic model for the quantity of heat used for preparation of hot warm water, a simulation model using experimental data must be done. First, data collected during 90 winter days were analyzed. In figure 3, the graph representing the consumption of domestic warm water during a month may be observed. Variations are high, but quite according to time. The time seems to be the only input parameter to be taking into consideration.

Collected data were used for an autoregressive moving average, ARMA time series model

$$A(q)y(t) = C(q)e(t) \quad (1)$$

The appropriate order for the ARMA model can be selected using a number of procedures, for example, partial autocorrelation analysis and Akaike's Information Criterion (AIC) [9, 11]. For, analysis of domestic warm water demand, an autoregressive model is the most appropriate, corresponding to $C(q) = 1$.

The general representation of an autoregressive model (AR) is

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots.\alpha_m Y_{t-m} + e_t \quad (2)$$

where Y_t - output data at the time t, $Y_{t-1}, Y_{t-2}, \ldots..$ - input data at previous moments, e_t - white noise, representing the source of randomness.

Figure 4 presents the results obtained with the simulation model for domestic warm water consumption, described by the equations (3), (4)

The polynomials of the models are:

A(q) = 1 - 1.403 q^-1 + 0.3652 q^-2 +
+0.1674 q^-3 - 0.109 q^-4 (4)

C(q) = 1 + 0.2202 q^-1 + 0.08271 q^-2 +
+0.08509 q^-3 + 0.1968 q^-4 - 0.7593 q^-5 (5)

Validation with experimental data is very good as it may be observed in figure 4. The analysis points out that the loss function value is 1.37724 and FPE value is 1.62765 - sampling interval: 300 s.

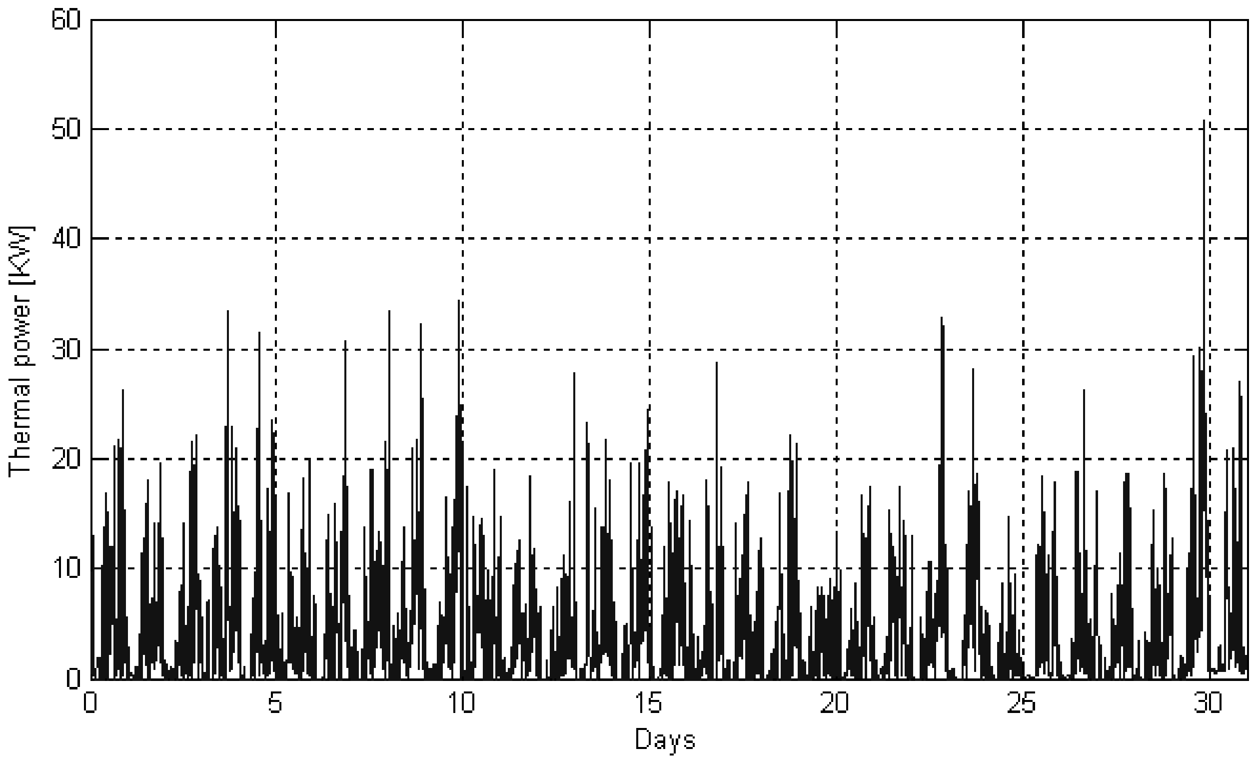

Figure 3. Daily thermal power consumption of domestic warm water during a month.

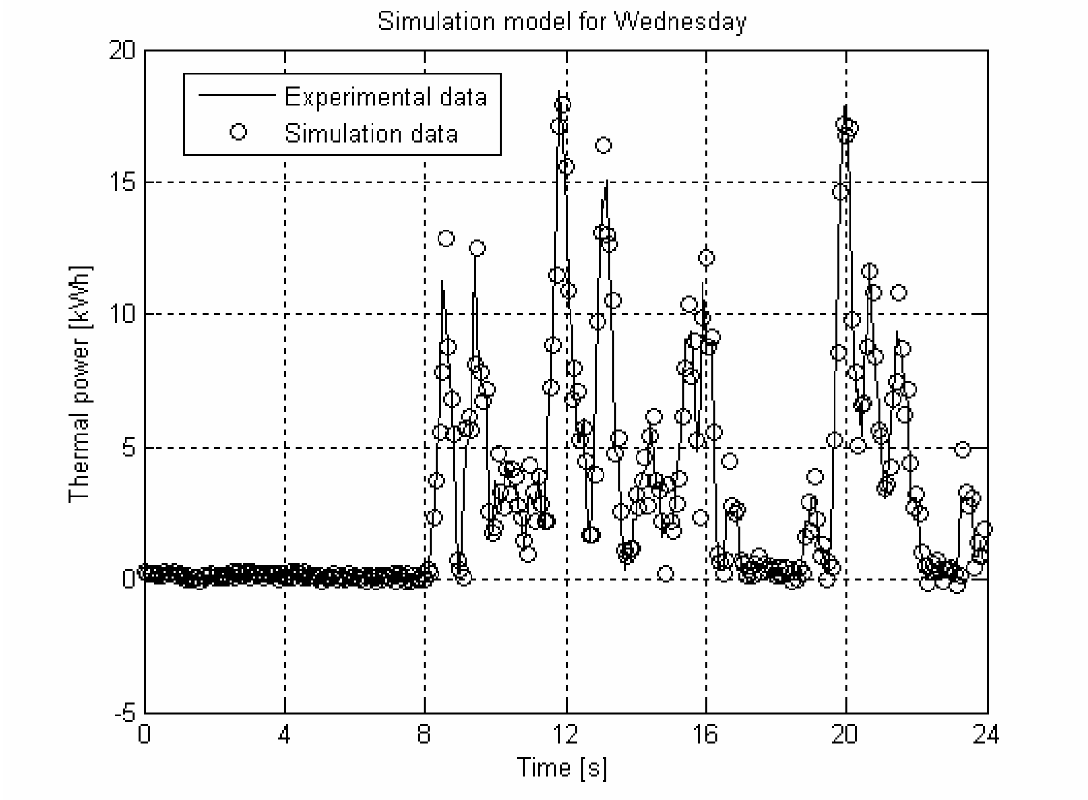

Figure 4. Simulation model for a working day .

5 Conclusions

The paper presents methodologies for simulation prognosis of heat demand taking into consideration two components: the space heating and the domestic warm water heat demand. Both statistical analyses lead to very good results.

Concluding, time-series analysis may be consider as an appropriate tool for prognosis in district heating systems.

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