Heat demand forecasting for concrete district heating system

Bronislav Chramcov

***Abstract*—**This paper presents the results of an investigation of a model for short-term heat demand forecasting. Forecast of this heat demand course is significant for short-term planning of heat production and it is most important for technical and economic consideration. Weather forecasts are an important input to many heat demand forecasting models. In this paper we propose the forecast model of heat demand based on the assumption that the course of heat demand can be described sufficiently well as a function of the outdoor temperature and the weather independent component (social components). Time of the day affects the social components. The time dependence of the load reflects the existence of a daily heat demand pattern, which may vary for different week days and seasons. Forecast of social component is realized by means of Box-Jenkins methodology. We have studied half-hourly heat demand data, covering a three (four) month period in two concrete district heating systems (DHS) of the Czech Power and Heating company. Comparison of accuracy of the prediction model with inclusion and without inclusion of outdoor temperature for 12 and 24 hours-ahead forecast are presented.

***Keywords*—**Box-Jenkins, Control algorithms, District Heating Control, Prediction, Time series analysis.

I. Introduction

THE paper deals with the utilization of time series prediction for control of technological process in real time. An improvement of technological process control level can be achieved by time series analysis in order to prediction of their future behavior. We can find an application of this prediction also by the control in the Centralized Heat Supply System (CHSS), especially for the control of hot water piping heat output [2].

In order to improve the control level of district heating systems, it is necessary for the energy companies to have reliable optimization routines, implemented in their organizations [11]. However, before a plan of heat production, a prediction of the heat demand first needs to be determined.

Due to the large operational costs involved, efficient operation control of the production sources and production units in a district heating system is desirable. Knowledge of heat demand is the base for input data for operation preparation of CHSS. Term "heat demand" is instantaneous required heat output or instantaneous consumed heat output by consumers. Term "heat demand" relates to term "heat consumption". It express heat energy, which is the customer supplied in a specific time interval (generally day or year).

The course of heat demand and heat consumption can be demonstrated by means of heat demand diagrams. The most important ones are:

- Daily Diagram of Heat Demand (DDHD) which demonstrates the course of requisite heat output during the day. (See Fig. 1)
- duration heat demand diagram - Y-coordinates represent heat demand and distance from zero represents duration of corresponding heat demand. Daily and yearly duration heat demand diagrams are currently known.

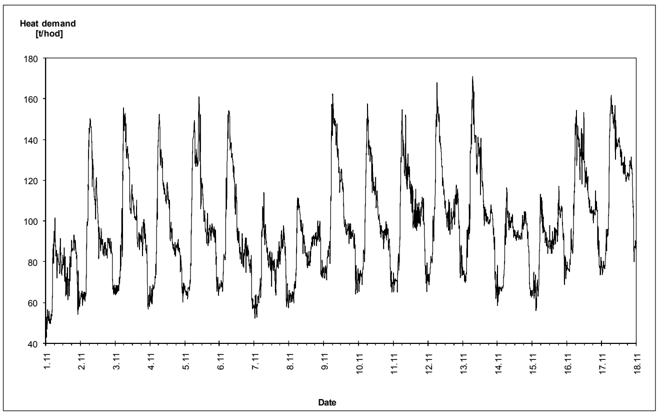

Fig. 1: DDHD for the concrete locality

These diagrams are most important for technical and economic consideration. Therefore forecast of these diagrams course is significant for short-term and long-term planning of heat production. It is possible to judge the question of peak sources and namely the question of optimal distribution loading between cooperative production sources and production units inside these sources according to time course of heat demand. The forecast DDHD is used in this case.

II. Problem formulation

Most forecasting models and methods for load prediction have already been suggested and implemented with varying degrees of success. They may be classified into two broad categories: classical (or statistical) approaches and artificial intelligence based techniques.

The statistical methods forecast the current value of a variable by using a mathematical combination of the previous values of that variable and previous or current value of exogenous factors, specially weather and social variables. These include linear models, solving by means of non-linear models, spectral analysis method, ARMA models, Box-Jenkins methodology etc. In recent times, much research has been carried out on the application of artificial intelligence techniques. These techniques are based on processing mass data. These include expert systems, neural networks, fuzzy neural models etc. However, the models that have received the largest attention are the artificial neural networks [7], [12], [13].

Most applications in the subject consider the prediction of electrical-power loads. Nevertheless was created several works, which solve the prediction of DDHD and its use for control of DHS. A number of these works are based on mass data processing [7], [9]. But these methods have a big disadvantage. It consists in out of date of real data. From this point of view is available to use the forecast methods according to statistical method. The basic idea of this approach is to decompose the load into two components, whether dependent and whether independent. The weather dependent component is typically modeled as a polynomial function of temperature and other weather factors. The weather independent component is often described by a Fourier series, ARMA model, Box-Jenkins methodology or explicit time function. Previous works on heat load forecasting [1], [6], show that the outdoor temperature, together with the social behavior of the consumers, has the greatest influence on DDHD (with respect to meteorological influences). Other weather conditions like wind, sunshine etc. have less effect and they are parts of stochastic component.

In this paper we propose the forecast model of DDHD based on the previous approach. The model is based on the assumption that the course of DDHD can be described sufficiently well as a function of the outdoor temperature and the weather independent component (social components). We have studied heat demand data in two concrete DHS of the Czech Power and Heating company. Comparison of accuracy of the prediction models is presented and some conclusions are given.

Many others works solve the question of economical heat production and distribution in DHS. Some methods able to predict dynamic heat demand for space heating and domestic warm water preparation in DHS, using time-series analysis was presented [10]. Other work present one step ahead prediction of water temperature returned from agglomeration based on input water temperature, flow and atmospheric temperature in past 24 hours [14].

III. Forecast Model of Heat Demand

As mentioned above, the model is based on the assumption that the course of DDHD can be described sufficiently well as a function of the outdoor temperature and the weather independent component (social components). Time of the day affects the social components. The time dependence of the load reflects the existence of a daily heat demand pattern, which may vary for different week days and seasons. Forecast of social component is realized by means of Box-Jenkins methodology [3]. This method works with fixed number of values, which are update for each sampling period.

For inclusion of outdoor temperature influence in calculation of prediction of DDHD was proposed general plan specified in Section 3.2.

A. The Box-Jenkins method

This methodology is based on the correlation analysis of time series and it works with stochastic models, which enable to give a true picture of trend component and also of periodic components. Because this method achieves very good results in practice, it was chosen for prediction of social component of DDHD.

The course of time series of DDHD contains mostly two periodic components (daily and weekly period). But general model according to Box-Jenkins enables to describe only one periodic component. We can propose two eventual approaches to calculation of forecast to describe both periodic components [5].

- The method that uses the model with double filtration
- The method – superposition of models

First we introduce simplified form (2) of general model according to BJ for the next using, when there is used substitution in the form (1). We can find more detailed analysis of general model in work [3].

$$F = \Phi_P^{-1}\left(B^s\right) \cdot \phi_p^{-1}(B) \cdot \Theta_Q\left(B^s\right) \cdot \theta_q\left(B\right) \cdot \nabla_s^{-D} \cdot \nabla^{-d} \tag{1}$$

$$z_t = F \cdot a_t \tag{2}$$

where: z_t is real value of heat demand in time *t*, a_t is white noise process, *B* is backward shift operator, *s* – seasonal period, $\Phi_P\left(B^s\right), \Theta_Q\left(B^s\right)$ are polynomials in B^s of degree *P* and *Q* of the seasonal AR and MA processes, $\phi_p(B), \theta_q\left(B\right)$ $\Phi_P\left(B^s\right), \Theta_Q\left(B^s\right)$ are polynomials in *B* of degree *p* and *q* of the AR and MA processes, ∇_s^D is the seasonal difference operator of order *D*, ∇^d is the difference operator of order *d*

The method that uses model with double filtration

We can describe model with double filtration through the substitution (1). The model in the form (3) is the result of it.

$$z_t = F \cdot \nabla_{s^*}^{D^*} \cdot a_t \tag{3}$$

where: *D* – degree of seasonal difference – daily (in equation 1), *D** - degree of seasonal difference – weekly, *s* – seasonal period - daily (in equation 1), *s** - seasonal period - weekly

It is important to adhere to this general plan for using the method that uses model with double filtration for calculation of DDHD prediction.

a) The filtration of time series is executed for the reason of elimination of weekly periodic component.
b) This filtered time series can be described by means of general model according BJ and then calculation of forecast by means of course can be executed; that is provided in work [3].
c) It is important to do back transformation that is inverse to the point a), because we have executed elimination of weekly periodic component.

The model in the form (3) enables to describe the DDHD course (i.e. it describes daily periodic component and also weekly one). It can be used for analysis and prediction of following regular influence of calendar (Saturday, Sunday).

The method – superposition of models

We can use second method i.e. superposition of models for elimination of regular influence of calendar. This method was published in the work [5]. This method is being used on two models in the form (2). These models are discerned by means of symbols * and **. The time series inscribed with symbol *, is series of values of DDHD outputs in every sampling period (e.g. 1 hour, 30 minutes, 15 minutes, etc.). And the time series inscribed by means of symbol ** is series of values of heat demand per day (the sampling period is 1 day). The plan of calculating prediction by means of the method of superposition of models is shown on the Fig. 2. We can find more detailed analysis in work [5].

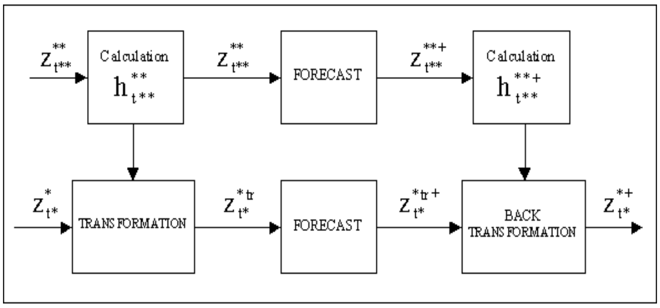

Fig. 2: Superposition of models - plan of calculating prediction

Legend to the Fig. 2: z_{t*}^{*} is real value of heat demand in every sampling period, z_{t**}^{**} is value of heat demand per day, h_{t**}^{**} is ratio of transformation, z_{t*}^{*tr} is transformed real value of heat demand in every sampling period, z_{t*}^{*tr+} is predicted value of transformed time series, z_{t*}^{*+} is predicted value of heat demand (after back transformation), z_{t**}^{**+} is predicted value of daily heat demand, h_{t**}^{**+} is ratio of transformation for predicted values of daily heat demand,.

1) Identification of Box-Jenkins model

Identification of time series model parameters is the most important and the most difficult phase in the time series analysis. Identification process firstly includes determination of a degree of differencing. After differencing the time series, we have to identify the order of autoregressive process AR(p) and order of moving average process MA(q). In our case, the Akaike Information Criterion (AIC) in the form (4) is used for testing. Adequacy of the model was tested [4] by means of Portmanteau test.

$$AIC(p,q) = n \cdot \ln \hat{\sigma}_a^2 + 2(p+q) \tag{4}$$

where: p, q is order of AR and MA process respectively, $\hat{\sigma}_a^2$ is a variance of residuals, n is a number of residuals.

B. Forecast algorithm for inclusion of outdoor temperature

Above mentioned methods do not describe sudden fluctuation of meteorological influences. In this case we have to include these influences in calculation of prediction. For inclusion of outdoor temperature influence in calculation of prediction of DDHD was proposed this general plan:

a) The influence of outdoor temperature filter off from time series of DDHD by means of heating characteristic (function that describes the temperature-dependent part of heat consumption)
b) Prediction of DDHD by means of Box-Jenkins method for this filtered time series
c) Filtration of predicted values for the reason of inclusion of outdoor temperature influence (on the base of weather forecast)

From the previous plan is evident that the principal aim is to derive an explicit expression for the temperature-dependent part of the heat demand. It is obvious that the temperature dependence is non-linear. For relatively high outdoor temperatures, the temperature has less influence. For example, the load will almost be the same for 25 °C and 27 °C. A corresponding conclusion is also true for relatively low temperatures, e.g. whether the outdoor temperature is -28 °C or -30 °C does not matter, the production units will produce at their maximum rate anyway.

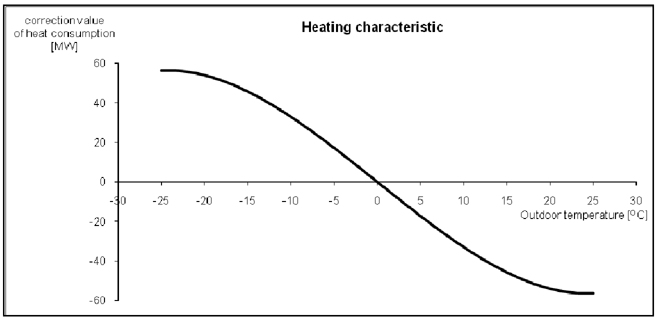

Fig. 3: The sample of heating characteristic (cubic function)

Regarding to previous consideration we can used the temperature-dependent part of heat demand in the form (5). Example of the course of heating characteristic for constants *x1 = 0.002, x2 = 3.5* is shown in the Fig. 3.

$$z_t^{kor} = x_1 \cdot T_t^3 - x_2 \cdot T_t \tag{5}$$

where: z_t^{kor} is correction value of heat demand in time t including outdoor temperature influence, T_t is real value of outdoor temperature in time t , x_1, x_2 are constants.

The temperature dependent part can assumed to vary as a piecewise linear function [5], see the illustrating example in Fig. 4. Here a function with five segments is used, but the number of segments can of course be chosen arbitrarily.

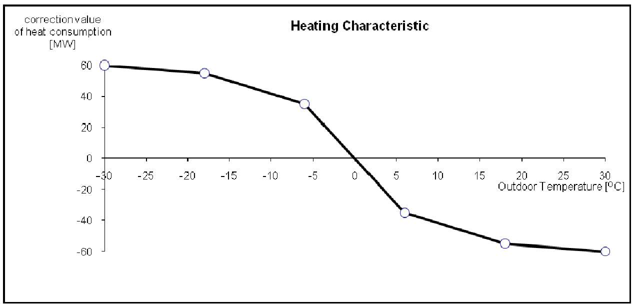

Fig. 4: The sample of heating characteristic (piecewise linear function)

Given the number of segments as a N_s. and the temperature levels as τ_i, $i = 1,2\ldots, Ns+1$. The parameters of heating characteristic are changed in these temperature levels. Now we can consider the temperature-dependent part of heat demand in the form (6).

$$\begin{aligned} &z_t^{kor} = \alpha_i \cdot T_t + \beta_i, \\ &\tau_i < T_t < \tau_{i+1},\ i = 1,\ldots, N_s \end{aligned} \tag{6}$$

where: z_t^{kor} is correction value of heat demand in time t including outdoor temperature influence, T_t is real value of outdoor temperature in time t , α_i is the slope of i-th segment, β_i is absolute equation term of i-th segment

Constants (x_1, x_2 and ,α_i, β_i) have to be determined for concrete locality empirically.

Filtration time series of DDHD that input in prediction model is defined in the form (7).

$$z_t^{filtr} = z_t - z_t^{kor} \tag{7}$$

where: z_t^{filtr} is heat demand in time t with filtering off the influence of outdoor temperature, z_t^{kor} is correction value of heat demand in time t including outdoor temperature influence, z_t is real value of heat demand in time t

The predicted values are necessary to filtrate after prediction calculation of filtering off time series for the reason of inclusion of outdoor temperature influence (on the base of weather forecast). We can define this operation in the form (8).

$$z_t^{+} = z_t^{filtr+} + z_t^{kor} \tag{8}$$

where: z_t^{filtr+} is predicted value of filter off time series of heat demand in time t, z_t^{kor} is correction value of heat demand in time t including outdoor temperature influence, z_t^{+} is predicted value of heat demand in time t.

The value z_t^{filtr+} is obtained by application of the equation (5) or (6) for this operation. We use weather forecast (temperature forecast).

IV. Calculation of Forecast for Specific Locality

Pursuant to the mentioned theory and literature a program was created in Matlab, which enables to choose available mathematical statistical model for calculation of prediction of DDHD course. All testing is based on lot of real data. These data were obtained in specific locality and they are processed for next using in text file form (see Fig. 5). The program is drawn in user's menu and by help of that it is possible to choose many parameters of forecast calculation (see Fig. 6).

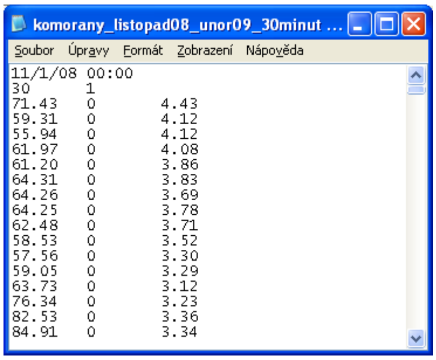

Fig. 5: The sample of text file

Selection of calculation method of prediction of DDHD course is a other possibility of submitted program. We can realize the calculation of prediction by means of the method that uses model with double filtration and the method – superposition of models.

After choosing one of the methods the calculation of prediction is started. At first in the course of calculation it is searched for the most suitable model, it is for optimum number of autoregression parameters and optimum number of parameters of moving average process. After following calculation of prediction, resulting graphic window is displayed. The example of this window is presented in the Fig. 9, Fig. 10, Fig. 12 and Fig. 13. In this window there is drawn course of DDHD, course of predicted data and probability

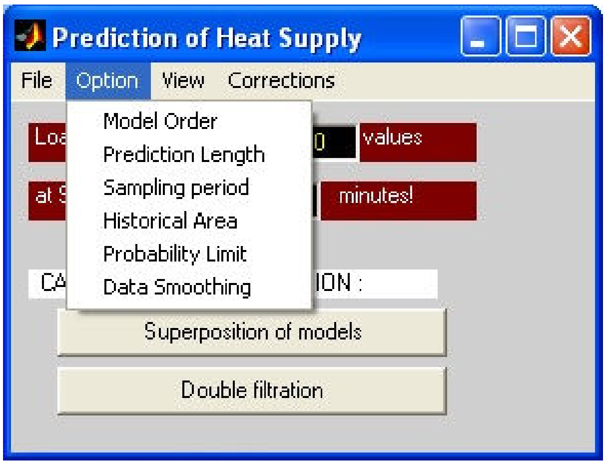

Fig. 6: User's menu of calculation program

limit. The result can be represented in concrete value form. These values are followed by calculation and they can be displayed in resulting window. The example of this window is shown on Fig. 11 and Fig. 14. In this window it is possible to find also optimum number of autoregression parameters and optimum number of parameters of moving average process.

A. Data for experiments

It is necessary to stress that the real data are used for all experiments and tests of proposed forecast model. The real data were obtained due to close cooperation of our research workplace with energy plant operations. In our case it is close cooperation with company MST a.s. – Power and Heating plant Olomouc, Power and Heating Plant Otrokovice, a.s. and company United Energy a.s. - Power and Heating plant Most-Komořany.

Measured data from two district heating systems in the region Most, Czech Republic are used in our experiments. The larger system is situated to locality Most-Komořany. This system has a typical day load (winter day) of about 100-140 MW. The smaller system is situated to locality Litoměřice and it has typical day load of about 28-35 MW. These time series contain besides time and type of the day, the value of heat demand and outdoor temperature for every 30 minutes. Measured data of period November, 2008 – February, 2009 for the locality Most-Komořany and period January, 2004 – March, 2004 for locality Litoměřice were available.

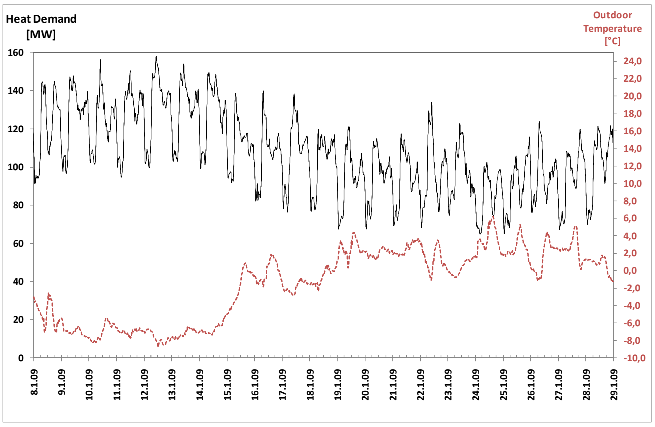

Fig. 7: Heat demand and Outdoor Temperature (dotted line) for system in the locality Most-Komořany

In Fig. 7 measured values of heat demand and outdoor temperature in the locality Most-Komořany for 3 weeks of January, 2009 are presented. In Fig. 8 measured values of heat demand and outdoor temperature in the locality Litoměřice for 2 weeks of February, 2004 are presented.

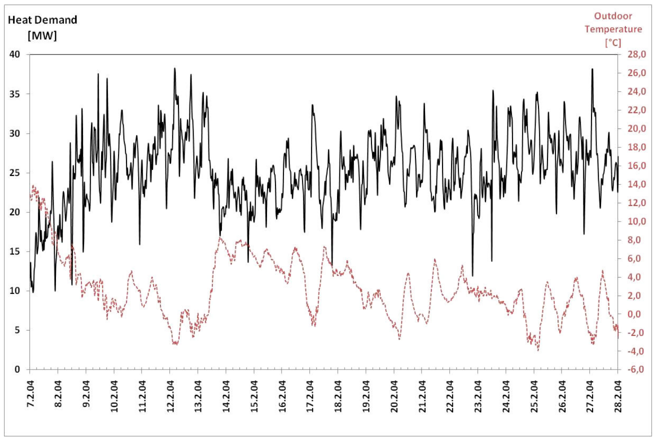

Fig. 8: Heat demand and Outdoor Temperature (dotted line) for system in the locality Litoměřice

The course of both previous time series of DDHD displays only one periodic component (daily period). Therefore general model according to Box-Jenkins is used for forecast of social component.

B. Results of heat demand forecast in concrete locality

The models were tested on data from the locality Litoměřice from two following weeks (28.2.2004 - 12.3.2004) and on data from the locality Most-Komořany from two following weeks (13.1.2009 – 26.1.2009). 24 hours-ahead and 12 hours-ahead forecast were made twice a day at 6.00 AM and 6.00 PM. The model with inclusion of outdoor temperature and without inclusion of outdoor temperature was used. Accuracy of the forecast is analyzed and summarized by means of Mean Absolute Percent Error (MAPE). MAPE is defined in the form (9) and it can be used to compare different predictions [8]. Root Mean Squared Error (RMSE) is defined in the form (10) and it is the square root of the arithmetic mean of the sum of the squares of the prediction errors [8].

$$MAPE = \frac{100}{n} \cdot \sum_{i=1}^{n} \frac{e_i}{z_i} \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \left(e_i^{\,2}\right)} \tag{10}$$

where: e_i is the difference between the actual value of time series z_i and the forecast value, n is the number of forecasted values

Table 1. presents results of heat demand prediction with inclusion of outdoor temperature for the locality Most-Komořany. Accuracy of heat demand forecast without inclusion of outdoor temperature is presented in Table 2. The samples of the graphic output of these forecasts are shown in the Fig. 9 and Fig. 10.

Table 1: Accuracy of the forecast model for 24, 12 hours ahead forecasts with inclusion of outdoor temperature for the locality Most-Komořany

Date, Time	24 hours-ahead forecast		12 hours-ahead forecast	
	MAPE [%]	RMSE [MW]	MAPE [%]	RMSE [MW]
13.1.2009, 6:00 AM	1.75	2.97	1.78	3.21
13.1.2009, 6:00 PM	2.95	5.24	1.74	2.73
14.1.2009, 6:00 AM	3.99	6.07	4.17	6.88
14.1.2009, 6:00 PM	4.35	6.26	4.84	6.63
15.1.2009, 6:00 AM	3.33	4.89	3.36	5.27
15.1.2009, 6:00 PM	3.62	4.90	3.08	4.20
16.1.2009, 6:00 AM	4.72	5.53	3.86	5.14
16.1.2009, 6:00 PM	6.90	9.38	5.63	6.37
17.1.2009, 6:00 AM	5.09	7.60	7.41	10.25
17.1.2009, 6:00 PM	4.35	6.36	2.01	2.27
18.1.2009, 6:00 AM	5.65	7.08	6.78	8.82
18.1.2009, 6:00 PM	5.79	7.01	4.39	4.56
19.1.2009, 6:00 AM	4.95	6.03	5.98	7.14
19.1.2009, 6:00 PM	3.33	4.18	3.02	3.36
20.1.2009, 6:00 AM	2.99	3.64	3.40	4.45
20.1.2009, 6:00 PM	2.70	3.28	2.63	2.62
21.1.2009, 6:00 AM	3.48	4.13	2.76	3.85
21.1.2009, 6:00 PM	6.55	7.37	4.36	4.54
22.1.2009, 6:00 AM	5.58	6.82	8.02	9.07
22.1.2009, 6:00 PM	7.51	9.78	3.56	3.68
23.1.2009, 6:00 AM	9.47	10.75	10.59	12.54
23.1.2009, 6:00 PM	8.26	8.29	8.75	8.61
24.1.2009, 6:00 AM	6.59	7.38	7.72	7.93
24.1.2009, 6:00 PM	4.15	5.18	4.75	6.01
25.1.2009, 6:00 AM	5.40	7.07	3.23	3.79
25.1.2009, 6:00 PM	9.57	11.16	7.93	9.52
26.1.2009, 6:00 AM	7.34	8.63	9.83	10.88
26.1.2009, 6:00 PM	5.39	6.29	4.99	5.73
Average value	5.21	6.55	5.02	6.07

Table 2: Accuracy of the forecast model for 24, 12 hours ahead forecasts without inclusion of outdoor temperature for the locality Most-Komořany

Date, Time	24 hours-ahead forecast		12 hours-ahead forecast	
	MAPE [%]	RMSE [MW]	MAPE [%]	RMSE [MW]
13.1.2009, 6:00 AM	2.56	4.21	3.20	5.15
13.1.2009, 6:00 PM	4.81	8.03	3.90	5.44
14.1.2009, 6:00 AM	5.41	7.48	4.31	7.31
14.1.2009, 6:00 PM	17.36	21.45	13.00	14.72
15.1.2009, 6:00 AM	6.48	9.28	8.32	11.69
15.1.2009, 6:00 PM	10.83	13.21	7.88	8.56
16.1.2009, 6:00 AM	5.65	7.36	3.25	5.08
16.1.2009, 6:00 PM	7.11	10.76	5.09	6.63
17.1.2009, 6:00 AM	6.07	10.21	9.46	14.05
17.1.2009, 6:00 PM	5.68	8.52	2.61	3.10
18.1.2009, 6:00 AM	7.54	9.29	8.59	11.47
18.1.2009, 6:00 PM	7.98	8.73	6.46	6.36
19.1.2009, 6:00 AM	7.92	8.67	8.40	9.11
19.1.2009, 6:00 PM	5.00	5.70	5.33	5.96
20.1.2009, 6:00 AM	3.83	4.39	4.63	5.40
20.1.2009, 6:00 PM	3.00	3.54	2.89	2.93
21.1.2009, 6:00 AM	4.33	5.10	2.99	3.94
21.1.2009, 6:00 PM	8.22	9.68	5.49	5.93
22.1.2009, 6:00 AM	8.74	9.78	9.33	10.76
22.1.2009, 6:00 PM	11.67	13.63	9.30	9.72
23.1.2009, 6:00 AM	14.34	14.81	14.09	16.65
23.1.2009, 6:00 PM	17.97	16.30	16.42	13.82
24.1.2009, 6:00 AM	12.19	13.24	17.02	17.21
24.1.2009, 6:00 PM	7.89	8.26	9.09	9.44
25.1.2009, 6:00 AM	10.39	11.28	6.57	6.91
25.1.2009, 6:00 PM	13.99	16.02	12.98	13.65
26.1.2009, 6:00 AM	10.44	10.71	11.25	12.26
26.1.2009, 6:00 PM	9.87	9.86	11.26	10.27
Average value	8.47	9.98	7.97	9.05

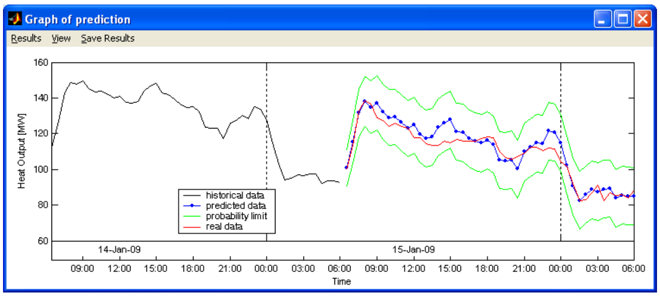

Fig. 9: 24 hours ahead forecast (with inclusion of outdoor temperature) of heat demand on 15.1.2009 6:00 AM in the locality Most-Komořany

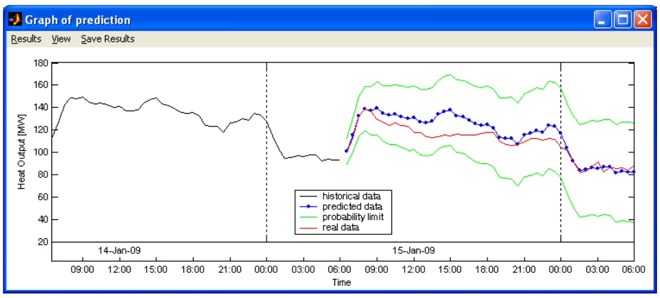

Fig. 10: 24 hours ahead forecast (without inclusion of outdoor temperature) of heat demand on 15.1.2009 6:00 AM in the locality Most-Komořany

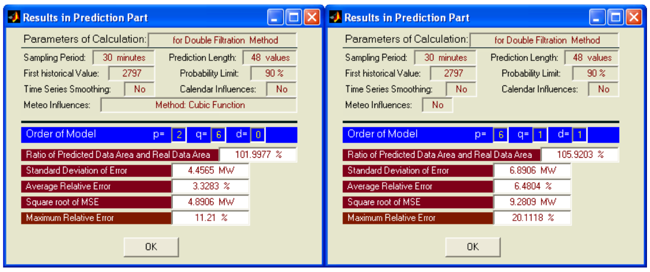

Fig. 11: Result windows for 24 hours ahead forecast of heat demand on 15.1.2009 6:00 in the locality Most-Komořany

From the results, we conclude that the prediction model with inclusion of outdoor temperature achieves for the locality Most-Komořany very good results. MAPE for the test period is at any time less than 10 percent and RMSE seldom exceed the value of 10MW. Average value of MAPE in the test period is approximately 5% and average value of RMSE is approximately 6 MW. Obviously, we also observe that the value of MAPE and RMSE are lower for a half a day ahead forecast than for a day ahead forecast.

Further, the results of heat demand prediction with inclusion of outdoor temperature for the locality Litoměřice are presented in Table 3. Accuracy of heat demand forecast without inclusion of outdoor temperature is presented in Table 4. The samples of the graphic output of these forecasts are shown in the Fig. 12 and Fig. 13.

Table 3: Accuracy of the forecast model for 24, 12 hours ahead forecasts with inclusion of outdoor temperature for the locality Litoměřice

Date, Time	24 hours-ahead forecast		12 hours-ahead forecast	
	MAPE [%]	RMSE [MW]	MAPE [%]	RMSE [MW]
28.2.2004, 6:00 AM	5.14	1.64	5.63	1.84
28.2.2004, 6:00 PM	8.26	3.04	4.79	1.42
29.2.2004, 6:00 AM	9.94	3.47	10.96	3.92
29.2.2004, 6:00 PM	9.70	3.30	8.48	2.81
1.3.2004, 6:00 AM	8.94	3.00	10.99	3.73
1.3.2004, 6:00 PM	7.26	2.25	5.77	1.81
2.3.2004, 6:00 AM	6.19	1.89	7.92	2.35
2.3.2004, 6:00 PM	5.17	1.84	4.13	1.13
3.3.2004, 6:00 AM	7.18	2.55	6.24	2.36
3.3.2004, 6:00 PM	6.29	2.24	7.45	2.53
4.3.2004, 6:00 AM	5.24	1.87	4.55	1.62
4.3.2004, 6:00 PM	7.73	2.54	5.99	2.11
5.3.2004, 6:00 AM	9.25	3.04	10.06	3.13
5.3.2004, 6:00 PM	7.46	2.63	7.71	2.76
6.3.2004, 6:00 AM	8.43	2.64	7.25	2.49
6.3.2004, 6:00 PM	8.69	2.53	8.87	2.60
7.3.2004, 6:00 AM	8.89	2.73	8.60	2.50
7.3.2004, 6:00 PM	9.28	3.08	7.98	2.61
8.3.2004, 6:00 AM	9.22	3.11	11.34	3.77
8.3.2004, 6:00 PM	6.58	2.12	7.42	2.41
9.3.2004, 6:00 AM	5.29	1.62	5.38	1.73
9.3.2004, 6:00 PM	5.93	1.87	5.15	1.52
10.3.2004, 6:00 AM	6.37	1.94	6.69	2.14
10.3.2004, 6:00 PM	5.84	1.66	5.62	1.61
11.3.2004, 6:00 AM	5.43	1.54	5.72	1.64
11.3.2004, 6:00 PM	5.83	1.65	5.13	1.44
12.3.2004, 6:00 AM	7.04	1.81	7.11	1.90
12.3.2004, 6:00 PM	7.42	1.96	7.16	1.75
Average value	7.28	2.34	7.15	2.27

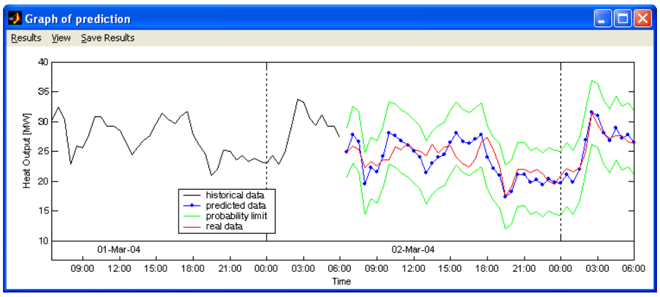

Fig. 12: 24 hours ahead forecast (with inclusion of outdoor temperature) of heat demand on 2.3.2004 6:00 AM in the locality Litoměřice

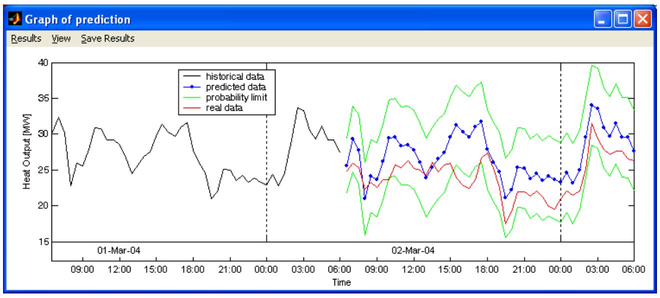

Fig. 13: 24 hours ahead forecast (without inclusion of outdoor temperature) of heat demand on 2.3.2004 6:00 AM in the locality Litoměřice

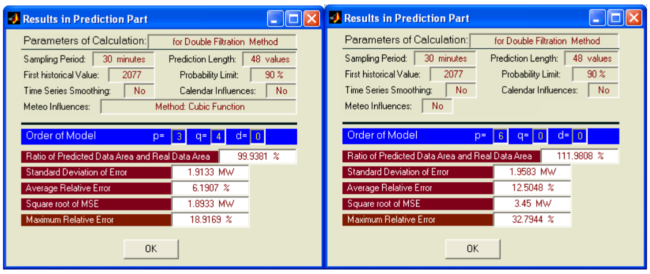

Fig. 14: Result windows for 24 hours ahead forecast of heat demand on 2.3.2004 6:00 in the locality Litoměřice

Table 4: Accuracy of the forecast model for 24, 12 hours ahead forecasts without inclusion of outdoor temperature for the locality Litoměřice

Date, Time	24 hours-ahead forecast		12 hours-ahead forecast	
	MAPE [%]	RMSE [MW]	MAPE [%]	RMSE [MW]
28.2.2004, 6:00 AM	5.50	1.78	6.03	1.98
28.2.2004, 6:00 PM	9.57	3.64	5.46	1.66

29.2.2004, 6:00 AM	10.72	3.97	13.01	4.70
29.2.2004, 6:00 PM	9.88	3.42	8.09	2.72
1.3.2004, 6:00 AM	10.72	3.53	12.21	4.14
1.3.2004, 6:00 PM	12.08	3.85	6.75	2.38
2.3.2004, 6:00 AM	12.51	3.45	12.68	3.86
2.3.2004, 6:00 PM	6.57	2.42	5.92	1.67
3.3.2004, 6:00 AM	14.80	5.37	8.23	3.15
3.3.2004, 6:00 PM	12.94	4.74	18.73	6.25
4.3.2004, 6:00 AM	7.16	2.46	5.54	1.90
4.3.2004, 6:00 PM	11.32	3.52	10.41	3.31
5.3.2004, 6:00 AM	9.66	3.24	13.27	4.03
5.3.2004, 6:00 PM	7.40	2.58	6.11	2.19
6.3.2004, 6:00 AM	15.81	4.55	8.48	2.89
6.3.2004, 6:00 PM	18.76	4.76	19.69	5.03
7.3.2004, 6:00 AM	11.55	3.30	13.29	3.48
7.3.2004, 6:00 PM	11.57	3.75	8.52	2.80
8.3.2004, 6:00 AM	12.67	4.17	16.66	5.21
8.3.2004, 6:00 PM	7.70	2.51	8.45	2.71
9.3.2004, 6:00 AM	7.64	2.42	6.13	2.13
9.3.2004, 6:00 PM	8.09	2.39	6.64	1.92
10.3.2004, 6:00 AM	8.50	2.40	8.76	2.58
10.3.2004, 6:00 PM	7.63	2.19	6.25	1.84
11.3.2004, 6:00 AM	6.80	2.03	6.78	1.92
11.3.2004, 6:00 PM	8.82	2.49	7.39	2.22
12.3.2004, 6:00 AM	7.96	2.05	8.64	2.33
12.3.2004, 6:00 PM	7.09	1.99	7.19	1.72
Average value	10.05	3.18	9.48	2.96

From the experiments for the locality Litoměřice, we conclude that the prediction model with inclusion of outdoor temperature achieves again very good results. MAPE for the test period is at any time less than 10 percent and RMSE seldom exceed the value of 3 MW. Average value of MAPE in the test period is approximately 7% and average value of RMSE is approximately 2 MW. Obviously, we also observe that the value of MAPE and RMSE are lower for a half a day ahead forecast than for a day ahead forecast.

C. *Review of the results*

Realized experiments for both district heating systems demonstrate possibility of using of forecast model with inclusion of outdoor temperature for improvement of heat demand prediction. Results in the Table 5 attest to this fact. Average values of MAPE and RMSE for all experiments of the both district heating systems are presented in the Table 5.

From the results, we conclude that the MAPE for prediction with inclusion of outdoor temperature is approximately 3% less than MAPE without inclusion of outdoor temperature. Likewise, the RMSE is approximately 3 MW (locality Most-Komořany) or 1 MW (locality Litoměřice) lower than RMSE for prediction without inclusion of outdoor temperature. The accuracy of prediction (expressed by MAPE) is better for district heating system in the locality Most-Komořany. This fact is due to higher typical day load (100-140 MW) than the typical day load (28-35 MW) in the smaller system (locality Litoměřice).

Table 5: Overview of results of all experiments for the both district heating systems

	Most-Komořany		Litoměřice	
	MAPE [%]	RMSE [MW]	MAPE [%]	RMSE [MW]
24 hours ahead forecasts **with** inclusion of outdoor temperature	5.21	6.55	7.28	2.34
24 hours ahead forecasts **without** inclusion of outdoor temperature	8.47	9.98	10.05	3.18
12 hours ahead forecasts **with** inclusion of outdoor temperature	5.02	6.07	7.15	2.27
12 hours ahead forecasts **without** inclusion of outdoor temperature	7.97	9.05	9.48	2.96

A deeper analysis of the results shows that the worse prediction was achieved on the days of weekend.

A concluding remark is that accuracy of weather forecasting can have a great impact on the accuracy of heat demand forecasting.

V. Conclusion

This paper presents the Box-Jenkins methodology for building up the forecast model of time series of DDHD and the possibility of improvement of this forecast model with help of inclusion of outdoor temperature influence. The proposed forecast method was successfully applied to real data from concrete district heating systems. The effectiveness of proposed forecast model was demonstrated through a comparison of the real heat demand data with short-term (24, 12 hours) forecasted values. In term of the average MAPE in the test period our approach achieved 5% and 7% error respectively.

Heat demand forecast plays an important role in power system operation and planning. Accurate heat demand prediction saves costs by improving economic load dispatching, unit commitment, etc. Model described should prove useful for the control in the Centralized Heat Supply System (CHSS), especially for the qualitative-quantitative control method of hot-water piping heat output – the Balátě System [2].

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Bronislav Chramcov was born in Uherské Hradiště, Czech Republic, in 1975. He studied Automatization and control technology at the Faculty of Technology in Zlin of the University of Technology in Brno, and he took his degree in 1998. In 2006 he graduated his doctoral degree from the Faculty of Applied Informatics of Thomas Bata University in Zlin. His doctoral thesis was focused on the utilization of time series prediction for control of technological process. He is working now as a lecturer at the Faculty of Applied Informatics of Thomas Bata University in Zlin. His research activities are focused on Control Algorithms for District Heating Systems, Time Series Forecast in Energy or Using of Fuzzy Logic for Time Series Forecast.