Design of a Model for Heat Demand Prediction Using the Neural Network Synthesis

BRONISLAV CHRAMCOV, PAVEL VAŘACHA
Tomas Bata University in Zlin
Faculty of Applied Informatics
nam. T.G. Masaryka 5555, 760 01 Zlin,
CZECH REPUBLIC
{chramcov, varacha}@fai.utb.cz http://web.fai.utb.cz

Abstract: - This paper deals with design 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. 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). Forecast of social component is realized by means of Box-Jenkins methodology. For inclusion of outdoor temperature influence in calculation of prediction of heat demand is used the heating characteristic (function that describes the temperature-dependent part of heat consumption). The principal aim is to derive an explicit expression for the heating characteristics. The Neural Network Synthesis is used for optimal finding of the expression.

Key-Words: - Modelling, Prediction, Box-Jenkins, Control algorithms, Neural Network Synthesis

1 Introduction

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 Centralized Heat Supply System (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 one is the Daily Diagram of Heat Demand (DDHD) which demonstrates the course of requisite heat output during the day (See Fig. 1).

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 [1].

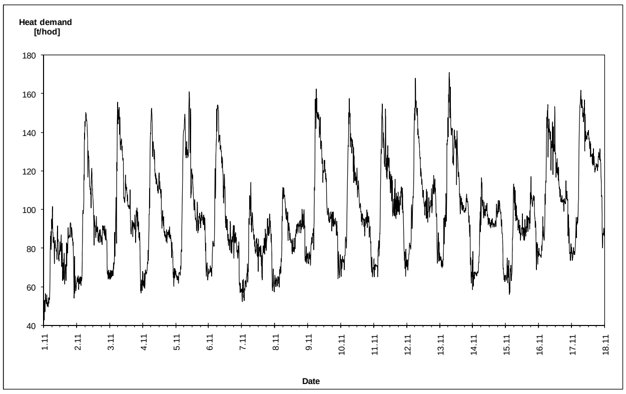

Fig. 1: DDHD for the concrete locality

2 State of Art

Most forecasting models and methods for prediction of heat load or heat demand 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 methods based on artificial intelligence techniques process mass data [2]. These include expert systems, neural networks, fuzzy neural models etc.

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.

Most applications in the subject consider the prediction of electrical-power loads. Nevertheless there was created several works, which solve the prediction of DDHD and its use for control of District Heating System (DHS) or for a planning the most economical, technical and environmental optimal energy distribution system. A number of these works are based on mass data processing [3], [4]. However these methods have a big disadvantage. It consists in out of date of real data. This problem solves for example [5]. This paper presents methods to perform heat demand prediction of individual households based on neural network techniques. Using different input sets and a so called sliding window, the quality of the predictions can be improved significantly. Simulations show that these improvements have a positive impact on controlling the distributed microgenerators.

Out of date of real data problem is eliminated using 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 [6], [7], show that the outdoor temperature, together with the social behaviour 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. For example the papers [8] and [9] use the statistical methods for heat demand prediction. The article [8] presents a load prediction method which estimates heat and electricity load profiles for various building categories. The method is based on statistical analyses of hourly simultaneous measured district heat and electricity consumption in several buildings, as well as background information of the measured buildings.

In this paper we propose the forecast model of DDHD based on the statistical method approach with using the ANN for modeling the function of the temperature-dependent part of heat demand. To create ANN optimally performing heating characteristics Neural Network Synthesis can be used. The method was successfully used in the field of head demand prediction [10] or identification of district heating network before [11]. Nevertheless the method provides very good results applied on broad variety of different task, for example on cancer classification [12].

3 Method for Heat Demand Forecast

As mentioned above, a number of works are based on mass data processing. 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 in our case the methodology of Box –Jenkins [13]. This method works with fixed number of values, which are update for each sampling period.

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 [14].

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

3.1 Forecast algorithm for inclusion of outdoor temperature

Above mentioned method according to Box-Jenkins do not model meteorological influences. In this case we have to include these influences in calculation of prediction. According to above mentioned reviews we assume only outdoor temperature influence. 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 characteristics (function that describes the temperature-dependent part of heat consumption)
b) Prediction of HSDD 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 load. 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. Regarding to previous consideration we have to find the explicit function of heating characteristics in the form (1), where z_t^{kor} is correction value of heat consumption in time t including outdoor temperature influence, T_t is real value of outdoor temperature in time t. Finding this function using artificial neural network (ANN) is presented in the next chapter.

$$z_t^{kor} = f(T_t) \tag{1}$$

Filtration time series of DDHD that input in prediction model is defined in the form (2) where z_t^{filtr} is heat consumption in time t with filtering off the influence of outdoor temperature, z_t^{kor} is correction value of heat consumption in time t including outdoor temperature influence, z_t is real value of heat consumption in time t.

$$z_t^{filtr} = z_t - z_t^{kor} \tag{2}$$

After prediction calculation of filtering off time series is necessary to filtrate the predicted values for the reason of inclusion of outdoor temperature influence (on the base of weather forecast). We can define this operation in the form (3), where z_t^{filtr+} is predicted value of filter off time series of heat consumption in time t, z_t^{kor} is correction value of heat consumption in time t including outdoor temperature influence, z_t^{+} is predicted value of heat consumption in time t.

$$z_t^{+} = z_t^{filtr+} + z_t^{kor} \tag{3}$$

The value z_t^{filtr+} is obtained by application of the equation (1) for this operation. We use weather forecast (temperature forecast).

4 ANN Performing Heating Characteristics

This chapter provides all important information necessary to understand how optional ANN for heat load prediction can be obtained by the method application. The algorithm of symbolic regression called Analytic Programming [14] as well as the evolutionary algorithm Self Organizing Migration Algorithm (SOMA) [15] have to be described first as they are both integral parts of the method.

4.1 Analytic Programming

Main principle (core) of analytic programming (AP) is based on discrete set handling (DSH). DSH shows itself as universal interface between evolutionary algorithm (EA) and a symbolically solved problem. This is why AP can be used almost by any EA.

Briefly put, in AP, individuals consist of non-numerical expressions (operators, functions,…), which are within evolutionary process represented by their integer indexes. Such index then serves like a pointer into the set of expressions and AP uses it to synthesize resulting function-program for Cost Function evaluation.

All simple functions and operators are in so called General Function Set (GFS) divided into groups according to the number of arguments which can be inserted during the evolutionary process to create subsets GFS_{3arg}, GFS_{2arg}...GFS_{0arg}.

Table. 1: Example of GFS and its subsets

GFS Degree	Contains
GFS_{all}	$f(x_1, x_2, x_3)$, +, -, *, /, Power, Abs, Round, Sin, Cos, t, K, τ, 1, 2
GFS_3	$f(x_1, x_2, x_3)$
GFS_2	+, -, *, /, Power
GFS_1	Abs, Round, Sin, Cos
GFS_0	t, K, τ, 1, 2

Functionality of discrete set handling can be seen on the concrete example in Fig. 2. Number of actually used pointers from an individual before synthesized expression is closed is called ***depth***.

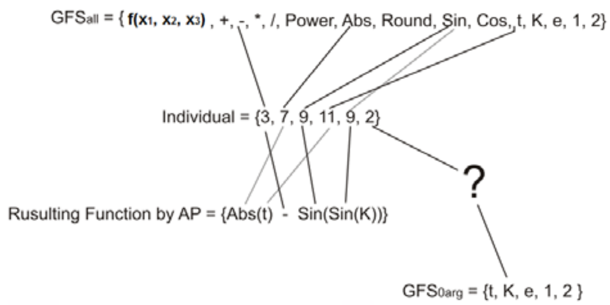

Fig. 2: Main principles of AP

ISBN: 978-1-61804-076-3

Constant Processing
Synthesized ANN, programs or formulas may also contain constants "K" which can be defined in GFS_0 or be a part of other functions included in GFS_{all}. When the program is synthesized, all Ks are indexed, so K_1, K_2, …, K_n, are obtained and then all K_n are estimated by second EA. In this case the EA is, again, asynchronous implementation of SOMA.

This is especially convenient for an ANN synthesis. K_n can be interpreted as various weights and thresholds and their optimization by SOMA as ANN learning.

4.2 SOMA All-to-One
Several different versions of SOMA exist, nevertheless, this article is focused on most common All-to-One version, which is most suitable for asynchronous parallel implementation. All basic All-to-One SOMA principles important for correct understanding of executed experiment are described below.

Parameter definition
Before starting the algorithm, SOMA's parameters: Step, PathLength, PopSize, PRT and Cost Function need to be defined. The Cost Function is simply the function which returns a scalar that can directly serve as a measure of fitness. In this case, Cost Function is provided by AP.

Creation of Population
Population of individuals is randomly generated. Each parameter for each individual has to be chosen randomly from the given range <Low, High>.

Migration loop
Each individual from population (PopSize) is evaluated by the Cost Function and the Leader (individual with the highest fitness) is chosen for the current migration loop. Then, all other individuals begin to jump, (according to the Step definition) towards the Leader. Each individual is evaluated after each jump by using the Cost Function. Jumping continues until a new position defined by the PathLength is reached. The new position $x_{i,j}$ after each jump is calculated by (4), where $t \in <0,by\ Step\ to, PathLegth>$ and *ML* is actual migration loop. It is shown graphically in Fig. 3. Later on, the individual returns to the position on its path, where it found the best fitness.

$$x_{i,j}^{MLnew} = x_{i,j,start}^{ML} + (x_{L,j}^{ML} - x_{i,j,start}^{ML})tPRTVector_j \qquad (4)$$

Before an individual begins jumping towards the Leader, a random number $rnd \in <0, 1>$ is generated (for each individual's component), and then compared with PRT. If the generated random number is larger than PRT, then the associated component of the individual is set to 0 using PRTVector. This situation is possible to write in the form (5), where $j=1,\dots n_{param.}$

$$\begin{aligned} rnd_j < \mathrm{PRT}\ \mathit{then}\ \mathrm{PRTVector_j} = 0 \\ \mathit{else}\ \mathrm{PRTVector_j} = 1 \end{aligned} \qquad (5)$$

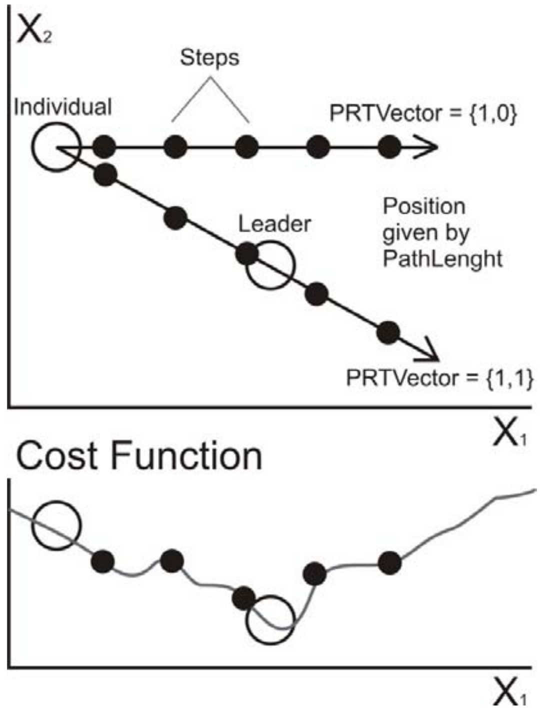

Fig. 3: PRTVector and its action on individual movement

Hence, the individual moves in the N-k dimensional subspace, which is perpendicular to the original space. This fact establishes a higher robustness of the algorithm. Earlier experiments demonstrated that without the use of PRT, SOMA tends to determine a local optimum rather than global one.

Test for stopping condition
If a divergence between current Leader and Leader from the last migration loop is less than defined number, stop and recall the best solution(s) found during the search.

4.3 Neural Network Synthesis
There is a very easy way of using AP for ANN synthesis. The most important part is to define items from which ANN will be composed. In this case GFS contains only three items.

Most important item of (6) is Artificial Neuron (AN) (7) with hyperbolic tangent as transfer function (8). Weight of output, steepness and thresholds are computed as K in AP (9). Graphical sample of AN is shown in the Fig.4.

$$GFSall = \{+, AN, K*Tt\} \quad (6)$$

$$GFS1 = \{AN\} \quad (7)$$

$$AN(S) = w\frac{e^{2\lambda(S+\phi)}-1}{e^{2\lambda(S+\phi)}+1} \quad (8)$$

$$AN(S) = K_1\frac{e^{2K_2(S+K_3)}-1}{e^{2K_2(S+K_3)}+1} \quad (9)$$

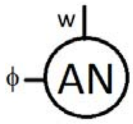

Fig. 4: Graphical example of AN

To allow more inputs into one ANN simple plus operator (10) is used, graphical example presents the Fig.5. Finally, (11) represents weighted input data, graphical example is shown in the Fig. 6.

$$GFS_2 = \{+\} \quad (10)$$

$$GFS0 = Tt*x \quad (11)$$

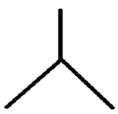

Fig. 5: Graphical example of plus operator

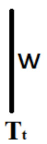

Fig. 6: Graphical example of weighted input

Under such circumstances, translation of an individual to ANN can be easily grasped from Fig. 7.

Whole process is cyclical. Individuals provided by EA are translated to ANNs. ANNs are evaluated in accordance with training data set and their global errors are used to set fitness to these individuals. Consequently, a new generation is chosen and the whole process is repeated in next migration loop.

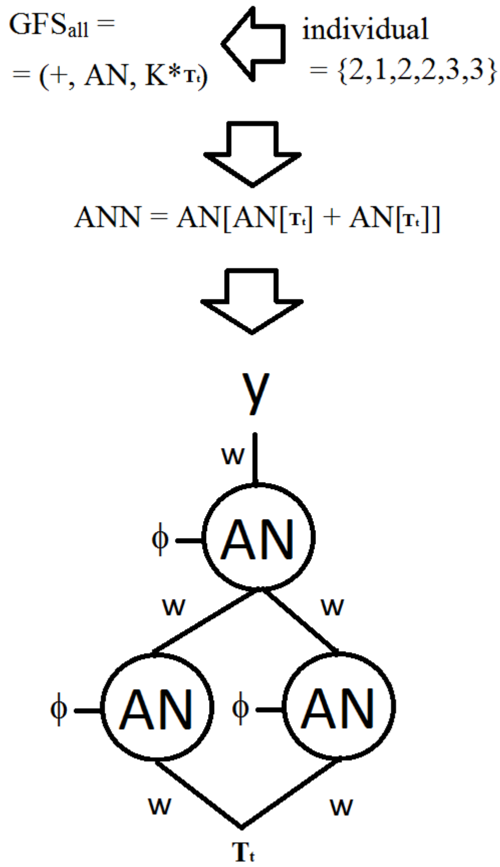

Fig. 7: Translation of an individual to ANN

5 Conclusion

This paper presents methodology for building up the forecast model of time series of DDHD. This forecast model use the heating characteristics for inclusion of outdoor temperature influence. The function of heating characteristics is proposed by means of Neural Network Synthesis.

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 [1].

Acknowledgement:
This work was supported in part by the Ministry of Education of the Czech Republic under grant No.MSM7088352102 and in part by European Regional Development Fund within the project CEBIA-Tech No. CZ.1.05/2.1.00/03.0089

References:

[1] J. Balátě. *Design of Automated Control System of Centralized Heat Supply*. Brno, 1982. Thesis of DrSc (Doctor of Science) Work. TU Brno, Faculty of Mechanical Engineering.

[2] N. E. Mastorakis, V. M. Mladenov, M. N. S. Swamy, "Improved Neural Network for Checking the Stability of Multidimensional Systems", *10th Symposium on Neural Network Applications in Electrical Engineering*, Belgrade, Serbia, September 23-25, 2010

[3] O. Lehtoranta, J. Seppälä, H. Koivisto, and H. Koivo. ”Adaptive district heat load forecasting using neural networks”, *In Proceedings of Third international Symposium on Soft Computing for Industry*. Maui, USA, June, 2000.

[4] H.S. Hippert, C.E. Pedreira and R.C. Souza. “Neural networks for short-term load forecasting: a review and evaluation”, *IEEE Transactions on Power Systems* . February 2001, Volume 16, Issue 1, s. 45-55. ISSN 0885-8950.

[5] V. Bakker, M.G.C. Bosman, A. Molderink, J.L. Hurink and G.J.M. Smit. “Improved heat demand prediction of individual households”, *In Proceedings of IFAC Conference on Control Methodologies and Technology for Energy Efficiency, CMTEE'2010*. Vilamoura: IFAC, March 2010, pp. 110-115, ISBN: 978-390266168-5.

[6] E. Dotzauer. “Simple model for prediction of loads in district-heating systems,” *Applied Energy*. November-December 2002, Volume 73, Issues 3-4, s. 277-284. ISSN 0306-2619.

[7] L. Arvastson. *Stochastic modelling and operational optimization in district-heating systems”*. Lund, 2001. 240 s. Doctoral thesis. Lund University, Centre for Mathematical Sciences. ISBN 91-628-4855-0.

[8] L. Pedersen, J. Stang and R. Ulseth. “Load prediction method for heat and electricity demand in buildings for the purpose of planning for mixed energy distribution systems”, *Energy and Buildings*, 2008, Volume 40, Issue 7, pp. 1124-1134.

[9] B. Chramcov. “Utilization of Mathematica environment for designing the forecast model of heat demand”, *WSEAS Transaction on Heat and Mass Transfer [online]*. January 2011, Volume 6, Issue 1, pp. 21-30.

[10] P. Vařacha and R. Jašek. ”ANN synthesis for an agglomeration heating power consumption approximation”, *In Recent Researches in Automatic Control: Proceedings of the 13th WSEAS international conference on Automatic control, modelling & simulation* (ACMOS). Lanzarote: WSEAS Press, 2011. p. 239-244. ISBN 978-1-61804-004-6

[11] E. Král, V. Dolinay, L. Vašek and P. Vařacha. “Usage of PSO Algorithm for Parameters Identification of District Heating Network Simulation Model”, *In 14th WSEAS International Conference on Systems. Latest Trands on Systems*. Volume II, Rhodes, WSEAS Press (GR) , 2010. p. 657-659. ISBN/ISSN: 978-960-474-214-1

[12] P. Vařacha. “Neural network synthesis dealing with classification problem”, *In Recent Researches in Automatic Control: Proceedings of the 13th WSEAS international conference on Automatic control, modelling & simulation* (ACMOS). Lanzarote: WSEAS Press, 2011. pp. 377-382. ISBN 978-1-61804-004-6.

[13] G.E. Box and G.M. Jenkins. *Time series analysis : forecasting and control*. Rev. ed. San Francisco : Holden-Day, 1976. 575 s. ISBN 0-8162-1104-3..

[14] P. Dostál. *Machine Processing of Daily Diagram Course Prediction of Loading the Centralized Heat Supply System*, Brno, 1986. Doctoral thesis. TU Brno, Faculty of Mechanical Engineering.

[15] Z. Oplatková and I. Zelinka. “Investigation on Shannon - Kotelnik Theorem Impact on SOMA Algorithm Performance”,. *In European Simulation Multiconference*, 2005, Riga, ESM , 2005. p. 66-71. ISBN/ISSN: 1-84233-112-4.

[16] L. Kouřil and I. Zelinka. **“**Evolutionary Synthesis of Rules for Programming the Turing Machine”, *Trilobit* , 2010. vol. 2 pp. 10-21. ISSN: 1804-1795