Energy xxx (2015) 1–8

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Appraisal of soft computing methods for short term consumers' heat load prediction in district heating systems

Milan Protić [a], Shahaboddin Shamshirband [c, **], Mohammad Hossein Anisi [c], Dalibor Petković [b, *], Dragan Mitić [a], Miomir Raos [a], Muhammad Arif [c], Khubaib Amjad Alam [d]

[a] University of Niš, Faculty of Occupational Safety, Čarnojevića 10A, 18000 Niš, Serbia
[b] University of Niš, Faculty of Mechanical Engineering, Department of Mechatronics and Control, Aleksandra Medvedeva 14, 18000 Niš, Serbia
[c] Department of Computer System and Technology, Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, 50603, Malaysia
[d] Department of Software Engineering, Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, 50603, Malaysia

A R T I C L E I N F O

Article history:
Received 4 September 2014
Received in revised form
22 January 2015
Accepted 24 January 2015
Available online xxx

Keywords:
District heating systems
Heat load
Prediction
SVR

A B S T R A C T

District heating systems can play a significant role in achieving stringent targets for CO_2 emissions with concurrent increase in fuel efficiency. However, there are numerous possibilities for future improvement of their operation. One of the potential domains is control, where short-term prediction of heat load can play a significant role. With reliable prediction of consumers' heat consumption, production could be altered to match the real consumers' needs. This will have an effect on lowering the distribution cost, heat losses, and especially primary and secondary return temperatures, which will consequently result in increased overall efficiency of district heating systems. This paper compares the accuracy of different predictive models of individual consumers in district heating systems. For that purpose, we designed and tested numerous models based on the SVR (support vector regression) with a polynomial (SVR–POLY) and a radial basis function (SVR–RBF) as the kernel functions, with different set of input variables and for four prediction horizons. Model building and testing was performed using experimentally obtained data from one heating substation. The results were compared using the RMSE (root-mean-square error) and the coefficient of determination (R^2). The prediction results of SVR–POLY models outperformed the results of SVR–RBF models for all prediction horizons and all sampling intervals. Moreover, the SVR–POLY demonstrated high generalization ability, so we propose that it should be used as a reliable tool for the prediction of consumers' heat load in DHS (district heating systems).

1. Introduction

DHS (District heating systems) are based on a simple idea of central production of heat and further distribution of produced heat to final consumers. Every DHS comprises three basic elements – a heat source, a distribution network, and consumers – which are in most cases indirectly connected (through heating substations) to a distribution network. In order to compete with individual heating systems, DHS must use one of the five suitable strategic local energy resources: useful waste heat from thermal power stations (cogeneration); heat obtained from refuse incineration; useful waste heat from industrial processes; natural geothermal heat sources; and fuels difficult to manage, such as wood waste, peat, straw, or olive stones [1], and have an advanced control system that will decrease the cost of operation and distribution [2].

The main objective in optimal district heating control is efficient operation, which can be achieved only through matching heat production with the real consumers' needs. In that case, the average temperature in the distribution network is reduced, distribution heat losses are minimized, pumping costs are reduced, and, finally, more consumers can be connected to the existing distribution network with a further increase in efficiency. This approach can be regarded as demand side management and it has been used for years in electrical grid control. According to Ref. [3], DSM (Demand Side

* Corresponding author. Tel.: +381 643283048.
** Corresponding author. Tel.: +60 146266763.
E-mail addresses: shamshirband@um.edu.my (S. Shamshirband), dalibortc@gmail.com (D. Petković).

http://dx.doi.org/10.1016/j.energy.2015.01.079
0360-5442/© 2015 Elsevier Ltd. All rights reserved.

Nomenclature

DHS	district heating systems
SVR	support vector regression
RBF	radial basis function
RMSE	root-mean-square error [kW]
R^2	coefficient of determination
T_{st}	outdoor temperature sensor [°C]
T_{p1}	primary supply temperature sensor [°C]
T_{p2}	primary return temperature sensor [°C]
T_{s1}	secondary supply temperature sensor [°C]
T_{s2}	secondary return temperature sensor [°C]
$P(t)$	heat load in moment (t) [kW]
$T(t)$	outdoor air temperature in moment (t) [°C]
I_n	indicator variable

Management) is a portfolio of measures to improve the energy system at the side of consumption. In DHS, demand side management was first introduced in Ref. [4]. The authors reported the possibility of a temporal reduction (of 2–3 h) of heat load by 25% on average for individual buildings connected to a DH system upon the introduction of DSM strategy. The idea was further elaborated in Ref. [5], which proposed multi-agent architecture for automatic, distributed control of district heating systems. In addition, the author indicated the necessity of changing the focus in the control of DH systems from production and distribution to the consumers' side. This is of paramount importance since the consumers dictate the flow and temperature in the DH (district heating) network through substations in the DH system. In distributed control strategy, consumers' heat demand control is essential in structuring the overall control strategy for the entire district heating system. With a precise predictive model of consumer heat load, heat production, i.e. primary supply temperature and flow, can be adjusted to the real needs, which will have an effect on minimizing the production costs and distribution losses and decreasing the return temperature, which is of particular importance for combined heat and power plants.

One of the first systematic analyses of heat load for entire district systems was provided by Werner [6]. He performed a comprehensive study of factors affecting the value and character of heat load. Additionally, he proposed linear regression models for heat load in DHS. Further analysis of heat load in district heating systems was undertaken by Madsen et al. [7]. In this study different nonparametric and parametric methods and models were developed and tested with sampled data from the district heating system in Esbjerg, Denmark. It was concluded that the ARMAX model with trigonometric profile yields best results for the prediction horizon of less than 24 h. A review of parametric, non-, and semi-parametric methods and models for heat load was presented in Ref. [8]. Additionally, this report introduced methods for online prediction of heat load with available online meteorological forecasts. Dotzauer [9] presented a very simple heat load model and reported acceptable prediction results. Nielsen et al. derived a grey-box model for heat load of DHS consumers [10]. Additionally, they performed likelihood ratio tests of significance of environmental conditions for heat load. In some recent studies, SARIMA, Kalman filter [11], and neural networks [12] were used for heat load prediction.

For this study, we used a soft computing technique, SVR (support vector regression) [13,14], to build predictive models of DHS consumers' heat load. The basic idea behind the soft computing methodologies is to collect system input/output data pairs and then use this data for creating and validating the predictive models. The SVR algorithms specifically developed for regression problems are suitable for a large variety of regression problems, since they do not only take into account the error approximation of in-sample data, but also perform the generalization of the model. They are based on statistical learning theory and the structural risk minimization principle [15–17].

We used two SVR schemes with a radial basis function (SVR–RBF) and a polynomial function (SVR–POLY) as the kernel functions to predict heat load in district heating systems. Experimentally obtained data from one heating substation connected to the "Krivi vir" heating plant (Niš District Heating System, Serbia) were used for creating and testing the developed predictive models. The main purpose of this paper is to compare the performances of the developed SVR prediction models and determine whether these kinds of models are suitable for practical implementation in advance control strategies in DHS.

2. Material and methods

2.1. Experiment

Data acquisition and logging was carried out in one heating substation connected to the "Krivi vir" heating plant (part of the Niš District Heating System, Serbia). The substation installation schematic is shown in Fig. 1.

The heating substation is connected to the district heating system via a Schmidth plate heat exchanger, model SIGMA X13-NCL (Fig. 2). Table 1 contains the technical specification of the heat exchanger.

There is no domestic hot water preparation. In the secondary installation, heat is delivered across the two-pipe system to cast-iron radiators in sixty apartments. Flow control and, therefore, control of delivered heat to consumers is achieved by the Danfoss AVQM motorized flow control valve (Fig. 3).

In addition to motorized control, the valve has a control diaphragm for mechanical flow limitation in order to mechanically limit the excessive flow in the substation. Circulation of water on the secondary side is performed with the constant speed Grundfoss UPSD 50-180/F twin pump.

Control of delivered heat is achieved by the Danfoss ECL comfort 300 controller, which is placed in the control box with other electrical equipment. The controller works on the weather compensation principle and controls the temperature of delivered water to consumers/secondary side through a temperature control curve, according to the measured momentary outdoor temperature. There is no feedback from indoor temperature measurement. Two additional modules are integrated into the controller: ECA 84, for processing and storing the data from the energy calculator, and ECA 87, for data logging. The controller was connected to the HCP HAWK high speed GPRS (general packet radio service) modem for remote data transfer. Archived data from the ECA 87 module were read off regularly during the heating season.

Heat consumption was measured using the Danfoss heat metering set consisting of:

1. Calculator INFOCAL 5 (accuracy ±1.5%, Fig. 4(a)),
2. Ultrasonic flow sensor Danfoss SONO 2500 CT (flow measuring range ≤ 25,000 m^3/h, accuracy ±3%, Fig. 4(b)), and
3. A pair of temperature sensors, two Pt 500 temperature sensors (measurement range 0–170 °C, accuracy ±0.01%, Fig. 4(c)).

Primary supply and return temperatures were measured with RTD (resistance temperature detectors) temperature sensors (Pt 100, measurement range 0–170 °C, accuracy ±0.2%). Outdoor temperature was measured with an NTC (negative temperature coefficient) sensor (nominal resistance 5000 Ω at 25 °C,

Please cite this article in press as: Protić M, et al., Appraisal of soft computing methods for short term consumers' heat load prediction in district heating systems, Energy (2015), http://dx.doi.org/10.1016/j.energy.2015.01.079