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Extreme learning machine for prediction of heat load in district heating systems

Shahin Sajjadi [a], Shahaboddin Shamshirband [b,*], Meysam Alizamir [c], Por Lip Yee [b], Zulkefli Mansor [d], Azizah Abdul Manaf [e], Torki A. Altameem [e], Ali Mostafaeipour [f]

[a] Department of Construction Management, University of Houston, Houston, TX, USA
[b] Department of Computer System and Technology, Faculty of Computer Science and Information Technology, University of Malaya, 50603 Kuala Lumpur, Malaysia
[c] Young Researchers and Elite Club, Hamedan Branch, Islamic Azad University, Hamedan, Iran
[d] Research Center for software technology and management (SOFTAM), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Malaysia
[e] Advanced Informatics School, Universiti Teknologi Malaysia, Malaysia
[f] Industrial Engineering Department, Yazd University, Yazd, Iran

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ABSTRACT

District heating systems are important utility systems. If these systems are properly managed, they can ensure economic and environmental friendly provision of heat to connected customers. Potentials for further improvement of district heating systems' operation lie in improvement of present control strategies. One of the options is introduction of model predictive control. Multistep ahead predictive models of consumers' heat load are starting point for creating successful model predictive strategy. In this article, short-term, multistep ahead predictive models of heat load of consumer attached to district heating system were created. Models were developed using the novel method based on Extreme Learning Machine (ELM). Nine different ELM predictive models, for time horizon from 1 to 24 h ahead, were developed. Estimation and prediction results of ELM models were compared with genetic programming (GP) and artificial neural networks (ANNs) models. The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by the ELM approach in comparison with GP and ANN. Moreover, achieved results indicate that developed ELM models can be used with confidence for further work on formulating novel model predictive strategy in district heating systems. The experimental results show that the new algorithm can produce good generalization performance in most cases and can learn thousands of times faster than conventional popular learning algorithms.

1. Introduction

District heating is utility energy service based on provision of heat to remote customers (connected to system via heating substations) from available heat sources [1]. It enable utilization of waste or low-cost heat, which is the main precondition for district heating systems (DHS) competitiveness, when compared to onsite, individual, boilers. Another precondition is high heat density. Although some previous studies showed that sparse DHS (systems with low heat density) can be economic [2–4] their success is highly correlated with energy taxation which is country specific, even in EU. However, according to [5,6], 73% of EU 27 residents (502 million) lived in urban areas which indicate high heat density and wide prospects for further growth of DHS in Europe.

One possible way for further increase of competitiveness of DHS lies in improvement of present control strategy used. Prevailing control strategy is based on weather compensation control, where the primary supply temperature (temperature of the water from heat source) is determined from so-called "sliding diagram" [7]. This diagram provides the functional dependence between the momentary outdoor temperature and primary supply temperature of water pumped in DH network. Correlation between these two variables is almost linear, with two or three knee points and often corrected by operators after the years of usage.

However, district heating systems are complex, dynamic systems with high inertia and marked heterogeneity of users and this precondition of static correlation between the outdoor tem-

* Corresponding author. Tel.: +60 146266763.
E-mail addresses: shamshirband@um.edu.my (S. Shamshirband), altameem@ksu.edu.sa (T.A. Altameem).

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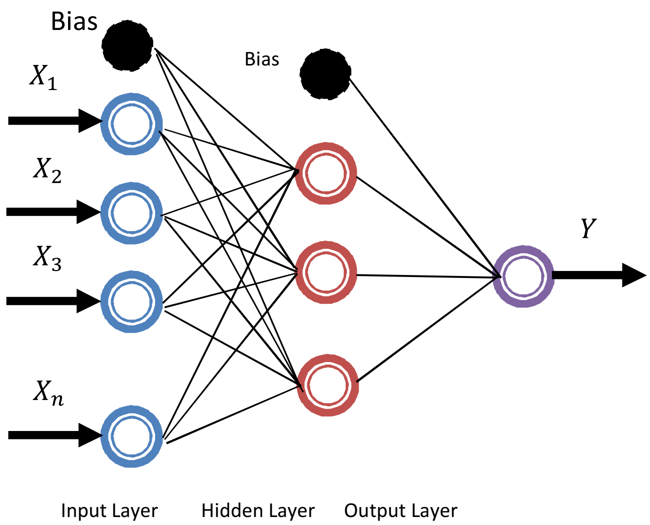

Fig. 1. The topological structure of the extreme learning machine network used in this study.

perature and heat pumped in the network does not hold. As a consequence, primary return temperature is frequently higher than needed, which is especially evident during the periods of moderate cold weather. Therefore, in order to reach the higher efficiency in DHS operation, control strategy should be directed towards lowering primary return temperatures. By lowering primary return temperature in DHS following effects on overall operation could be achieved: increased electrical output from CHP-plants (usually used as heat sources), increased heat recovery from industrial excess heat and geothermal heat, lowered distribution losses and increased coefficient of performance if heat pumps are used in heat generation [8]. Economic benefit of reduced primary return temperature was estimated at 0.05–0.5 €/MWh for 1 °C of reduced temperature [9].

In order to get the lowered primary return temperatures, produced and delivered heat from heat supply units must closely correspond to heat demanded by consumers, increased for appropriate distribution losses. Taking into account that changes in supply temperature in heat source will be "sensible" at the peripheral parts of network after considerable time, due to transport delay (water temperature changes "travel" at speed of water in network) in distribution network, the required heat to be pumped in network should be known in advance (few hours ahead), in order to avoid excessive heat input in network with very important precondition that consumers get the required heat. Therefore, predictive heat load models of all, or at least most influential, consumers in system are indispensable as inputs for advanced model predictive control. Predictive models should provide few hours ahead forecasts of required heat, where the prediction horizon can be defined according to endmost consumer in network.

In this article, we motivate and introduce the heat load prediction models of consumers, for different prediction horizon, using the data acquired from one heating substation in DHS Novi Sad, Serbia. Proposed models are developed using the soft computing approach, namely Extreme Learning Machine (ELM) [10–17]

2. System and data description

Collection of data used for subsequent analysis and building the prediction models was conducted in District heating system Novi Sad, Serbia. District heating system Novi Sad is the second biggest in Serbia with 6 heat supply units (Table 1) and one main manifold

Table 1
Heat supply units in District heating system "Novi Sad".

Name of heat supply unit	Installed power of heat supply [MW]	Fuel type
"West"	256	Natural gas
"East"	104	Natural gas
"North"	46	Natural gas
"South"	185	Natural gas
"Petrovaradin"	11,6	Natural gas
"Dudara"	2,9	Natural gas

which is used for transferring the heat from CHP unit "Novi Sad" towards the three supply units inside the town and backward.

Base load for consumers connected to heat supply units "East", "North" and "South" is covered from CHP unit "Novi Sad" via central manifold and additional heat is provided from heat supply units themselves (peak load).

Consumers are connected to district heating network (214,2 km) via heating substations. There are 3.795 heating substations in district heating system. Distribution network is implemented as 3 pipe system. One pipe is used for distribution of heat for space heating, second is used for distribution of heat for preparing domestic hot water and third is common return.

Data used for development of predictive models were taken during the heating season 2009/2010 in one of the systems' heating substation. Following variables were measured on 15 min interval:

- Outdoor temperature [°C]
- Primary supply temperature [°C]
- Primary return temperature [°C]
- Flow on primary side [m^3/h]

All the data (for above mentioned variables), together with heat load data (which were internally calculated in Ultrasonic heat meter) were regularly downloaded via SCADA system. Data was averaged on 1 h interval. No data cleaning was performed. Initially five time series were created and subsequently used for further analysis and model building. Summary of collected data is provided in Table 2. The heat power provided to the district heating network by the heat plant depends on the supply and return temperature and the flow of the water. These values can be measured, and the supplied power can be calculated as

$$P_{sup}(t) = c_p \dot{m}(t)(T_S(t) - T_R(t)) \quad (1)$$

where

$P_{\text{sup}}(t)$– is the power supplied to the district heating system by the heat plant,

c_p– is the specific heat capacity of water,

$\dot{m}(t)$ – is the mass flow of the water,

T_S – is the supply temperature at the power plant,

T_R – is the return temperature at the power plant.

3. Soft computing prediction algorithms

3.1. Extreme learning machine

Huang et al. [18] developed Extreme Learning Machine (ELM) as a novel learning algorithm for single hidden layer feed forward networks (SLFNs).

This approach has some priority compared with conventional neural networks including:

1) ELM is easy to use, and it method increase not only makes learning extremely fast but also produces good generalization performance [18];