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DEVELOPMENT OF HEAT LOAD PREDICTIVE MODELS IN DISTRICT HEATING SYSTEMS USING THE BOOSTING METHOD

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INTRODUCTION

The basic idea of district heating systems (DHSs) is the use of local fuel, or heat sources that would otherwise remain unused, in order to meet the heating demands of local consumers using a centralised heat source and a distribution network that delivers the heat to end consumers.

Optimization of DHSs in Serbia, which would significantly reduce heat production and distribution costs, is possible in two key ways:
- by substituting the existing heat sources with 'strategic' ones (cogeneration facilities, incineration, geothermal and solar systems) and
- by changing the manner of DHS operation through introduction of modern and intelligent control strategies aimed towards balancing the produced and consumed heating energy.

This paper explains the procedure of creating predictive models of consumers using boosting method. In addition, conventional tools for statistical analysis are used to conduct an unbiased verification of predictive performance of the developed models. The predictive models were created and tested using the data from two heat substations, one from DHSs in Niš and other from DHS in Novi Sad, Serbia.

MATERIAL AND METHODS

Data acquisition – district heating systems in Niš and Novi Sad

In Niš, data acquisition was conducted during the 2009/2010 heating season. In addition to the data from the Niš DHS, data from the DHS in Novi Sad were also acquired, but during the 2010/2011 heating season. The goal of such an approach was to examine the universality of the methodology and algorithms used to create predictive thermal models of consumers and the possibility of replicating these methods and algorithms in another DHS.

Table 1. Descriptive statistics of time series – heating substation in the Niš DHS

Variable	Min.	Max.	Mean	Standard deviation
Outdoor temperature [°C]	-10.77	19.08	5.31	5.26
Primary supply temperature [°C]	14.02	88.47	52.11	19.34
Primary return temperature [°C]	12.21	55.42	38.08	8.84
Water flow [ml/s]	0.00	6.57	3.62	2.59

Table 2. Descriptive statistics of time series – heating substation in the Novi Sad DHS

Variable	Min.	Max.	Mean	Standard deviation
Outdoor temperature [°C]	-7.60	24.40	5.70	6.52
Primary supply temperature [°C]	21.77	102.40	59.80	16.72
Primary return temperature [°C]	21.10	52.42	36.96	5.81
Water flow [ml/s]	0.00	1630.8	1310.1	282.00

An additional problem is that predictive models developed this way contain a large number of variables that are colinear. Therefore, graphs of the partial correlational function were produced in the following step to identify the most influential input variables.

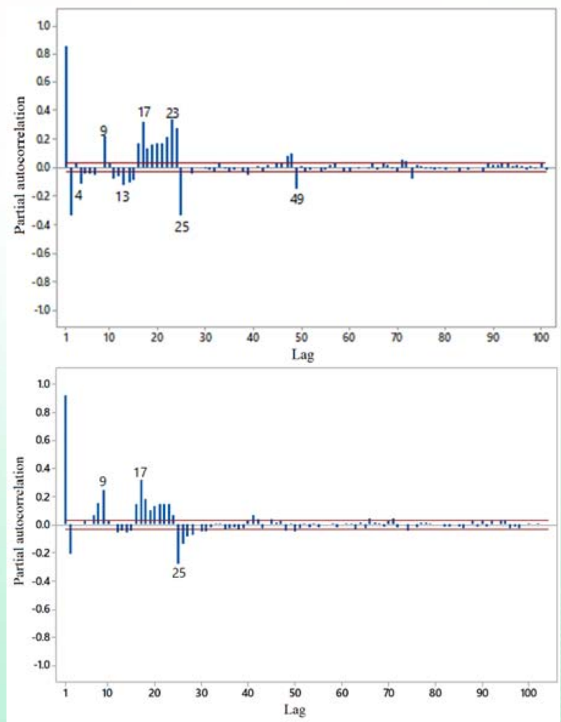

Fig. 1. Partial autocorrelation function for heat load
(above: DHS Niš, bottom: DHS Novi Sad)

RESULTS AND DISCUSSION

Table 3. Predictive performance of the Boosting heat load model for DHSs in Niš and Novi Sad; input variables: heat load with 1-48h and 1-24h delays

Prediction horizon	Predictive performance: Boosting method			
	DHS Niš		DHS Novi Sad	
	RMSE [kW] Previous 48h values	RMSE [kW] Previous 24h values	RMSE [kW] Previous 48h values	RMSE [kW] Previous 24h values
1h ahead	25.669	26.992	18.476	18.988
2h ahead	31.227	32.151	22.662	23.580
3h ahead	32.862	33.492	24.134	25.238
4h ahead	33.355	33.942	25.076	25.874
5h ahead	33.567	34.140	25.673	26.227
8h ahead	33.624	34.202	26.671	26.961
12h ahead	33.694	34.072	26.697	27.028
24h ahead	33.787	34.110	27.498	27.535

Root-mean-square error (RMSE) was used as the criterion for assessing the predictive performance of the developed models, as it is the usual criterion in this type of analysis.

Table 4. Predictive performance of the Boosting heat load model for DHSs in Niš and Novi Sad; input variables: heat load with delay based on partial autocorrelation function

Prediction horizon	Predictive performance: Boosting method	
	Data – DHS Niš RMSE [kW] test set	Data – DHS Novi Sad RMSE [kW] test set
1h ahead	26.568	18.473
2h ahead	31.458	22.695
3h ahead	33.326	24.216
4h ahead	33.875	25.148
5h ahead	34.095	25.726
8h ahead	34.054	26.807
12h ahead	34.128	36.597
24h ahead	33.904	27.568

The results from the table above primarily indicate that prediction error increases with the increase of the prediction horizon, which was expected.

In addition, it is evident that predictive performance declines to a certain extent with the reduction in the number of input variables. This conclusion can be generalized for the DHSs in both considered cities.

Results shown in Table 5 cannot lead to a general conclusion, because the results are inconsistent and greatly depend on the extent of the prediction horizon. In the majority of the cases, there was some improvement. It should also be noted that the developed predictive models were considerably simplified compared to the model from the previous stage.

CONCLUSION

Modelling was performed successively over several stages. The large number of input variables in the initial models was gradually reduced. In the final iteration, the input variables were determined according to the partial autocorrelation function graph. It was determined that a decline in the number of predictors causes only minimal improvement of the models' predictive performance. Nevertheless, this procedure produces considerably simpler models that are computationally less demanding. This is especially important considering that the primary goal is to integrate the developed models into a control environment. The conclusion is that the boosting method can be used for short-term prediction of consumer heat load in district heating systems, but further improvements are necessary.

In order to further improve the predictive performance of the models, it is also necessary to include exogenous inputs, which will presumably raise the quality of the developed models, of course, provided that their inclusion does not significantly increase computational costs.