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AN ONLINE MACHINE LEARNING ALGORITHM FOR HEAT LOAD FORECASTING IN DISTRICT HEATING SYSTEMS

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4DH
4th Generation District Heating
Technologies and Systems

Introduction

Heat load is the heat power that is required to satisfy a customer's heat demand

The heat is used for

- space heating
- heating tap water

Motivation

Heat load forecasting enables effective planning and management

Issues involved in heat load forecasting

- the heat load exhibits a stochastic and non-stationary behavior
- massive amounts of data are available during the operation of heating grids

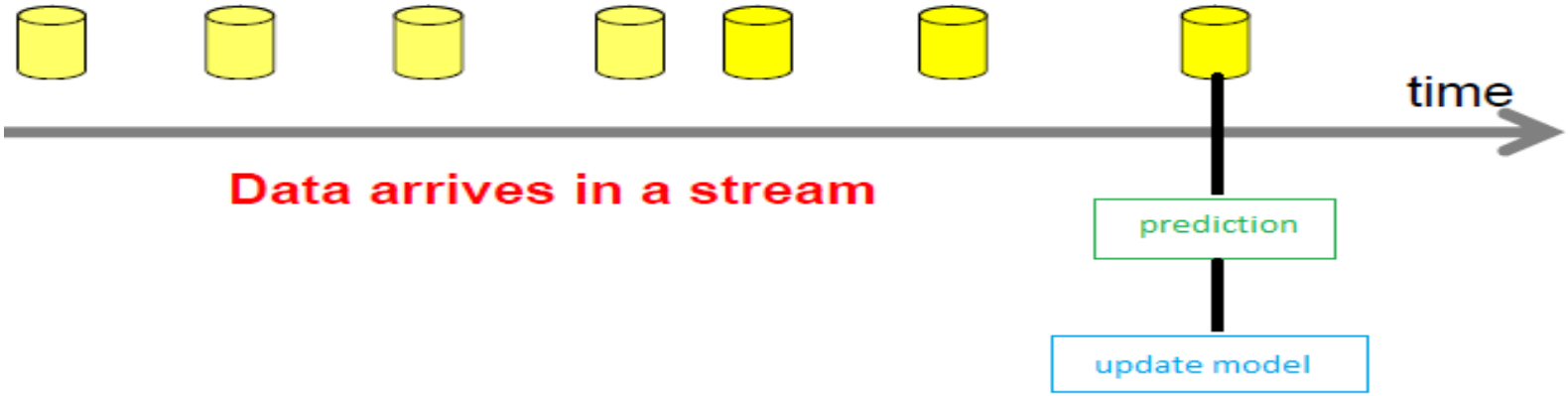
Background (1/2)

- Machine learning aims at building models that learn from data
- Supervised learning is a branch of machine learning and involves the prediction of one or more target variables
- In classification problems, the target variable takes discrete values, whereas in regression problems it takes continuous values.
- Application domains of machine learning include bioinformatics, computer vision, medical diagnosis and fraud detection.

Background (2/2)

Traditional machine learning algorithms use historical data to build their model

In online learning, the model is updated whenever new information becomes available



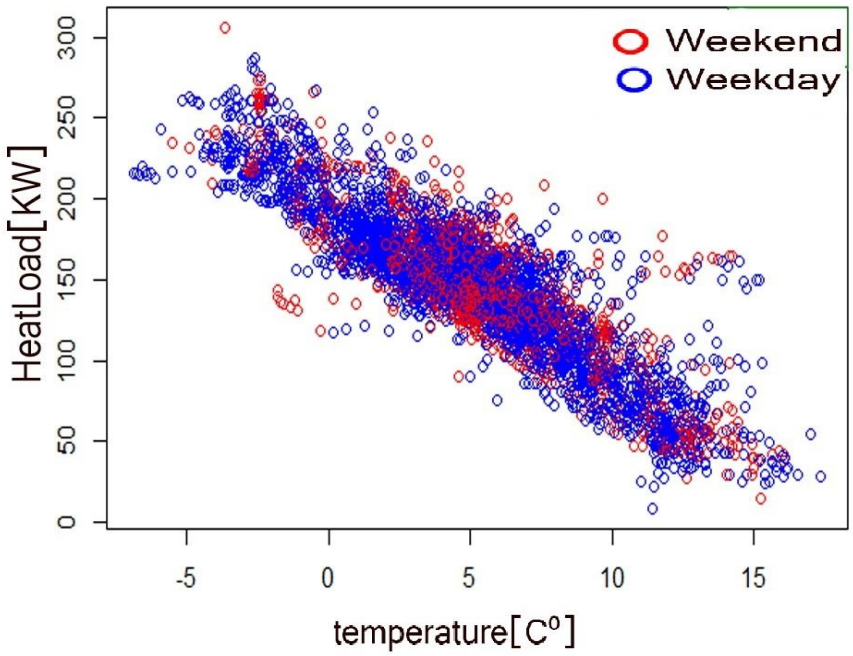
Data Description (1/2)

Operational data consist of hourly measurements from 26 buildings in a part of Karlshamn DH network that were collected from 01-10-2013 to 31-03-2014. Predictions are made 36 hours ahead

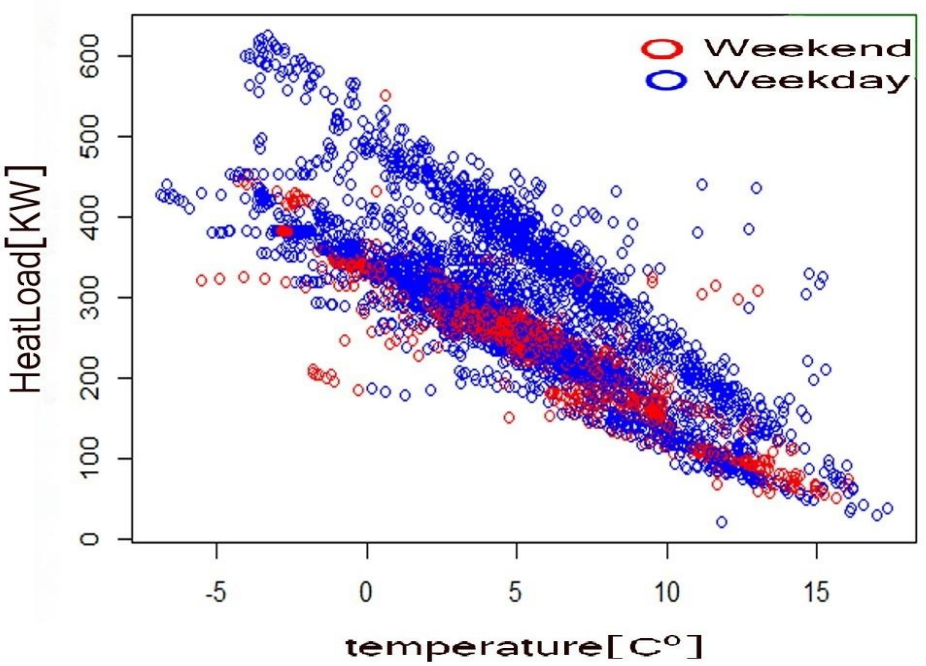
Time	Temperature (C°)	Weekend	Heat Load (KW)
00:00:00	7.00	0	1117.29
01:00:00	5.86	0	952.25
02:00:00	5.46	0	958.94

Data Description (2/2)

Residential building



Commercial building



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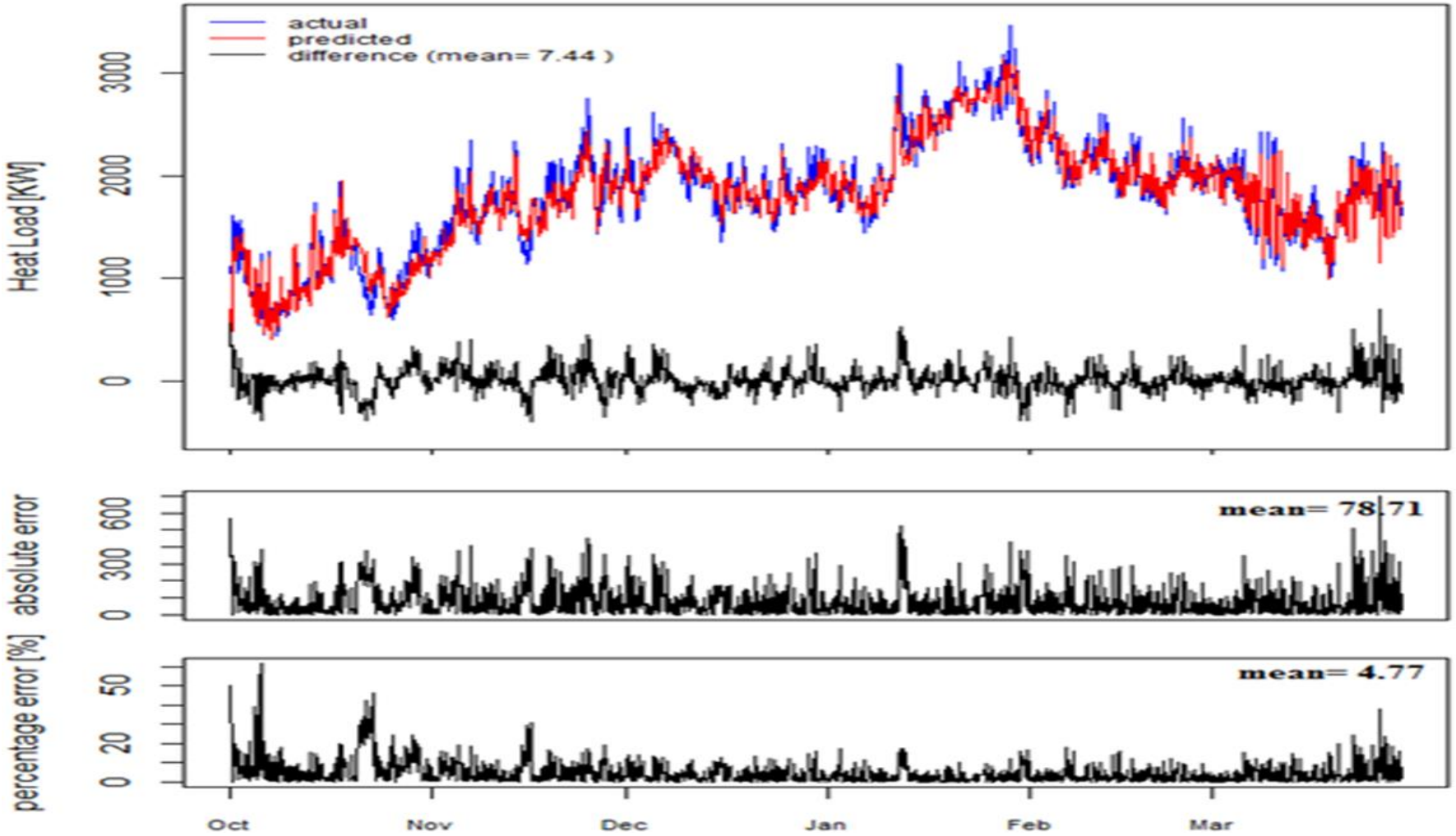
Method

- Online Algorithm (Fast Incremental Model Trees with Drift Detection)
- Mechanism for imputing missing values and detecting outliers
- Experiments using two software applications (WEKA and MOA)

Results


actual
predicted
difference (mean= 7.44)
Heat Load [KW]
0
1000
2000
3000
absolute error
0
300
600
mean= 78.71
percentage error [%]
0
20
50
mean= 4.77
Oct
Nov
Dec
Jan
Feb
Mar

Conclusions

We present an online algorithm that

- captures the behavior of the heat load
- is memory-efficient
- is robust against measurement and communication errors

Practical impact of this study on industry and society

- reducing operational costs for heat suppliers
- minimizing the use of peak-load boilers

Future work

Implement a more sophisticated technique to handle missing data and outliers. The behavior of the heat load varies according to the type of building and therefore an optimal solution cannot be achieved when the same approach is used for all types of buildings.

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Thank you very much for your attention!

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