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Forecasting short-term heat load using artificial neural networks: the case of a municipal district heating system

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Road map

- Introduction
- Method
- Data set
- Results
- Conclusion and future directions

Introduction

- Need for efficient and competitive district heating systems (DHS)

- Tools:
    - Lower costs of production
    - Reduce environmental emissions
    - Enhance reliability

- Possible mechanism for improvements in energy efficiency and production planning:
    - Forecasting techniques

Introduction

- Prediction of thermal load plays a vital role in the net income and short-term operation planning of DHS and cogeneration units.

- For large CHP and DHS operators, the implementation of advanced methods has led to better day-ahead generation planning. Lowering costs of electricity and heat production, hence increasing profits.

Introduction

- For some DHS and independent power producers (cogeneration units), these advanced systems are in many cases considered inaccessible tools due to their elevated costs, special software requirements and long hours of technical training.

- The main objectives are:
    - Assess the use of reanalysis data as a potential alternative to on-site weather measurements
    - Evaluate the predictive performance of an artificial neural network for the application in DHS.

Introduction

- Traditional methods:
  - Multiple regression
  - Decomposition
  - Exponential smoothing

→ Knowledge of the system and mathematical modelling (Equation with physical parameters)

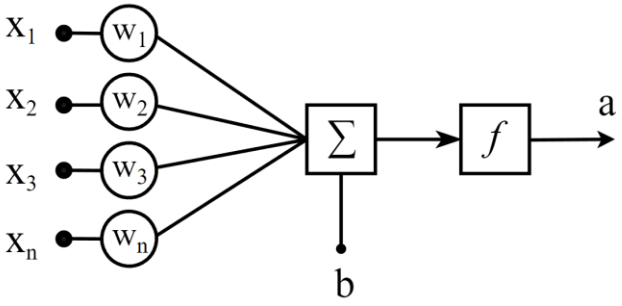
- Data-driven methods:
  - Support vector machines
  - Artificial neural networks
  - Fuzzy logic

→ Discovery of patterns

Method – Artificial neural networks

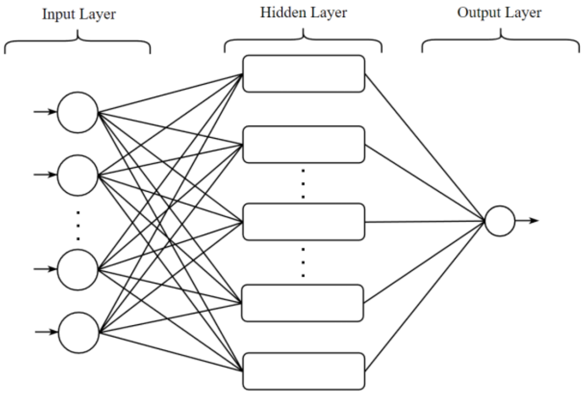
- Capability of analyzing data and model dependencies between complex nonlinear features.

- “Black-box model”, allowing operators to make effective operational decisions without the need of understanding the technical relations between descriptive and target features.



$$a = f\left(b + \sum_{i=1}^{n} w_i x_i\right)$$

Elements of a multi-input neuron

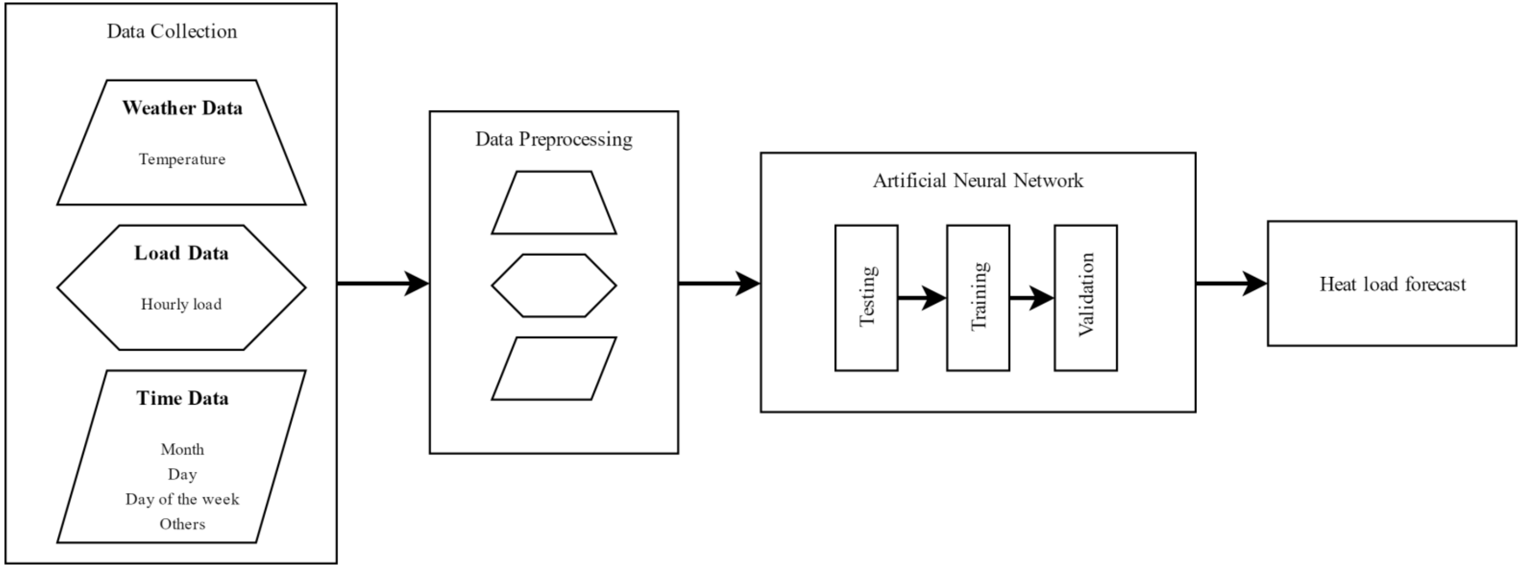


Two-layer neural network

Method

- Multi-layer feedforward neural network
    - One to two hidden layers
    - Two to thirty neurons in each hidden layer
    - Activation function: Sigmoid, Linear
    - Data split into training, testing and validation sets (70%, 15%, 15%).
    - Learning algorithm: Levenberg-Marquardt
- The best model was chosen based on the combinations (hidden layers, neurons) that gave the minimum RMSE and MAPE.

Simplified workflow of the heat load forecasting model



Data

- Heat demand influenced by:
    - Meteorological factors – outdoor temperature, wind, precipitation [8]
    - Social factors – working day, public holidays
    - Unforeseen events
- Good data in, good data out - significant effect on the predictive power of the model
    - Separate meaningful information from irrelevant information

Data Sources

- Weather data – Reanalysis of archived observations – forecast models and data assimilation systems
  - MERRA – observations from NASA's Earth Observing System satellites into a climate context (1979 – 2017) [12]
  - SARAH – Satellite Application Facility on Climate Monitoring, European Organisation for the Exploitation of Meteorological Satellites [15]
- Load data
  - Historical heat load data from DHS (2014 – 2016)
  - Moving window approach – 4 weeks prior to the forecast period
- Social factors and time data
  - i.e. , Holidays, working days, month, day of week

Input selection

- Experimental or based on trial and error method
- Data reduction technique – Principal component analysis (PCA): Component weights help understand which predictors are the most important.

$$PC_i = (a_{i1} * \text{Predictor 1}) + (a_{i2} * \text{Predictor 2}) + \ldots + (a_{im} * \text{Predictor } M)$$

1. Load for previous day
2. Outdoor temperature
3. Outdoor temperature for previous day
4. Dew point temperature
5. Wet bulb temperature
6. Specific humidity
7. Solar irradiance
8. Variable – Month
9. Variable – Hour of day
10. Variable – Day of week
11. Variable – Day of month
12. Variable – Day of year
13. Binary variable – Holidays
14. Binary variable – Working day

→

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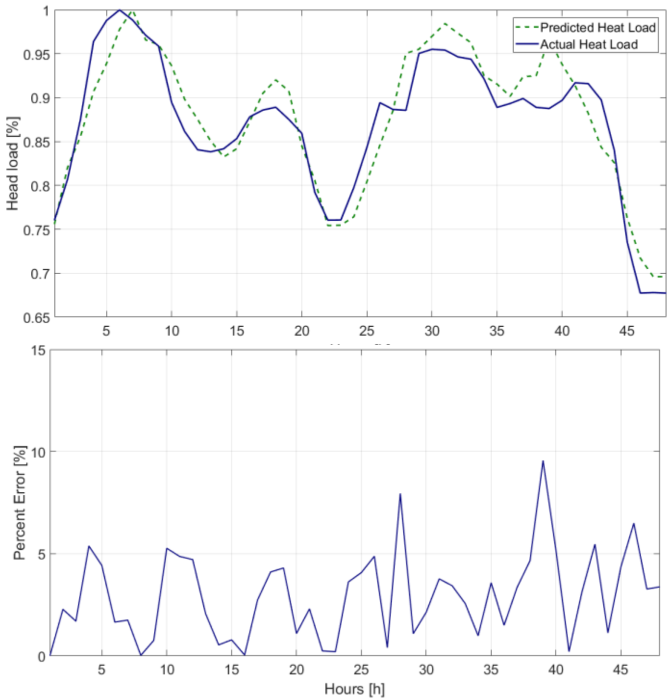
8. Binary variable – Holidays
9. Binary variable – Working day

Results

Training			Testing		
RMSE	R2	MAPE	RMSE	R2	MAPE
10.5138	0.9731	2.3381	10.6335	0.8383	3.1126



Conclusions

- ANN model capable of predicting short-term load values of a DHS
- Significant advantage over other classical methods, capability to quickly adapt.
- PCA approach was applied to reduce the dimensionality of the data and for the identification of uncorrelated input components.
- Future work includes the study of additional meteorological descriptive features and improvements in network complexity.
- Adapt the NN to forecast heat load from real-time input data

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Thank you for your attention