Application of Multilayer Perceptron Method on Heat Flow Meter Results for Reducing the Measurement Time

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Outline

1. Introduction
   - Experimental data
2. Methods
   - Heat Flux Method
   - Artificial Neural Networks – Multilayer Perceptron
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Introduction

- Buildings that exist today will very likely exist in foreseeable future, and this is a reason why EU Member states developed plans for building stock renovation
- Problems occur in assessment of building envelope performance of existing buildings
- To overcome the problem of assessing the envelope performance, in-situ U-value can be determined by using the Heat Flux Method
- One of the issues of current application of the HFM is the measurement duration
- This paper explores the possibilities of reducing the measurement time by predicting the heat flux rate using a multilayer perceptron

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Experimental data

- Measurement was carried out in the period 28th of February up until 3rd of March, in 2019
- Experimental data contains 510 data entries (heat fluxes and air temperatures) – link to data

Figure: Measurement site showing experimental setup.

Experimental data

- Analyzed wall is stated in Zagreb (Faculty of Civil Engineering, UNIZG) and oriented to east
- The internal environment was heated every day in the measurement period from 06:00 until 22:00 with radiators
- Air conditioning unit was turned off during the measurement
- Heat flux rate is mesured with heat flux sensor
- Indoor and outdoor temperatures were measured with thermocouples

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Methods

- The paper presents an application of MLP on HFM results for a 47.3 *cm* wall with designed U-value 0.91 $W/(m^2 K)$
- All the codes used for this paper can be found in GitHub repository of one of the authors – link to repository
- MLP is modeled with machine learning Python library Keras (generalization of Python library Tensorflow)
- Point of interest in the paper will be U-value calculated in accordance with the standard ISO 9869 by average method defined with expression

$$U = \frac{\sum_{j=1}^{N} q_j}{\sum_{j=1}^{N} (T_i - T_e)_j}$$

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Heat Flux Method

- HFM is based on measuring the heat flux density by heat flow sensor, and on measuring the internal and external air temperatures by temperature sensors

Table: Heat flux kit specifications – heat flux sensors and 2 thermocouples.

Model	gSKIN®Heat Flux Sensor
Sensitivity	10.93 $\mu V/(W/m^2)$
Correction factor	0.0137 $[\mu V/(W/m^2)]/$℃
Dimensions	30.0 x 30.0 *mm*
Thickness	2.0 *mm*
Electrical resistance at 22.5 ℃	$\leq$ 100 Ω
Relative error	$\pm$ 3 %
Temperature range	– 50 ℃ / + 150 ℃

Heat Flux Method

- Heat flux sensor is a device that produces an electrical signal that is linear function of the heat that is passing through it
- Sensors for air temperature measurements produce an electrical signal that is a linear function of its temperature

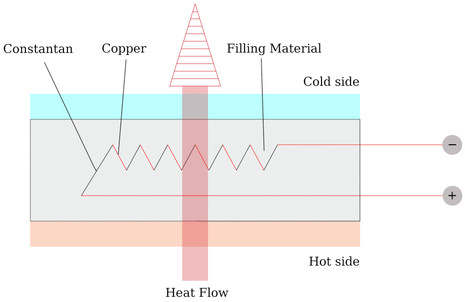

Figure: Schematic cross section of heat flux sensor.

Artificial Neural Networks – Multilayer Perceptron

- MLP is a class of feedforward ANN that consists of minimum three layers – visible input layer, hidden layer and output layer
- Input layer brings certain information to ANN model which with set of weights and biases carry information from neuron to neuron
- Each neuron in the hidden layer has activation function that transforms information and carries it to neuron from the next layer
- Loss function that compares predicted and true values is minimized by rearranging ANN model weights, biases and activation function parameters

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Artificial Neural Networks – Multilayer Perceptron

- Inputs are interior and exterior air temperatures used for feeding the ANN, and output is predicted heat flux
- Cost function is created using the mean squared error (MSE) and minimized with stochastic gradient descent extended with Adam
- Activation functions for all neurons from hidden layer is ReLU function, and activation function for output layer is linear function

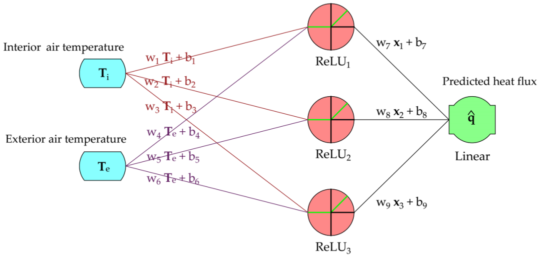

Figure: Schematic view of artificial neural network model.

Results

- RMSE: 1.573, MSE: 2.474, MAE: 1.218

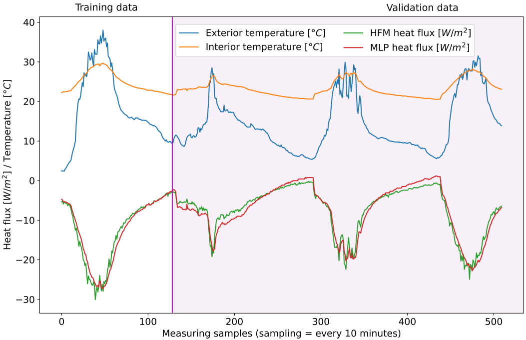

Figure: Heat flux prediction based on ANN training on 1/4 of measurement data.

Results

- RMSE: 1.195, MSE: 1.428, MAE: 0.826

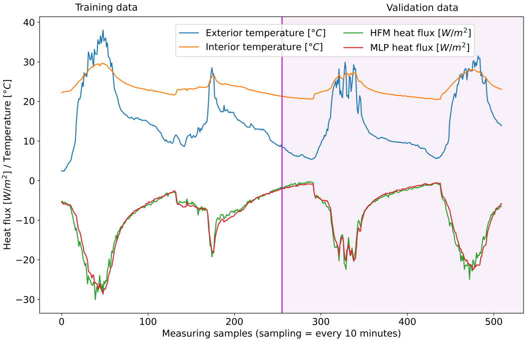

Figure: Heat flux prediction based on ANN training on 1/2 of measurement data.

Results

- RMSE: 1.202, MSE: 1.445, MAE: 0.828

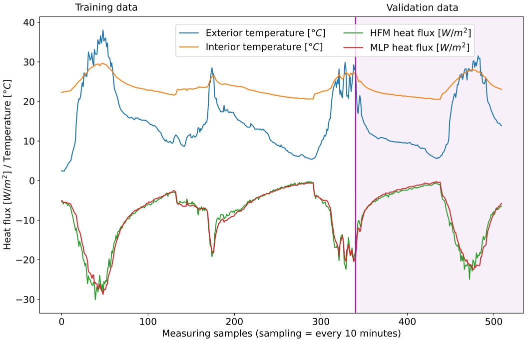

Figure: Heat flux prediction based on ANN training on 2/3 of measurement data.

Results

Table: ANN prediction parameters and comparison of predicted and measured U-value.

Training	RMSE	MSE	MAE	Measured U	Predicted U	Rel. difference
1/4 of data	1.573	2.474	1.218		1.126	8.73 %
1/2 of data	1.195	1.428	0.826	1.035	1.027	0.78 %
2/3 of data	1.202	1.445	0.828		1.021	1.39 %

Conclusion

- The paper shows promising results for application of MLP on heat flux results in order to decrease the time when the heat flux sensor must be used
- This allows us to transfer the heat flux sensor to other measuring place after satisfactory heat flux prediction is achieved
- This is a research on one set of measurement data, so to analyze the method's accuracy and potential risks, more field and laboratory tests should be carried out

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Thank You!

Questions and Suggestions?

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