Centrum Rzeczoznawstwa Budowlanego

**Inżynieria Bezpieczeństwa Obiektów Antropogenicznych 4 (2023) 134-143**
https://inzynieriabezpieczenstwa.com.pl/

Inżynieria Bezpieczeństwa Obiektów Antropogenicznych

# A neural network for monitoring and characterization of buildings

Anna ROMAŃSKA-ZAPAŁA [1*], Marek DUDZIK[2], Sabina KUC[3]

[1] *Cracow University of Technology, Faculty of Electrical and Computer Engineering, Department of Automation and Informatics, Cracow, Poland*
[2] *Cracow University of Technology, Faculty of Electrical and Computer Engineering, Department of Electrical Engineering, Cracow, Poland*
[3] *Cracow University of Technology, Faculty of Architecture, Chair of Architectural Engineering Design, Cracow, Poland*

**Abstract**

This paper continues work from part 1 where a high precision estimator for energy efficiency and indoor environment based on artificial neural networks (ANN) was examined. Part 1 demonstrated that creating a precise representation of a mathematical relationship one must evaluate the stability and fitness under randomly changing initial conditions. Now, we extend our requirements for the model to be rapid and precise. At the end of this work we obtain a road map for the design and evaluation of ANN-based estimators of the given performance aspect in a complex interacting environment. This paper also shows that ANN system designed may have a high precision in characterizing the response of the building exposed to variable outdoor climatic conditions. The absolute value of the relative errors, MaxAR, is less than 2%. It proves that monitoring and ANN-based characterization approach can be used for different buildings, including those with the best environmental performance.

**Keywords:** estimator design procedure, estimation, intelligent construction, intelligent building, control system

## 1 Introduction

In a companion paper [1] we claim that the use of artificial neural networks (ANN) is necessary for linking the next generation of smart buildings with the requirements of zero energy buildings and for the development of a new category, namely zero impact buildings (ZIB). Category ZIB represents the next generation of near-zero energy

* **Corresponding author:** E-mail address: (a.romanska@pk.edu.pl) Anna ROMAŃSKA-ZAPAŁA

https://dx.doi.org/10.37105/iboa.201
Received 3 December 2023
Available online 5 December 2023
ISSN 2450-1859, eISSN 2450-8721
Published by Centrum Rzeczoznawstwa Budowlanego

buildings with an advanced building automatic system that is developed for a specific combination of climate, service, and occupancy characterization under a monitoring and building characterization approach.

This paper proposes a universal methodology that includes buildings with light exterior structures e.g., houseboats exposed to rapid weather changes or buildings with rapidly changing occupancy where interior conditions may change in a short time. We must be able to design a changing control system ensuring the appropriate quality of the internal environment. In doing so, one must first understand interaction of factors shaping the indoor environment [2-6] and select a suitable estimator for which acceptance criteria are already in existence, e.g., PMV (percentage mean vote).

Despite the broad literature on consumer satisfaction and electronic management [7-13], we may return to these issues later in the work, because this approach is complex requires much larger memory space, and increases the cost of control systems [14,15]. At this stage of new technology development, we consider maintaining the precision and adding another attribute of the model, namely simple and rapid solution. Furthermore, in some cases, one may use the simple and rapid control system to the used control system and upgrade a specific estimator of the physical characteristics [16]. For further discussion on differences look in [17].

In this project, one started with another research [18] to logically extrapolate to [16], where we used all 20 parameters describing all possible factors modifying room temperature. In the next stage, i.e. in part 1 of this paper, we described how one can design a precise estimator for the concept of an operational temperature (selecting such a weather condition where both estimators, temperature and operational temperature appear to be a similar function of the climatic conditions (and both estimators are in the same category of mathematical functions.

The discussed estimator is a part of control system, shown in Figure 1, and as the verification of ANN uncertainty was performed under a steady state, the optimal temperature was a constant value.

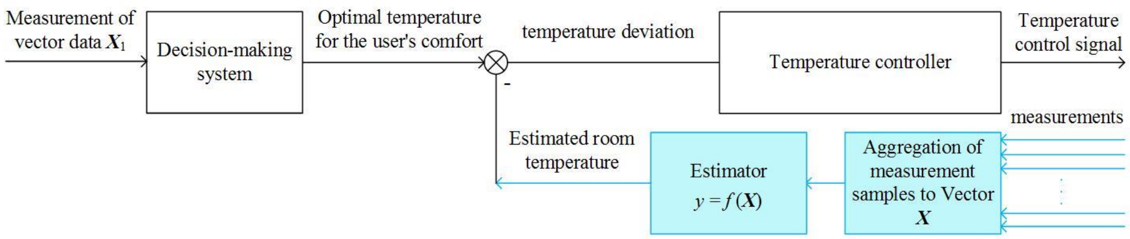


**Figure 1**. *Partial schematic use in the building control system*

## 2 Methods

The work is to identify the best but simple and fast estimator of the indoor temperature in relation to 20 factors affecting its value. The equation:

$$y=f(X)$$

where y represents the room temperature and X is a vector of 20 factors affecting this value. In doing so we are looking for the smallest number of neurons that fulfills conditions of independence on the initial values, stability, precision, and considerations for overfilling or underfilling, as well as it runs faster than the average [19, 20].

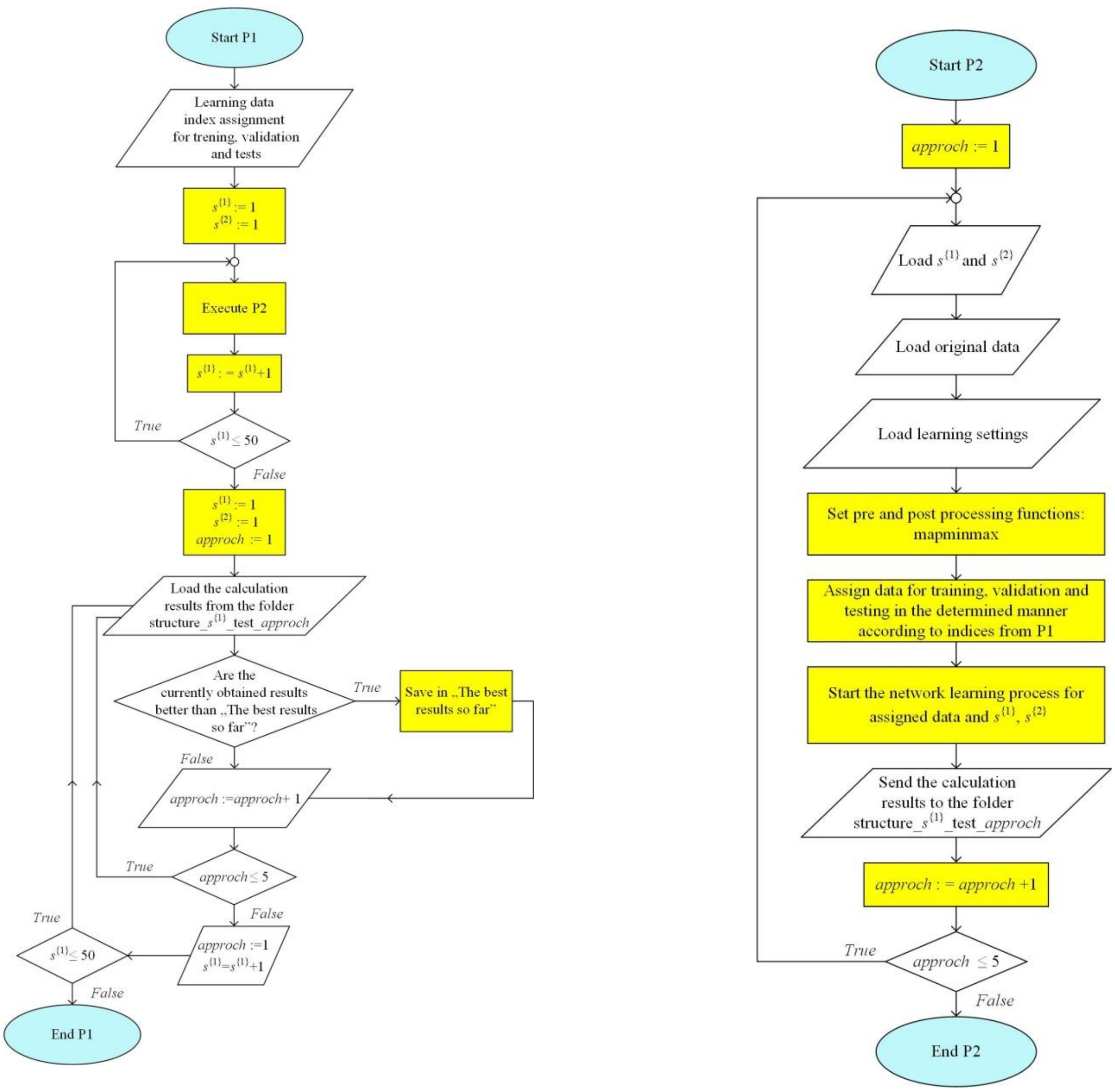


**Figure 2**. *The algorithm for identification of the best possible dimension of the matrix of the model describing the examined physical phenomenon: (a) Parent procedure P1; (b) Nested procedure P2 [1]*

This process, in principle, requires training and verification of all 50 cases of a 2-layered neural network, forward feeding structures, with one hidden layer where the number of neurons in the hidden layer varies from 2 to 50. In each iteration the number for neuron was increased by one. As initial weights and bias are ascribed in a random manner, the calculation for each case was repeated 5 times, indexed, and denoted as an approach. Figure 2 shows that the algorithm comprised a test loop P2 that was nested in the main loop P1. The results are shown in Figure 4, in form of the boxplots [20].

For a main criterion for the first neuron network, one uses a minimum value of the maximum absolute relative error [21] and it is compared with a similar value established for the given approach. Yet, in establishing criterium for network 1 the participating neural networks must have passed the criterion of independence from the initial conditions. This requirement warrants repeatability of the network performance [22].

$$MainCrit=\min\left[ \left( MaxARE_{TEST} \right)_{\left(s_{min}^{(1)},approch\right)} \right]$$

where:

$MainCrit$ – main criterion for choosing the best neural network structure,

$s_{min}^{(1)}$ – the smallest number of neurons in the hidden layer,

$MaxARE_{TEST}$ – maximum absolute relative error obtained for the testing stage:

$$MaxARE_{TEST}=\max\left(\left|\frac{y_{iTest}-y_{ANNiTest}}{y_{iTest}}\right|\right)$$

where:

$y_{iTest}$ – a target for the network in the testing stage,

$y_{ANNiTest}$ – an output for the network in the testing stage,

The choice of the main criterion was not straight forward. Yet, selecting the absolute value for the validated network ensures that results in the test stage, which by definition are within the range tested during the calibration, should be closer to the targets than the maximum established during the calibration of the network [23, 24]. Furthermore, this choice gives us a valid estimate of the uncertainty in the case of the model verification when the target values are the measured values.

Measurements were performed every 20 minutes, in summer, during a period of 21 days. The tested parameters in 20 min intervals are presented as vector X, such as Measured time in decimal notation every 20 min - Degree of opening valve for interior and for exterior earth–air heat exchanger (%), Exterior air temperature (mean of both earth–air heat exchangers), Relative humidity of exterior air measured on the inlet to earth–air heat exchangers, Irradiation, W/m2, measured on east, south, north elevations and on the roof, Temperature of the cooling water in the tank, Temperature of the cooling water on return from the tested room, Efficiency of the cooling exchanger (%), Steering of the floor cooling valve (%), Temperature: in the adjacent room on side 1, on side 2, in the adjacent room, in the room below, in the room above, Steering of the cooling valve for the floor system, Efficiency of ventilator in climate-convector (%) and *y* – room, Temperature.

The total number of measurements used in the project was 1409. Out of it 60% was used training ($X_{iTr},y_{iTr}$), 20% for validation ($X_{iVal},y_{iVal}$) and 20% for testing ($X_{iTest},y_{iTest}$). The algorithm used for data separation was as follows: first three records went to training, each next to validation and training.

The process of training was performed with *MATLAB* version *R2019b* on previously normalized data (preprocessing). After the analysis, the data will be denormalized (postprocessing) to establish a measure of the network efficiency. To this end, we selected the function of map-minmax [25, 26]. The map-minmax function is a linear transformation.

The Levenberg-Marquardt training algorithm [27] showed satisfactory performance in preliminary studies [28] and was used here. The structure of the ANN selected for this project is the feedforward with one hidden layer and one output layer [28], see Figure 3.

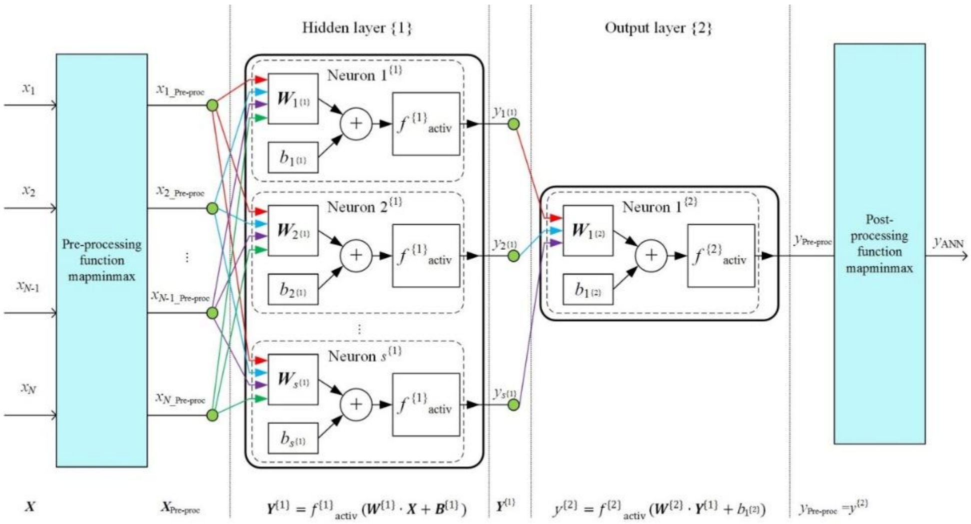


**Figure 3**. *The structure of a one approach of neural network used in the study [1]*

In the first part of the publication [1], the entire mathematical apparatus was shown and individual variables were described. a robustness study (chapter 3.1) and overfitting and underfitting study (chapter 3.2) of the examined neural network structures were performed. Therefore, the results for the optimization criterion are presented below. These results refer to a stable neural network with the fastest possible response.

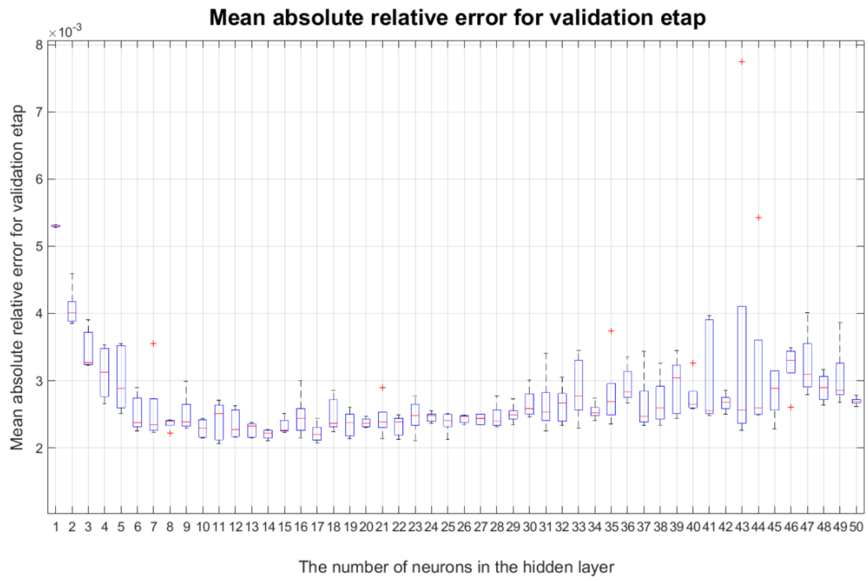


**Figure 4**. *Mean absolute relative error obtained for the obtained for the neural network structure with a certain number of neurons in a hidden layer*

To summarise the requirements for robust, independent from initial conditions, and not overfitted or underfitted structures we have only $s^{\{1\}}$=8,13,14. Furthermore, we are adding a requirement of a minimum precision [29]. Note that to speak about the accuracy of estimation the comparison must involve the measured target value.

MaxARE_TEST < 5%

Even though we talk about three structures, Figure 5 shows the maximum absolute relative error obtained for all tested networks [29]. As $s^{\{1\}}$=8 is the simplest and also the fastest (Table 1) of the acceptable structures, we select it as the final choice.

| $s^{\{1\}}$ | **8** | **13** | **14** |
|---|---|---|---|
| approch 1 | 0,0164 | 0,0105 | 0,0228 |
| approch 2 | 0,0192 | 0,0300 | 0,0280 |
| approch 3 | 0,0224 | 0,0242 | 0,0191 |
| approch 4 | 0,0401 | 0,0145 | 0,0290 |
| approch 5 | 0,0159 | 0,0194 | 0,0194 |

**Table 1.** *Maximum absolute relative error obtained for the test stage for neural network structures*

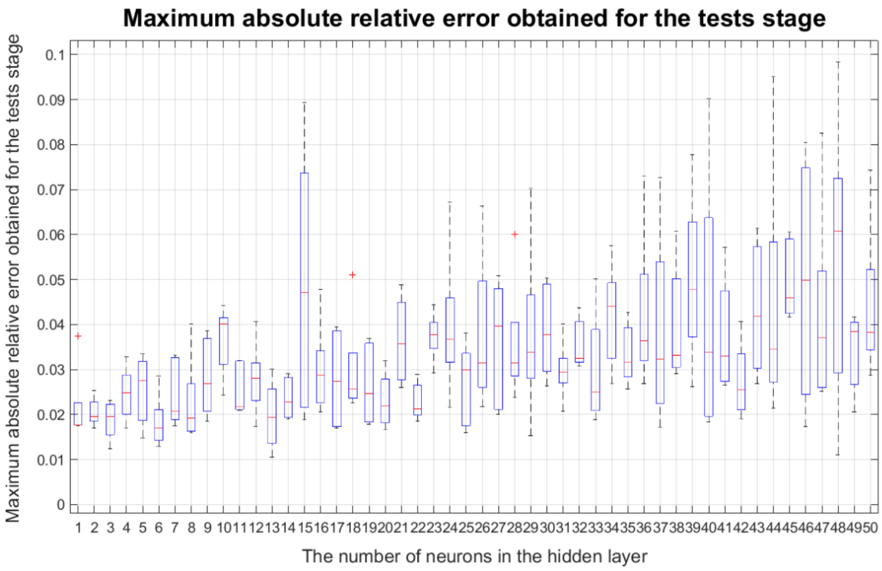


**Figure 5**. *Maximum absolute relative error obtained for the neural network structure with a certain number of neurons in a hidden layer*

## 3 Results

Training of the selected rapid neural network is shown in Figures 6 and 7. Figure 6 shows that epoch number 24 ends the training process, even though the error reduction continues to the end of the training process. Figure 7 shows gradient, momentum, and validation checks for the learning process for the fastest analyzed neural network and explains what happens at the 24th epoch.

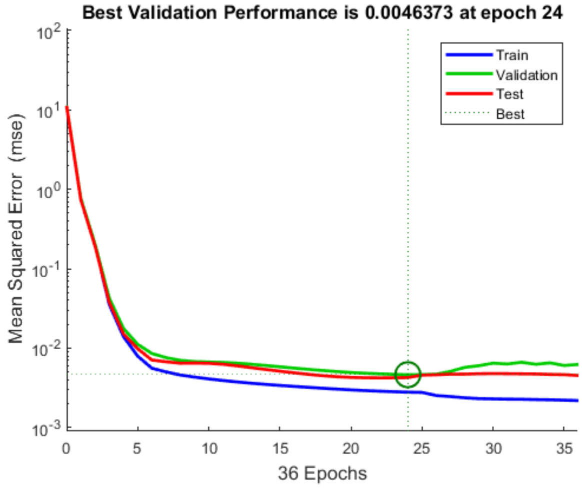


**Figure 6**. *Performance function values obtained during the learning process for the fastest analyzed neural network*

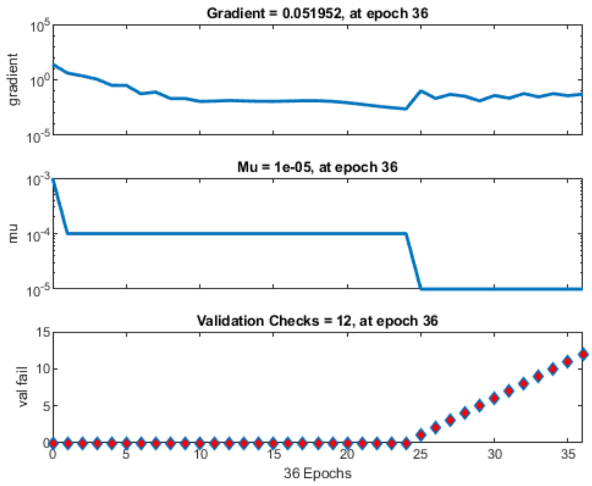


**Figure 7**. *Gradient, momentum, and validation checks values obtained during the learning process for the fastest analyzed neural network*

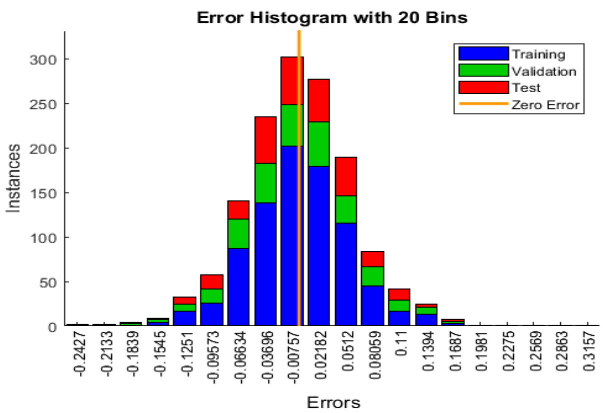


**Figure 8**. *Error histograms obtained during the learning process for the fastest analyzed neural network*

Figure 8 shows the histogram of errors in the network, as they relate to training, validation, and testing. As Figure 8 presents MSE i.e., a precision of the error distribution, it is only an interval consistency not a comparison with the target values.

## 4 Discussion

This article is a continuation of our first series of publications, which will examine the full design and testing process of an approach called "building performance monitoring and characterization". It presents only some of the obtained results related to the created neural network. The correct operation of the developed research methodology was indicated. Detailed results and comparative analysis will be discussed in the last article of this series. Throughout this series of 4 articles, we explore next-generation building technology that aims to achieve the highest occupant comfort while promoting a sustainable built environment with high precision but at low cost.

We started with a feasibility review [16] based on 20 parameters used in the experimental building to establish a mathematical model [30] and collected the data in such a way that both the traditional and scientifically valid energy representations could be used interchangeably. In this way, we were able to obtain extremely low uncertainty estimates (less than 2%) for both room temperature and operating room temperature. To avoid getting into building physics and explaining that current heating and cooling technology relies on radiation from traditionally small windows, we chose test data for the period of the year when the dry bulb air temperature is close to the operating temperature. Verification carried out under these conditions allows checking the precision and accuracy of the ANN models.

In this article, we added two requirements: (1) the solution must be fast and (2) it must be simple. The results show that even with these requirements, the model uncertainty is still within 2%. This is an extremely good result, since the influence of individual error components (initial weights and training error, underfitting and overfitting eliminated 47 of the 50 cases tried. The fact that 94% of the cases are not repeatable or precise may explain why many researchers go to the complicated neural network system or use a self-learning system.

This series of 4 articles aims to establish the limits of precision and accuracy (deviations from measured values), which are to serve as a reference point in the development of new technologies.

In practice, the number of measured parameters will be reduced to 2 for each air-conditioned room in the building core and 4 for rooms exposed to external factors. In this way, the research presented above provides a roadmap for the development of a stable, repeatable ANN with above-average precision.

Another noteworthy fact is that this ANN occupied only 9 KB of memory in the MATLAB cache and therefore can be easily used in any control system. Most likely, it can be used to modernize the currently used control system in an intelligent building. To sum up, we have created the basis for introducing an adaptive climate in buildings.

The above series of 4 articles concerns currently existing technology. Let's hypothesize, where are we headed? The accuracy of the energy efficiency of an apartment located in a multi-family residential building should be assessed. It is important to remember that the energy balance includes two different elements, one related to the temperature difference and the other to the air pressure difference within the building envelope. The former may be multidirectional in the presence of thermal bridges or zones with different internal temperatures, but we know the path of heat flow. It's no different when it comes to airflow. In the best case, we can know the inter-zone air flows (from one room to another room), but not the interstitial air flows (through sidewall ducts). This means that our modeling must take into account all heated (or cooled) spaces together and each room separately. Since the computation time increases with the complexity of the interacting nodes, we need to add measurements of air pressure differences between zones to separate air flows within the heating zone and between heating zones.

## 5 Conclusions

A rapid acting, stable, and reproducible ANN network with above-average precision has been established for the supplied data set highlighting the capability of a new Monitoring and Building Performance Characterization technology in a steady-state heating pattern.

## Bibliography


1. Dudzik, M.; Romanska-Zapala, A. and M Bomberg, A neural network for monitoring and characterization of buildings with environmental quality management, part 1: verification under steady-state conditions. Energies 2020, 13, 3469.
2. Bomberg, M.; Yarbrough, D.; Romanska-Zapala, A.; Kuc, S. Retrofits of residential buildings to slow the climate change. Current advances in geography, environment, and earth science. Hooghly, West Bengal, Book Publisher International, 2021, 1, 40-54.
3. Fedorczak-Cisak, M.; Bomberg, M.; Yarbrough, D.W.; Lingo, Lowell E.; Romanska-Zapala, A. Position paper introducing a sustainable, universal approach to retrofitting residential buildings. Buildings 2022, Vol. 12, 6,1-25.
4. Radziszewska-Zielina, E.; Kania, E. Problems in Carrying out Construction Projects in Large Urban Agglomerations on the Example of the Construction of the Axis and Highrise Office Buildings in Krakow. In Proceedings of the XXVI russian-slovak-polish seminar 2017 Theoretical Foundation of Civil Engineering, Matec web of conferences, 2017, 117, 00144.
5. Fedorczak-Cisak, M.; Kotowicz, A.; Radziszewska-Zielina, E.; Sroka, B.; Tatara, T.; Barnaś, K. Multi-criteria optimization of the urban layout of an experimental complex of single-family nzebs. Energies 2020, 13, 1541.
6. Radziszewska-Zielina, E.; Sladowski, G. Proposal of the use of a fuzzy stochastic network for the preliminary evaluation of the feasibility of the process of the adaptation of a historical building to a particular form of use. In Proceedings of the WMCAUS IOP Conf. series: Materials Science and Engineering 2017, 245, 072029.
7. Graf, R. and Weckesser, P. Autonomous room service in a hotel. IFAC proceedings volumes,1998, 31(3), 501-507.
8. Beatson, A.; Coote, I.; Rudd, J. Determining consumer satisfaction and commitment through self-service technology and personal service usage. J. Marketing Mgt 2006, 22, 853–882.
9. Lukanova, G. and Ilieva, G. Robots, artificial intelligence and service automation in hotels. in Ivanov, S. and Webster, C. (eds.) Robots, artificial intelligence and service automation in travel, tourism, and hospitality. Bingley: Emerald Publishing Limited, 2019, 157-183; https://doi.org/10.1108/978-1-78756-687-320191009.
10. Yu-Ning, X.; Li-xiao, G. Personalized intelligent hotel recommendation system for online reservation a perspective of product and user characteristics. In Proceedings of the Conference: Management and Service Science (MASS), September 2010; doi: 10.1109/icmss.2010.5576790.
11. Nnoor-A-Rahim; Hosain, K.; Islam, S.; Anjum, N.; Rana, M. An Electronic Intelligent Hotel Management System for International Marketplace. (IJACSA) International Journal of Advanced Computer Science and Applications 2011, 2(3); doi:10.14569/IJACSA.2011.020316
12. Almeida, A.; Azkune, G. Predicting human behavior with recurrent neural networks. Appl. Sci. 2018, 8, 305; doi:10.3390/app8020305.
13. Zhang, Z.; Vanderhaegen, F.; Millot, P. Prediction of Human Behaviour using artificial neural networks, advances in machine learning and cybernetics. In Proceedings of the 4th International Conference 2005, Guangzhou, China, 18-21 August 2005.
14. Dudzik, M.; Mielnik, R.; Wrobel, Z. Preliminary analysis of the effectiveness of the use of artificial neural networks for modeling time-voltage and time-current signals of the combination wave generator, In Proceedings of the International symposium on power electronics, electrical drives, automation and motion (SPEEDAM), Amalfi, Italy, 20-22 Jun 2018; WOS:000445031300179,
15. Gadek, K.; Dudzik, M.; Strek, A. A Novel Three-Head Ultrasonic System for Distance Measurements Based on the Correlation Method. Measurement Science Review 2014, 14, 6, 331-336.
16. Romanska-Zapala, A. and Bomberg, M. Can artificial neuron networks be used for control of HVAC in environmental quality management systems? In Proceedings of the Central European Symposium of Building Physics, Prague, Czech Republic, 23-26 September 201.

17. Kochenderfer, M.; Wheeler, T. Algorithms for optimization, The MIT press, Cambridge, Massachusetts, London, England, 2019.
18. Latka D.; Matysek P. The estimation of compressive stress level in brick masonry using the flat-jack method. In Proceedings of the International Conference on Analytical Models and New Concepts in Concrete and Masonry Structures, V. 193 P. 2017, 266-272; DOI: 10.1016/j.proeng.2017.06.213.
19. Dudzik M.; Stręk A.M., ANN Architecture Specifications for Modelling of Open-Cell Aluminum under Compression, Mathematical Problems in Engineering 2020, Volume 2020, Article ID 2834317, 2020-02-28; DOI: 10.1155/2020/2834317.
20. Tomczyk, K. Special signals in the Calibration of Systems for Measuring Dynamic Quantities. Measurement 2014, 49, 148–152.
21. Layer, E.; Tomczyk, K. Determination of Non-Standard Input Signal Maximizing the Absolute Error. Metrology and Measurement Systems 2009, Vol. XVII, 2, 199–208.
22. Tomczyk K.; Piekarczyk M.; Sokal G. Radial Basis Functions Intended to Determine the Upper Bound of Absolute Dynamic Error at the Output of Voltage-Mode Accelerometers. Sensors 2019, Vol. 19, 19, 1–15.
23. Tomczyk, K. Levenberg-Marquardt Algorithm for Optimization of Mathematical Models according to Minimax Objective Function of Measurement Systems. Metrology and Measurement Systems 2009, Vol. XVI, 4, 599–606.
24. Tomczyk, K. Impact of uncertainties in accelerometer modeling on the maximum values of absolute dynamic error. Measurement 2016, 80, 71–78.
25. Demuth, H.; Beale, M.; Hagan, M. Neural Network Toolbox 6 User's Guide; The MathWorks Inc., 2009. Mathworks doc-umentation: mapminmax. Available online: https://www.mathworks.com/help/deeplearning/ref/mapminmax.html (accessed on 21st Feb 2019).
26. Madsen, K.; Nielsen, H.B.; Tingleff, O. Methods for non-linear least squares problems. In Informatics and Mathematical Modelling. Technical University of Denmark, 2nd ed.; April 2004. Available online: http://www2.imm.dtu.dk/pubdb/views/edoc (accessed on 21st Feb 2019).
27. Huang, X.; Cao, H.; Jia, B. Optimization of Levenberg Marquardt Algorithm Applied to Nonlinear Systems. Processes 2023, 11, 1794. https://doi.org/10.3390/pr11061794
28. Sedgwick, P. Pearson's correlation coefficient, ENDGAMES, BMJ, 2012; 345:e4483; doi: 10.1136/bmj.e4483.
29. Sikorski, A. Bezpośrednia regulacja momentu i strumienia maszyny indukcyjnej, tom 19, Oficyna Wydawnicza Poli-techniki Białostockiej, Białystok, 2009; ISBN 8360200742, 9788360200742.
30. Lstiburek, J. W. Toward an understanding and prediction of airflow in buildings. Ph.D. Thesis at U. of Toronto, 1999.