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MULTI-OBJECTIVE OPTIMIZATION AND SIMULATION FOR MULTIPLE MODELS OF WALLS TO ESTIMATE HEAT GAIN USING ARTIFICIAL NEURAL NETWORK MODEL

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Abstract
In homes all around the world and other hot climates, different types of walls are frequently used to provide small heat gains from the outside. Climate-related factors have been the subject of several studies, but there has been relatively little quantitative study on the best wall types and thicknesses. In this study, an effort was made to determine how much heat would be gained by a different form of wall. The HAP program allows us to change the parameters flexibly and easily calculate the heat gain. We used this advantage to collect data for our analysis, 432 models have been produced for three distinct wall types—light, medium, and heavy—made of various materials and thicknesses using the HAP software, where the direction of the walls and the color of their outer surface were considered. Using a function from a neural network that was built later, the optimal wall model was determined by the multi-objective Genetic algorithm method. The results showed that for the optimal wall, which were 9.548, 9.598, and 9.62 W/m^2, heat gain for ANN, HAP, and transient thermal analysis by Ansys, respectively, showed a close agreement among the methods.

Keywords: *hap software, wall design, optimization, heat gain, insulation wall, artificial neural network.*

1. Introduction

Improved building energy efficiency has the potential to make significant progress toward a sustainable economy, as buildings account for 40% of primary energy usage and 24% of greenhouse gas emissions (Berggren and Wall, 2018). When compared to other industries, the construction industry may dramatically cut energy consumption and, as a result, greenhouse gas emissions (Liu et al., 2023). Heat transfer calculations are commonly employed in buildings for a variety of purposes, including calculating how much energy is lost or gained via the structure's envelope (heat conduction), conducting environmental studies inside the building, and troubleshooting difficulties with specific materials or structural parts

(Dai et al., 2019; Kusuda, 1977).

Exterior wall conduction, interior mass conduction, heat gain/loss conversion to cooling and heating loads, and ground heat loss from the slab-on-grade floor and basement walls are all issues related to conduction heat transfer that arise in the context of buildings, and the rate at which heat moves through walls can be changed by changing the thickness of the walls or increasing the thickness of the layer of insulation (Cao et al., 2016). Weather variables like temperature changes, sunlight, air movement, and so on affect transitory wall conduction and heat transfer. Increasing the thermal insulation of the building envelope and limiting heat loss through walls is one of the most effective ways to increase a structure's energy efficiency and lower its energy usage, walls absorb around 35% of the heat (Li et al., 2022).

Because all heat transfer mechanisms are present and building components have many layers of different materials, thermal analysis of a full structure is hard and time-consuming. Because variables such as ambient temperature, wind velocity, and solar irradiation change over time, the design is sometimes time-dependent. In addition to ventilation and infiltration, heat gains from occupancy, equipment usage, lighting, and solar radiation through fenestration must be addressed (Kareem Jalghaf et al., 2022). As a result, numerous approaches exist to estimate a structure's energy use (Al-Sanea, 2002). To evaluate heating and cooling loads, the Designer must analyze temperature swings in walls and roofs, taking into account internal and external factors (Höglund et al., 1967). The heat transfer across a layer is proportional to the temperature difference across the layer and the heat transfer area but is inversely related to the layer thickness. It is referred to as "transient conduction" when the mechanism of thermal energy transmission happens during a time period in which temperatures fluctuate at any position within an object. Temperature fields that change over time are referred to as transient" conduction. If necessary, heat conduction through the composite wall can be predicted. Assuming this is correct, we just need boundary conditions on the outer wall surface, with the interior wall surface subjected to the same circumstances (Omle et al., 2023).

Cognitive computing systems called artificial neural networks (ANNs) analyze and simulate nonlinear data using algorithms that only vaguely resemble the operations of the human nervous system (Premalatha and Valan Arasu, 2016; Masood and Ahmad, 2021). This machine learning technique is commonly applied in the field of construction engineering to forecast the behavior of several numerical problems in the future (Xue et al., 2019; Verma and Kumar, 2023). The ANN model is divided into three layers: input, hidden, and output. Depending on the intended problem, each input and output layer may have one or more layers. It is common to add two or more levels to the concealed layer. The purpose of the created model and the data that were gathered typically define the input and output layers, but the hidden layer is frequently controlled by the rating weight, transfer function, and bias of each layer toward other levels (Masood and Ahmad, 2021). Artificial Neural Networks (ANNs) are capable of determining a correlation between the inputs and outputs of a certain system through an iterative calculation procedure known as the training process (Xue et al., 2019), (Verma and Kumar, 2022). The weights and biases given to the inputs can be changed during training to maximize outputs and minimize errors, ultimately accomplishing the intended purpose. There are several strategies for building multi-variable linear or non-linear prediction models, including regression polynomials like Multivariable fractional polynomials: the MFP algorithm (Sauerbrei et al., 2006), Inverse Distance Weighting (IDW) (Moayedi et al., 2019), and Artificial Neural Networks (ANN) (Lu and Wong, 2008). Individuals are increasingly focusing their attention on ANN in particular (Jang et al., 2019). The training of input-output pairs from tests is used to portray complex and non-linear functional connections between a variety of factors. Artificial Neural Networks multi-layered perceptron can be compared to a multi-mapping black box analysis function (Gardner and Dorling, 1998). Due to their adaptability and capacity for self-learning, Artificial

Neural Networks (ANN) have been successfully used in a wide range of applications, including predicting indoor temperature (Pandey et al., 2012), heat radiation modeling (Tausendschön and Radl, 2021), optimizing the energy efficiency of residential buildings (Gao, 2022), and predicting temperature distribution (Askar et al., 2021). For that reason, ANN needs data to build it so HAP software can estimate the heat gain through building components.

The HAP (Hourly Analysis Program) is a versatile software program that includes a variety of energy analysis tools for assessing the efficacy and cost-efficiency of prospective HVAC system designs for commercial buildings. It could be feasible to conduct energy evaluations using only the input data and output from system design simulations. The HAP software and various tools are used to predict the heat gain in summer season as our main innovation.

This paper aims to analyze the heat gain through different types of walls in the summer season at Miskolc city, Hungary. To achieve this goal, the paper is organized as follows: First, we use HAP software to collect the input and output parameters for each wall sample. Second, we build an artificial neural network (ANN) to predict the heat gain for any given input. Third, we optimize the input parameters using a genetic algorithm to find the optimal wall sample that minimizes the heat gain. Fourth, we simulate the thermal performance of the optimal wall sample using ANSYS transient thermal analysis.

2. Methodology

2.1. Walls Model

The research model is a room with external walls on all four sides: north, east, west, and south. It is situated in Miskolc, Hungary, with a latitude of 48.1 and a longitude of 22. The four walls are 10 m^2 in size and 2.7 m tall. The HAP program was used to practically calculate the thermal gains of three different types of walls (a light-weight wall, a medium-weight wall, and a heavy-weight wall), as shown in Fig. 1. Each wall has five layers of different materials, arranged from the inside to the outside in the following order: gypsum board, concrete block, air space, board insulation, and stainless steel wall covering. By varying the kind of materials used for the wall layers and the thickness of each layer and changing the exterior surface color by changing the absorptivity, emphasis was placed on the heat lost through the wall to generate data. The materials utilized as well as the thickness of each layer, are shown in Table 1.

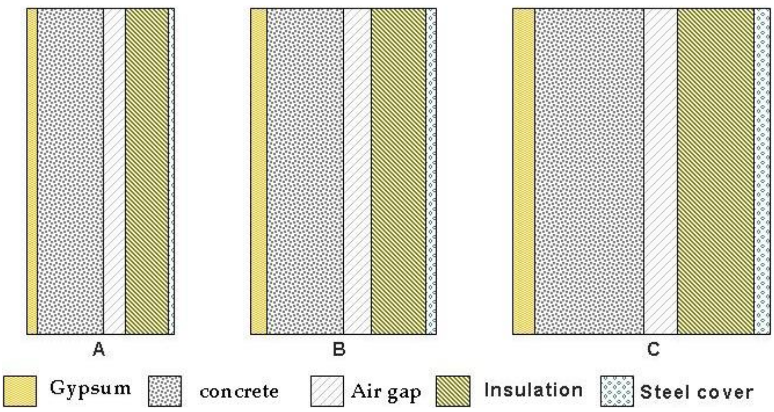

***Figure 1**. Show the three types of the wall (A)light-weight wall, (B) Medium-weight wall and (C) heavy-weight wall.*

***Table. 1.** The materials and thicknesses used for each layer.*

<table>
<tr><th>Wall type</th><th></th><th>Layer 1</th><th>Layer 2</th><th>Layer 3</th><th>Layer 4</th><th>Layer 5</th></tr>
<tr><td rowspan="3">Light weight wall</td><td rowspan="2">The material</td><td rowspan="2">gypsum plaster</td><td>Light weight concrete</td><td rowspan="2">Air space</td><td rowspan="2">RSI-1.2 board insulation</td><td rowspan="2">Steel wall covering</td></tr>
<tr><td>Heavy weight concrete</td></tr>
<tr><td>The thickness of layer [cm]</td><td>1.27</td><td>10, 15 and 20</td><td>1</td><td>0, 10 and 15</td><td>0.1</td></tr>
<tr><td rowspan="3">Medium weight wall</td><td rowspan="2">The material</td><td rowspan="2">gypsum board</td><td>Light weight concrete</td><td rowspan="2">Air space</td><td rowspan="2">RSI-1.9 batt insulation</td><td rowspan="2">Steel wall covering</td></tr>
<tr><td>Heavy weight concrete</td></tr>
<tr><td>The thickness of layer [cm]</td><td>1.27</td><td>20, 25 and 30</td><td>1</td><td>15, 20 and 25</td><td>0.2</td></tr>
<tr><td rowspan="3">Heavy weight wall</td><td rowspan="2">The material</td><td rowspan="2">gypsum board</td><td>Light weight concrete</td><td rowspan="2">Air space</td><td rowspan="2">RSI-6.7 batt insulation</td><td rowspan="2">Steel wall covering</td></tr>
<tr><td>Heavy weight concrete</td></tr>
<tr><td>The thickness of layer [cm]</td><td>1.6</td><td>30, 35 and 40</td><td>1</td><td>25, 30 and 35</td><td>0.3</td></tr>
</table>

2.2. Design of models

The HAP program is used to get the results to decrease the size of the training database while keeping the sample representative, and we have five layers in the three outside walls: Layer 1 has one material and one thickness, and layer 2 has two materials and three thicknesses; layer 3 has one material and one thickness; layer 4 has one material and three thicknesses; Layer 5 has one material and one thickness. So the number of models created is $\{[(1\times1) \times (2\times3) \times (1\times1) \times (1\times3) \times (1\times1)] \times 4\} \times 2 = 144$ models for one type of wall and for three walls, we collect 3x144 = 432 models. So that, during the optimization stage, we can select the parameters that are most useful and the parameters that aid in selecting the kind and thickness of a material.

In order to collect the data needed to create a neural network, we will use this tool to configure the weather data for Miskolc, choose the space, specify the type of wall for that space, and only include the heat gain through the wall in each model's design condition.

3. Artificial Neural Network Model

3.1. Generating data

The goals of this study are to calculate heat gain and cost, so HAP Software constructed wall models and estimated heat gain for each model under the assumption that the price of each Watt gain equals a unit price. Each layer's resistance serves as the input data, and since each layer has a dimension of five parameters, there are a total of 12 parameters in the input to produce the data sets needed for an artificial neural network's training procedure. The gathered data were then normalized to fit the [0.1–0.9] range, representing the data's lowest and maximum values. In order to get optimal fitting in a shorter amount of time, the normalization step is seen as essential (Moradzadeh et al., 2020).

3.2. ANN Model

This study employed the MATLAB neural network fitting tool (nftool) to create and train a neural network model. The nftool is a user-friendly tool that allows selecting data, creating a network, training it, and evaluating its performance using various metrics such as the average square error and regression analysis. The neural network model used in this study had a specific structure, as shown in Fig. 2 and 3. It had 12 input layers, each representing a different parameter related to the wall's characteristics, such as the resistance, orientation, absorptivity, and thickness of each layer. It also had an output layer with a purlin transfer function, which predicted the cost and heat gain of the wall. Between the input and output layers, there was a hidden layer with 11 neurons and a sigmoid transfer function, which performed the nonlinear transformation of the input data. The nftool was used to train the neural network model by Levenberg-Marquardt backpropagation „LM" with the available data and evaluate its accuracy and reliability.

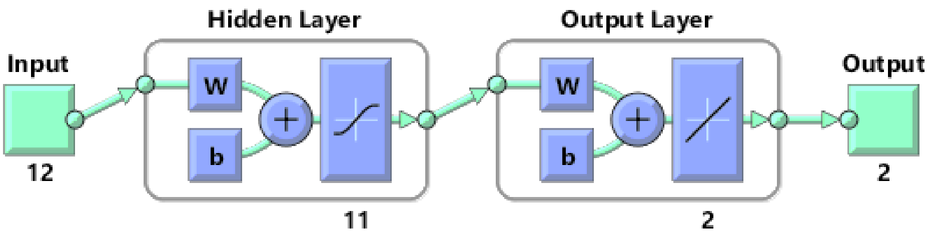

Figure 2. *Artchitecture neural network model schematic from Matlab.*

3.3. Training steps

The trial-and-error test is used to determine the number of neurons and hidden layers. Finding the ideal number of iterations (epochs) from which to get a low mean square error (MSE) and a high R^2-value is the main goal of the network's training process. Iteration's impact in reducing the MSE has been the subject of several research. To be ready for the planned ANN, the collected dataset (a total of 432 data) has been divided into three groups. The system takes 70% of the data for training, 15% for validation, and 15% for testing. Based on the compatibility of the projected compaction features with the actual collected data, the trained, validation, and tested ANN has been utilized to determine the appropriate network topology.

High predictive performance is shown by a decline in MSE in Eq. 1, which is consistent with the outcomes of the analytical model. Indicating a significant correlation between the outcomes of the analytical model and the ANN prediction outputs, *R*-Squared shows how well a regression model (independent variable) predicts the outcome of observed data (dependent variable) and its approach to one (Pandey et al., 2012).

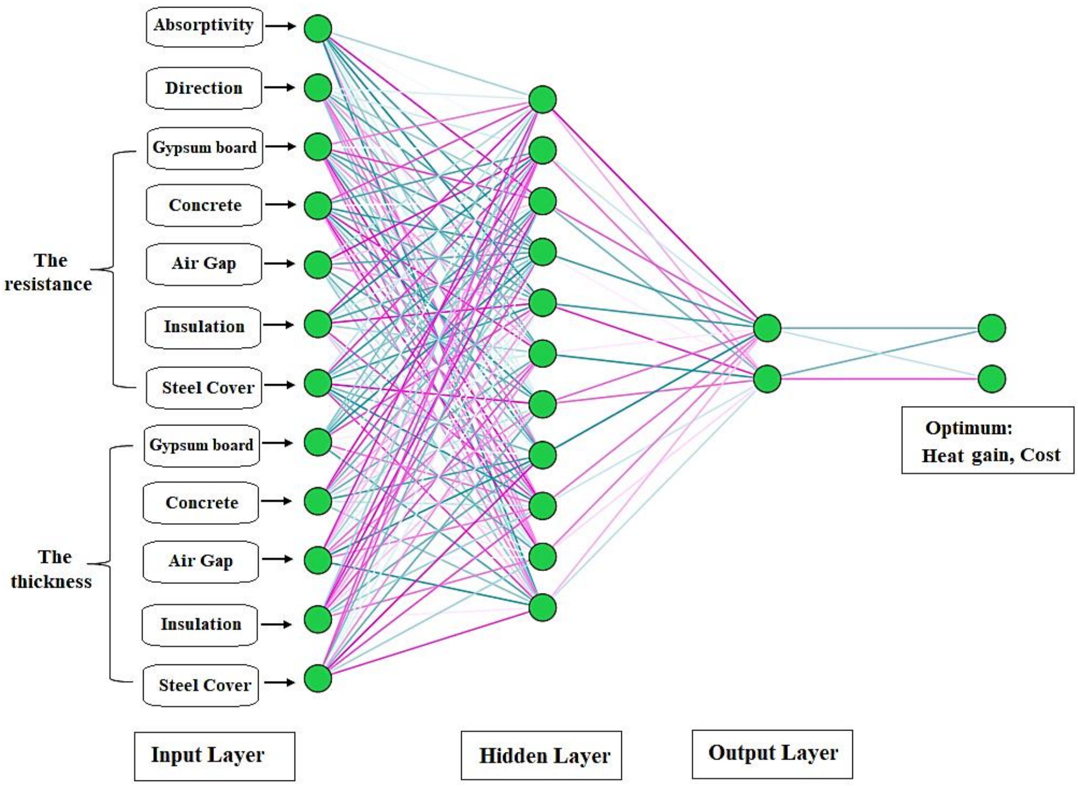

Figure 3. *The architecture of the ANN models.*

$$MSE = \frac{\sum_{i=1}^{n}\left(x_{N,i} - y_{N,i}\right)^2}{n} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(x_i - y_i\right)^2}{\sum_{i=1}^{n}\left(y_i\right)^2} \tag{2}$$

Where x_i *and* y_i are the actual and predicted values, respectively.

3.4. The Optimization

A multi-objective genetic algorithm, a population-based tactic, draws inspiration from the "survival of the fittest" principle in evolutionary biology. It enhances workable solutions through the application of selection, mutation, and crossover operators, as well as cutting-edge fitness functions and strategies (Long et al., 2015). For issues with several objectives or criterion, a multi-objective genetic algorithm optimization approach can locate a collection of ideal solutions. In this study, we want to develop a wall that lowers expenses and heat gain. We need to strike a balance between two competing goals. You may be able to identify a collection of trade-off solutions that are in some ways optimum with the use of a multi-objective genetic algorithm. To identify trade-offs and offer a technical framework for decision-making, Multi-Objective Optimization (MOO) models capture the numerous, usually at odds with one another, and frequently incommensurable components of solution evaluation. Due to competing objectives, MOO usually produces several non-dominated (Pareto optimum) solutions as opposed to a single optimal solution. We reduce expenses and heat gain. This MOO model is non-linear and combinatorial due to calculations based on wall performance. The front, neutral zone is thus defined by a MOGA (multi-objective genetic algorithm). The 'multi-obj' function of the GA toolbox in MATLAB does optimization, while the ANN in MOGA analyzes heat gain and cost. The number of variables in the problem is 12, and the population size for the algorithm is 200. The upper and lower bounds of the variables are normalized to be between 0.1 and 0.9.

3.4.1. Input parameters

The choice factors take into account the whole range of potential measures that may be used for wall retrofitting (Hazim et al., 2021) (such as absorptivity, direction, material type, thickness, etc.). The collection of retrofit operations includes combinations of options for layer materials, including concrete, gypsum plaster, air gap, insulation, steel wall covering, and various thicknesses for each layer. Twelve different sorts of decision variables are described in relation to the possible options for five layers' thermal resistance, five layers' thickness, one for each wall's orientation, and one for absorptivity.

3.4.2. Output functions

The HAP immediately measures the heat gain through the walls, where the total heat gain is the sum of the energy gain across the layers. The total heat gain is based on the equation:

$$Q = U.A.(T_{out} - T_{in}) \tag{3}$$

Where *A* is the area of the wall [m^2], U is: Overall heat transfer coefficient [W/m^2K], and T_{out}, T_{in} are the ambient inside and outside temperature [K].

The MOGA employs the ANN model to determine the optimal rate of heat gain after training the neural network model.

The total cost of the wall investment is Cost (X), where X represents the vector of all declared decision factors. We may compute this cost based on the size and kind of wall being built. For the unit volume of each layer and the heat gain for each wall it is indicated by a unit price.

3.5. Simulation by ANSYS

We used ANSYS for this study because it is a reliable and accessible tool for solving the problem of convection and radiation heat transfer in a wall with a comfortable interior zone and exterior environment. We performed a transient thermal analysis to investigate the heat gain of the optimum wall and compare it with the heat gains obtained by HAP and ANN. The detiels we will present it in the result part after we make the optimization.

4. Results and discussion

4.1. ANN

The result of the neural network for the data of the wall samples can be presented with the performance with the number of epoches in Fig. 5 and the errors below 10^{-4} for the training, testing, and validation. Fig. 4 displays the network's MSE performance during training, validation, and testing.

The regression graphing (R) in Fig. 5 illustrates the relationship between the neural network's outputs and the system's goals, demonstrating the network's excellent fit with the system. The system was trained to 99.97% with 99.98% of validation. Testing shows that the diagnosis was 99.97%, which is appropriate.

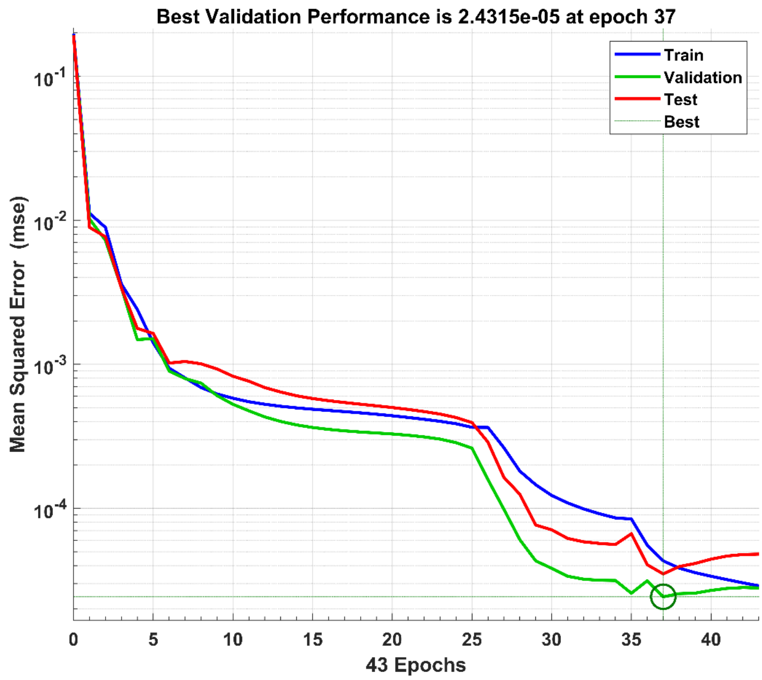

Figure 4. *Diagram illustrating the network's MSE performance with the number of iterations.*

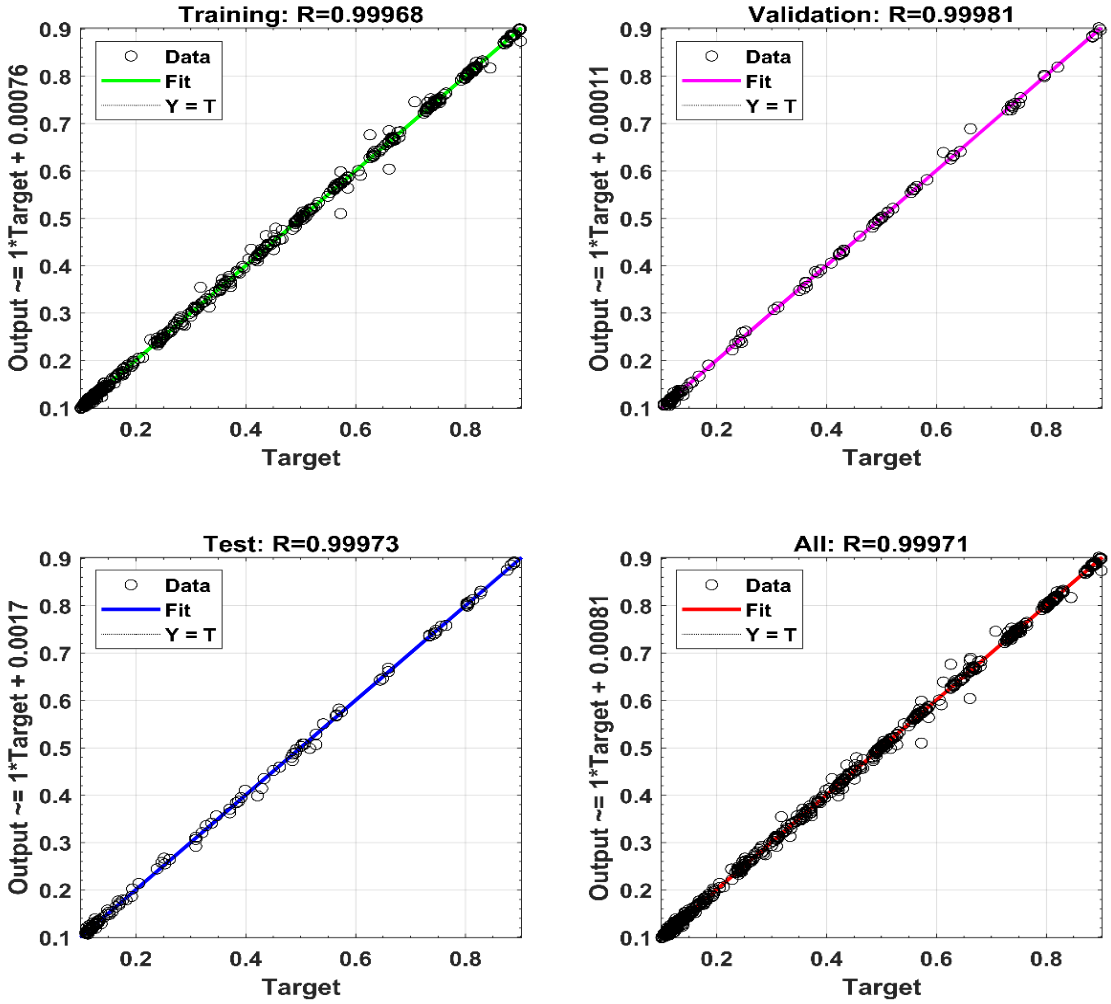

Figure 5. *Regression graphing (R) schematic for training, validation, testing, and all data.*

The results for data of the wall for all models can see in Fig.6 show the heat gain and number of samples. It can be seen that the network and HAP fit up extremely well.

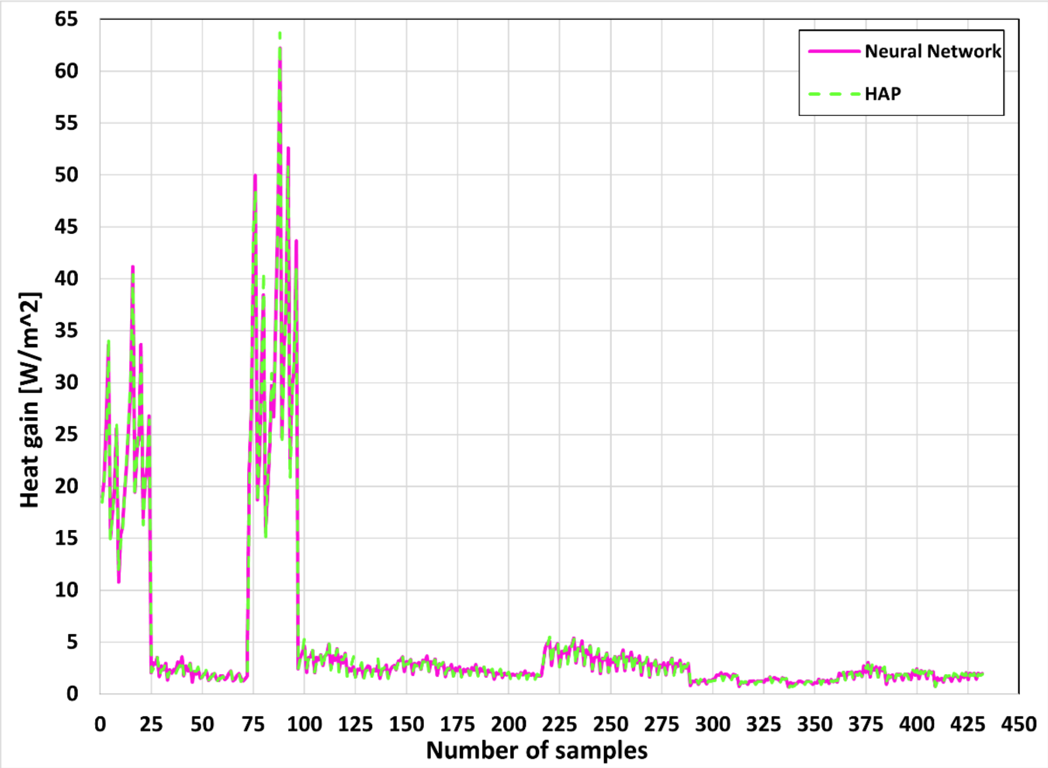

Figure 6. *Experimental and prediction heat gain with the number of samples.*

4.2. Optimum

After creating the neural network using the data, we used the Genetic Algorithm (GA) to determine the Pareto set for the Multi-Objective Optimisation (MOO) issue, as shown in Fig. 8. The Pareto set is a group of options that meet the objectives, but more study is necessary to determine the best option (Meng et al., 2018). As a result, we employed the improved minimum distance selection method (IMDSM) to standardize the Pareto solutions and choose the best option, or "knee point." Equation 4 can be used to represent this (Chen et al., 2017). The ideal wall model may then be specified. Fig. 7 using equation (4), the minimum diameter that balances the heat gain and the cost for the wall samples can be calculated, and Table 2 display the ideal wall model's outcome.

$$D_{min} = \sqrt{\sum_{\tau=1}^{n} \left(\frac{f_{c\tau}(x)}{min(f_{\tau}(x))} - 1 \right)^2} \tag{4}$$

Table 2. *The properties and thickness of the optimal wall layers.*

Name	*Thickness* [m]	*K* [W/m K]	ρ [kg/m^3]	*Cp* [J/kg K]
Gypsum board	0.0127	0.2246	720.8	1340
Heavy weight concrete	0.106	0.82	977.1	840
Air space	0.050	0.193	1.1	1.007
RSI-6.7 batt insulation	0.338	0.05	8	840
steel wall covering	0.001	50.6	7833	500

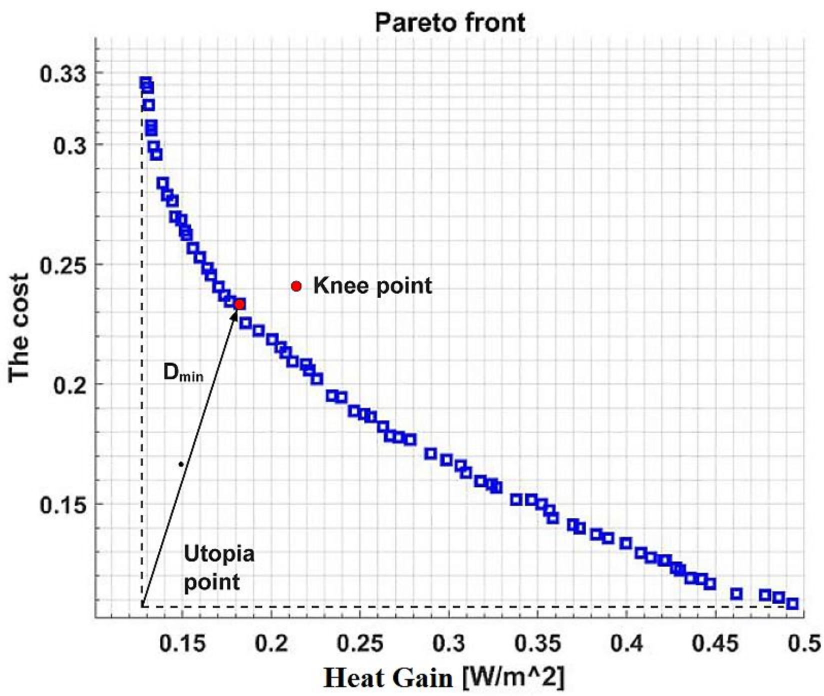

Figure 7*. The optimal model solutions and knee points of the Pareto optimal front.*

4.3. Simulation

The problem was considered transient thermal with constant thermal characteristics (see Table 2). Fig. 8 depicts the geometry and mesh of the best wall model. We consider the problem of a 1-meter square space. The length and width are both one meter. Table 2 shows the thickness of the layers. The mesh element size is 0.02 m, with 37500 elements and 193035 nodes.

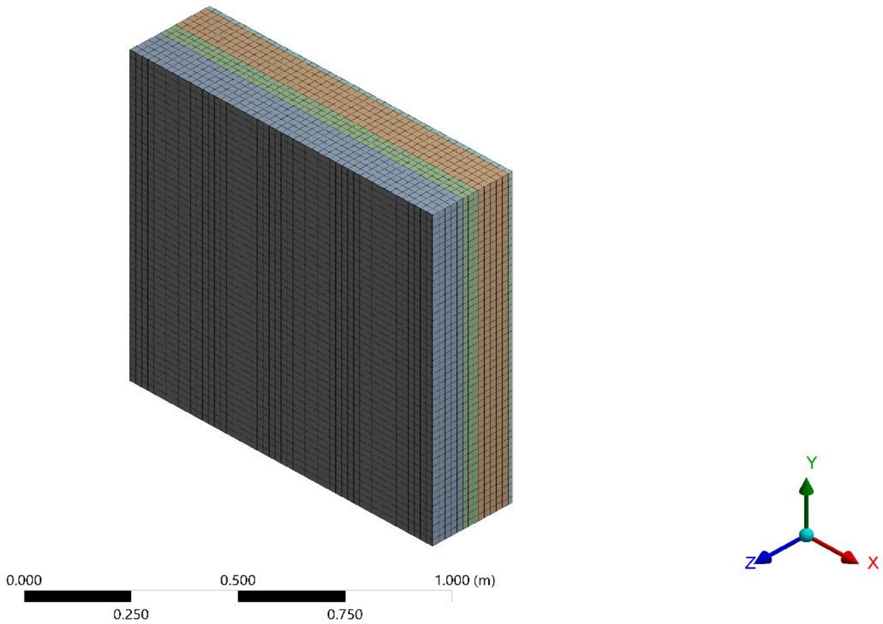

Figure 8. *The wall model's geometry and mesh.*

Table 3 shows the beginning and boundary conditions. It is obtained from the HAP program for Miskolc City weather data for the design day in July. As you can see, the inside state is constant, but the external condition changes.

Table 3. *The initial and boundary conditions for simulation case optimal wall.*

h_i [W/m^2 K]	h_o [W/m^2 K]	T_i [K]	T_o [K]	ε	$T_{initial}$ [K]
8.289	9-18	295	297-309	0.65	298

To perform the transient thermal analysis, the Ansys Workbench by Mechanical APDL solver was employed. The convergence criterion was set to a maximum change of 10-4 °C in the nodal temperature per iteration. The results of the analysis presented by post-processing. The optimum wall design was evaluated by examining the temperature distribution on its surface. The temperature contour of the 3D transitional thermal analysis for the optimum wall is shown in Fig. 9. The figure illustrates the variation of temperature along the wall, with the highest values at the outside surface close to the envirinment and the lowest values at the inner surface close to the comfort zone.

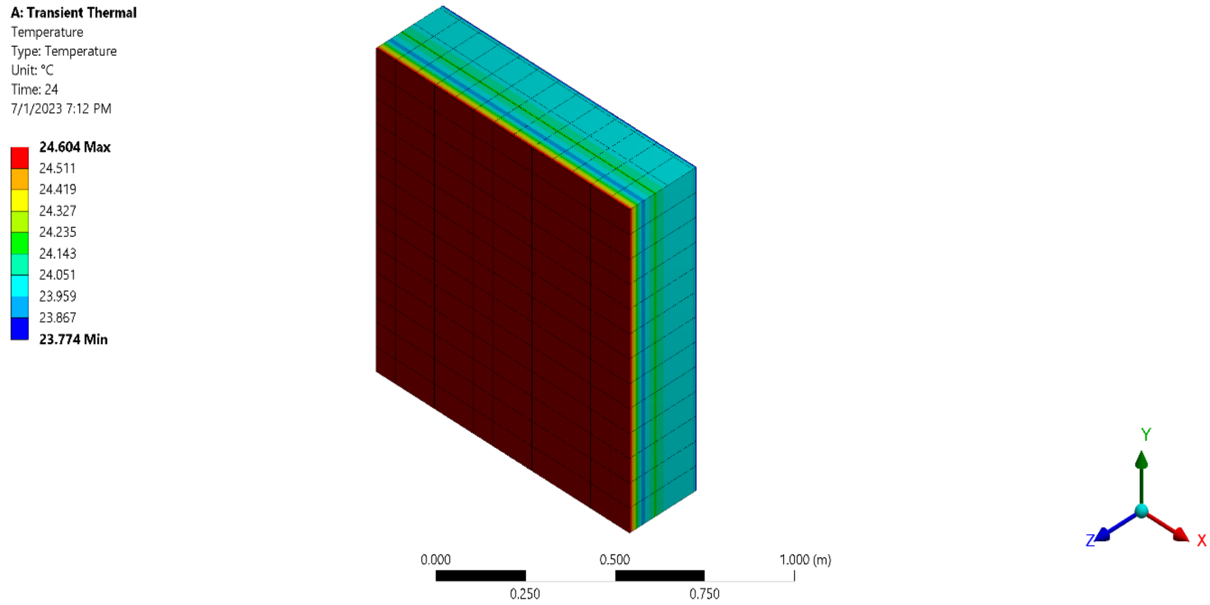

Figure 9. *Temperature [C°] distribution along the wall thicknesses.*

Table 4. *The heat gain through the wall.*

	ANN	HAP	ANSYS
Heat gain [W/m^2]	9.548	9.598	9.62
Relative difference to HAP %	0.52	0	0.23

5. Conclusion

The aim of this paper was to study the heat gain through the wall from the outside during the summer season in Miskolc, Hungary. We used HAP software to create different models of the wall with various materials and thicknesses. We collected data on the heat gain and the cost of each model. We then applied a multi-objective genetic algorithm to train an artificial neural network (ANN) that can predict the heat gain and the cost of any wall model. We also used Ansys software to perform a transient thermal analysis of the wall and compare the results with the ANN and HAP predictions. We found that the best model that minimizes both heat gain and cost has a heat gain of 9.548 W/m2 for ANN, 9.598 W/m2 for HAP, and 9.62 W/m2 for Ansys, showing a good agreement among the three methods. This paper demonstrates the effectiveness of using ANN and genetic algorithm for optimizing the wall design and reducing the cooling load of buildings.

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