- $S_{terasă}$ representing the terrase surface [m^2];
- $S_{fe.usi}$ representing the total outside windows and doors [m^2];
- $R_{pereți}$ being the thermal resistance of the walls [m^2K/W];
- $R_{terasă}$ being the thermal resistance of the terrace [m^2K/W];
- $R_{fe.uși}$ being the thermal resistance of the windows and doors, obtained as the ponderate mean in regard to the surface [m^2K/W].
- The variable chosen to represent the output parameter of the neural network and also the output neuron is:
- Q_h being the annual energy consumption for heating [kWh/year] .

3.3 Construction of the ANN's training file

The set of data used for the ANN's training is comprised of 9 values for each building, numbering a total of 630 input values and 70 output values.

These values were measured on different residential buildings from Brad town, in Hunedoara County over a period of two years (before and after thermal insulation). The file is actually a spread sheet with 11 columns (one for each parameter and the number of the building) and 70 lines (one for each case). Out of this training file, 15 cases were selected for the verifying file that will be used for the validation of the ANN.

4. The construction and the training of the ANN

The program Tiberius Data Mining, version 7.0.4, was used for the construction of the neural networks, for which an academic license was obtained. In order to determine the right architecture of the network, a series of trials were made. The final architecture is composed of 10 neurons on the input layer (9 corresponding to the input parameters and one to the Bias), and one neuron on the output layer corresponding to the output parameter.

Regarding the neurons on the hidden layer a series of configurations were examined in order to reduce the errors, arriving at a number of 9 neurons. The final architecture of the artificial neural network created is being presented in Figure 1. The training process was conducted at different rates starting with 0.7 and ending with 0.1 in the interest of decreasing the error. The number of epochs was originally established at 5000. The last adjustment for the synaptic weights occurred after 1952 epochs.

The annual energy consumption targeted values for the network's testing; the modeled values and the errors between the two of them for 10 of the 70 test cases contained in the test file are shown in Table 1. Differences between the targeted values introduced and the model output of the neural network do not exceed 5 [%] which allows for the next step to occur, which is the validation of the method for determining the specific heat loss.

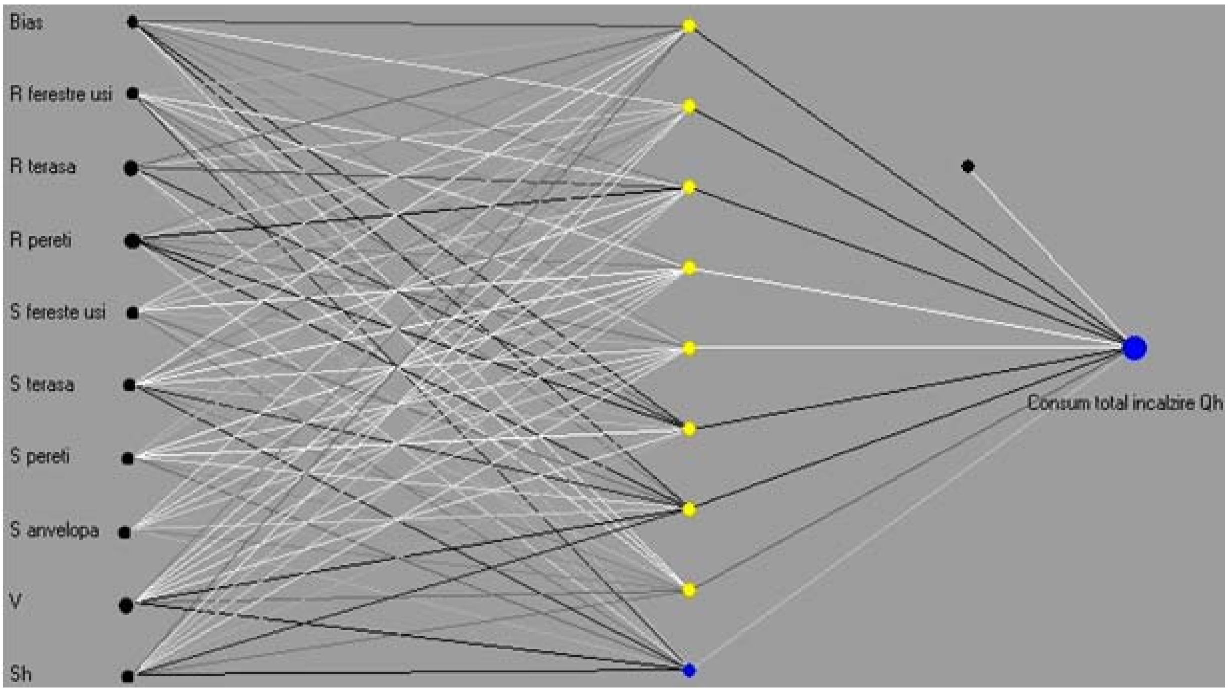

Figure 1: The architecture of the neural network used to determine the annual energy consumption for the heating of a residential building

Table 1: The testing results of the ANN for determining Q_h

Case no.	1	2	3	4	5	6	7	8	9	10
Targeted Q_h value	812413,31	991621,71	1068491,07	778135,93	378765,57	256045,36	268847,16	216596,67	274113,41	256045,36
Modeled Q_h value	812284,71	990254,46	1069104,99	779028,33	382685,09	251880,29	273957,84	217161,54	275125,92	255965,82
Error	128,60	1367,25	-613,92	-892,39	-3919,51	4165,07	-5110,68	-564,87	-1012,51	79,54

The chart for the targeted values and the modeled values of the specific heat loss and the error between them for 70 cases on which the neural network gets validated are shown in Figure 2. It can be seen an almost perfect overlap between the two graphs, which demonstrates the networks capability to determine the required value with sufficient accuracy.

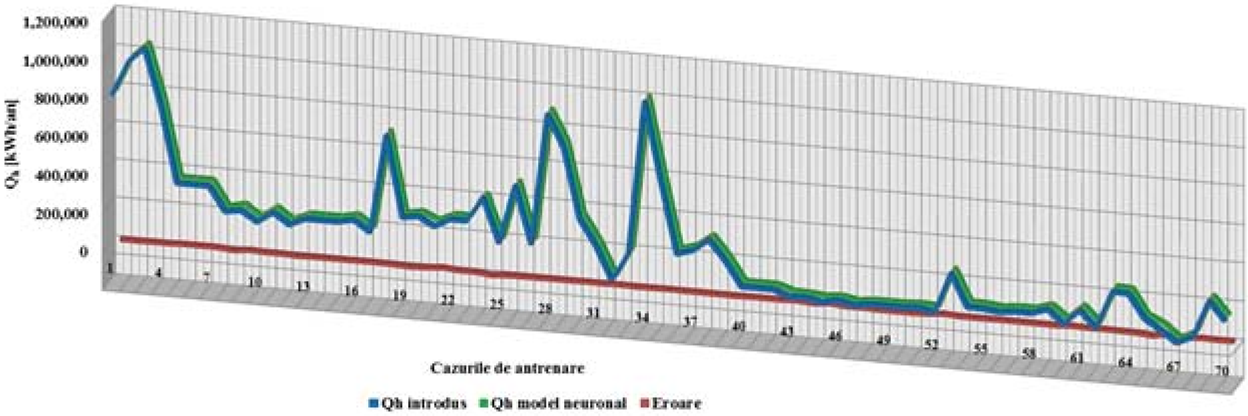

Figure 2: The chart for the targeted, the modeled values and the error for the ANN

Once trained for these cases, the neural network can predict the annual energy consumption for heating for new cases, by modifying any of the input neurons values. The new values must not exceed the trained interval by a large amount; otherwise the possibility of error will increase.

Table 2 contains the relative contribution of the neurons in the hidden layer which help to determine the final result for the 70 cases used. It can be seen that each neuron of the hidden layer contributes at some point to the correct solving of the non-linearity between the input parameters and the output result. This insight demonstrates the importance of the wall structure on the final energy consumption, giving good references on the actions that need to be taken in optimization strategies.

Table 2: The level of importance of each neuron in the result of the output parameter

Neuron Number	*Neuron's Name*	*Relative Importance*	*Level of Importance*
1	R pereți	1,000	||||||||||||||||||||||||||||||||||||||||
2	R terasă	0,497	||||||||||||||||||||
3	R ferestre uși	0,179	||||||||
4	Sh	0,142	|||||||
5	V	0,110	|||||
6	S ferestre uși	0,102	||||
7	S terasă	0,063	|||
8	S anvelopă	0,021	||
9	S pereți	0,009	|

In the end a software program was generated by the network that can determine the annual energy consumption for heating residential buildings in the conditions mentioned above. The last two columns of the program are showing the minimum and maximum values experimented by the neural network in the training process. The software's interface generated with the neural networks is shown in Figure 3. This program was used afterwards in the prediction of the total annual energy consumption for heating of the entire town of Brad, summing 120 residential buildings with 3989 apartments.

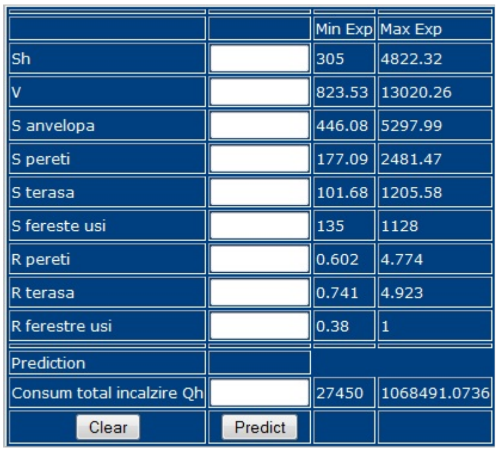

Figure 3: The interface of the software program created with the neural network

Even though only 5% of the buildings were rehabilitated thermally, the software helped to predict the total energy consumption before and after the process of rehabilitation. Knowing this information is crucial in establishing the strategies to reduce energy consumption and redesigning the new thermal energy production, transport and distribution plans for the town. After analyzing the data there was an estimated 6.041.611,21 [Gcal/year] drop in energy consumption after the rehabilitation process, making this a priority before other measures.

Having this prediction helps a lot in the establishment of the energy policy of the town also, knowing in advance the quantity of thermal energy needs in the near future.

5. Conclusions

The application of the neural network in order to determine the energy consumption in residential buildings can be done successfully due to their ability to overcome the problems of non-linearity between the input parameters and the values to be calculated. This method can be used for all kind of predictions in energy consumption areas, thermal energy being the first to be experimented in this case.

The software program generated by using neural networks allows the determination of accurate values in a very short period of time for any input values that don't exceed the intervals that the networks experienced during training. And so it can be a powerful tool for the establishment of energy policies for town administrations.

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