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Article

Building Behavior Simulation by Means of Artificial Neural Network in Summer Conditions

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Abstract: Many studies in Italy showed that buildings are responsible for about 40% of total energy consumption, due to worsening performance of building envelope; in fact, a great number of Italian buildings were built before the 1970s and 80s. In particular, the energy consumptions for cooling are considerably increased with respect to the ones for heating. In order to reduce the cooling energy demand, ensuring indoor thermal comfort, a careful study on building envelope performance is necessary. Different dynamic software could be used in order to evaluate and to improve the building envelope during the cooling period, but much time and an accurate validation of the model are required. However, when a wide experimental data is available, the Artificial Neural Network (ANN) can be an alternative, simple and fast tool to use. In the present study, the indoor thermal conditions in many dwellings built in Umbria Region were investigated in order to evaluate the envelope performance. They were recently built and have very low energy consumptions. Based on the experimental data, a feed forward network was trained, in order to evaluate the different envelopes performance. As input parameters the outdoor climatic conditions and the thermal characteristics of building envelopes were set, while, as a target parameter, the indoor air temperature was provided. A good training of network was obtained with a high regression value (0.9625) and a very small error (0.007 °C) on air temperature. The network was also used to simulate the envelope behavior with new innovative glazing systems, in order to evaluate and to improve the energy performance.

Keywords: Artificial Neural Network (ANN); building envelope behaviour; unsteady simulations; cooling conditions

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1. Introduction

The Energy Performance of Building Directive [1], issued in 2010, is the main and common European legislative instrument to promote energy performance of buildings and to reduce the CO_2 emissions, taking into account cost-effectiveness and local conditions.

The objective of European Union is to obtain an energy saving of 20% until 2020; specifically in transportation and buildings' sectors an important energy reduction is required.

Many studies carried out in Europe highlighted that the building sector is responsible for about 40% of total energy consumptions, mainly due to worst thermal and energy performance of building envelope [2].

In particular, in Italy, the energy consumption due to bad building envelopes is an important subject to study and to improve in order to obtain an important energy saving; in fact, a great part of the Italian buildings were built before the 1970s and 80s. Furthermore, in recent years, the energy demand for cooling has considerably increased with respect to the one for heating; in fact, many international reports showed how the energy demand has decreased since 2000 but this trend is in contrast with the increase in electricity consumption mostly due to cooling energy demand during the summer period, especially in the southern countries [2].

In order to reduce the cooling energy demand and the related electric energy consumptions, without compromising indoor thermal comfort, a careful study on building envelope performance is necessary [3–5]. New design solutions for the building envelope can be evaluated with simulation software, in order to obtain energy saving ensuring indoor thermal comfort, but much time and an accurate validation of the simulation model are always required in order to obtain reliable results [6].

Artificial Neural Network (ANN) could be an alternative tool for evaluating the thermal behavior of building envelope during summer period, basing on experimental data. It could be a useful and speedy tool for evaluating the thermal performance of buildings and it can be also used for testing the effect of new design solutions considering the real human contribution within the environment, which is only and very approximated with the common simulation software.

Several studies were carried out for predicting the thermal behavior of buildings envelope [7–13] and for evaluating the energy demand [14–23] by using Artificial Neural Network (ANN). Pandey *et al.* [7] evaluated the indoor temperature using two prototype rooms (1m × 1m × 1m) in which different cooling techniques were built and tested; specifically ANN was developed using different training functions and considering the external climate conditions (outdoor temperature, wind speed, and solar intensity). Mustafaraj *et al.* [8] evaluated the thermal behavior (indoor air temperature and relative humidity) in an open office by training an ANN with internal and external climate data monitored during three different seasons. Another interested work [10] developed an ANN that is able to optimize the thermal properties of external walls, in order to improve the thermal efficiency of dwellings; specifically, the thermal conductivity and the volumetric specific heat were evaluated and optimized. Other works implemented ANN for a similar goal: in order to predict the building's temperature [12], for improving the thermal conditions in residential buildings [13], or for improving both energy consumption and thermal comfort sensation [11].

In some of these works [14–23] the ANN approach was also compared with other methods used for the evaluation of energy consumptions; Tso *et al.* [18] compared three different methods (regression analysis, decision trees and Neural Network) for predicting energy consumptions, highlighting how both decision tree, and Neural Network approaches are viable alternatives to the regression method.

A similar analysis was carried out by Kialashaki *et al.* [20], who used two different methods in order to evaluate the energy demand of the residential sector in the United States; specifically, they used the multiple linear regression technique and the Artificial Neural Network.

Geem *et al.* [21] used the Neural Network in order to estimate the energy demand of South Korea; the values obtained by Neural Network were compared with the ones returned by applying a linear regression model or exponential model. This study highlighted that the ANN model estimated the energy demand better than the other two methods.

Neto *et al.* [23] compared the Neural Network approach with a model simulation implemented in Energy Plus and highlighted that both methods are suitable for the evaluation of energy consumption.

The main part of these works developed the ANN by using experimental data and specifically they provided the external climate conditions for the training of the network; however, these input parameters were mainly related to outdoor air temperature and solar radiation. These adopted approach led to good results, but did not consider all the parameters that influenced the thermal behavior of buildings' envelope, as the periodic thermal transmittance (ψ), the attenuation factor (F_d) and the interactions with semitransparent surface. However, they mainly affect the thermal behavior during the summer period. Therefore, in this paper an ANN was developed considering all the parameters that can affect the thermal behavior of buildings' envelopes during the summer season; this way it could be a useful tool able to improve the building envelope performance.

Specifically, the aim of the present paper is to implement a feed forward Neural Network on the basis of several experimental campaigns carried out in residential buildings built in Umbria Region in order to evaluate the effects of new solutions used to improve the energy buildings' performance and thermal comfort.

In order to collect the necessary input data to provide for the training of network, the thermal characteristics of buildings' envelope and the thermal comfort sensation during cooling period were evaluated in about 20 new residential buildings. These dwellings are recently built and have a very low energy consumption for heating. They are provided with a high efficiency heating plant but without cooling plants. The indoor thermal sensation and the energy consumptions monitored during the cooling period are influenced only by the building envelope and by human actions.

The developed ANN was used to simulate the behavior of the buildings by substituting the conventional glazing systems with innovative ones [24–26].

2. Methodology

2.1. Experimental Data

In the Umbria Region, several residential buildings were built with innovative materials and with new construction technologies including green technologies and sustainable solutions, such as natural building materials [27], due to specific regulations developed in order to reduce energy consumption.

Several dwellings were investigated [27] during heating and cooling period for one week for each season in order to evaluate the efficiency of new design solutions; specifically, the thermal comfort sensation in both seasons and in various dwellings in seven different cities in the Umbria Region was investigated. The indoor thermal conditions and particularly the indoor air temperature were monitored by using microclimatic probes linked to a BABUC C/M, 12-inputs acquisition system manufactured by LSI.

In compliance with Italian regulations, the envelope of all the investigated dwellings presents a very efficient thermal behavior, especially during cooling period; the thermal characteristics of all the investigated buildings' opaque envelopes are shown in Table 1, in which a code was used to identify each environment.

All the considered envelopes present a very low value of the periodic thermal transmittance (ψ), which influences the thermal behavior in unsteady state: the lower ψ is, the less the external temperature influences the internal one.

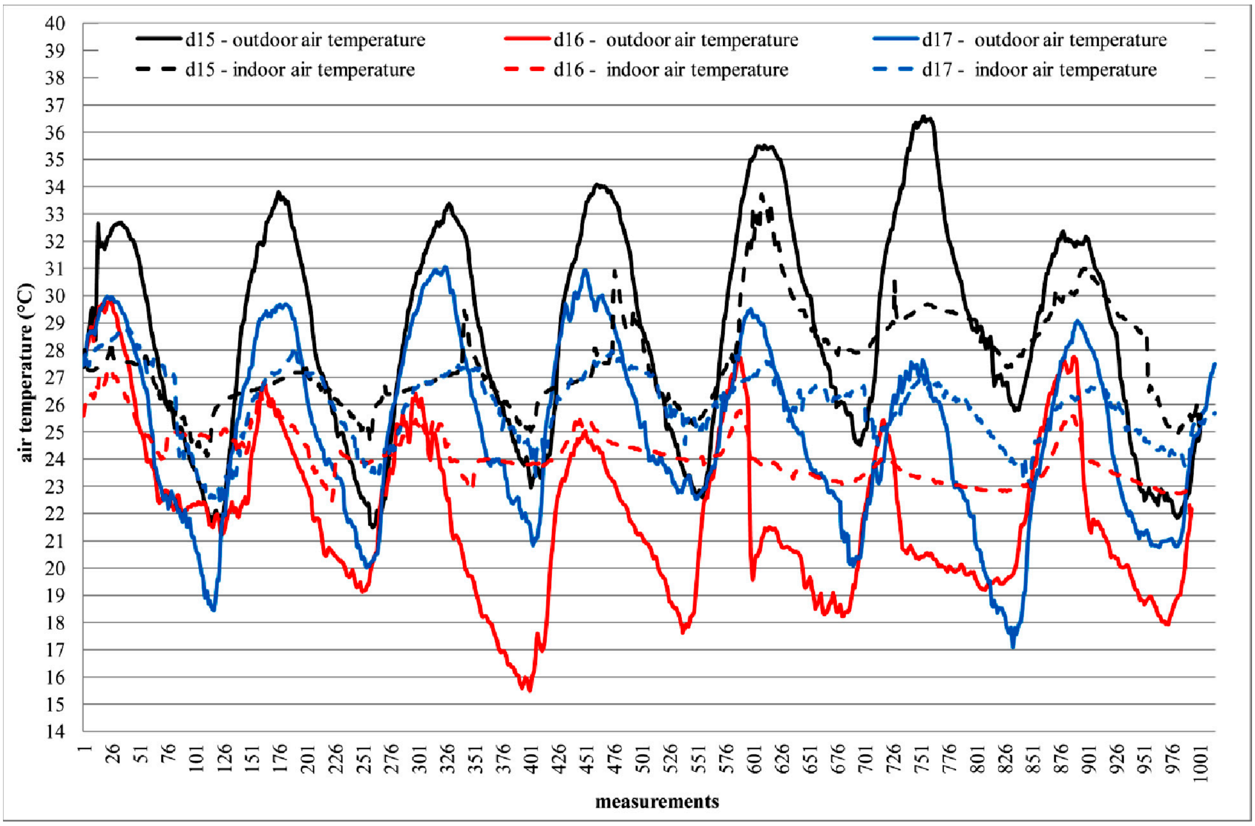
Table 1. Thermal characteristics of the investigated building opaque envelopes.

Dwelling	**Thickness s (m)**	**Thermal transmittance U (W/m²K)**	**Surface mass Ms (kg/m²)**	**Attenuation factor Fd (-)**	**Phase shift factor φ (h)**	**Periodic thermal transmittance ψ (W/m²K)**
d1	0.46	0.32	346.9	0.135	13.7	0.043
d2	0.46	0.32	346.9	0.135	13.7	0.043
d3	0.46	0.32	346.9	0.135	13.7	0.043
d4	0.47	0.29	330.7	0.114	14.7	0.033
d5	0.43	0.29	373.9	0.028	20.4	0.008
d6	0.53	0.26	365	0.071	17.3	0.019
d7	0.5	0.28	450	0.062	17.4	0.017
d8	0.43	0.39	374	0.08	17.5	0.031
d9	0.43	0.39	374	0.08	17.5	0.031
d10	0.43	0.44	414	0.113	16.3	0.049
d11	0.45	0.43	355	0.145	15	0.063
d12	0.45	0.43	355	0.145	15	0.063
d13	0.42	0.23	300	0.077	16.5	0.018
d14	0.42	0.23	300	0.077	16.5	0.018
d15	0.5	0.27	312	0.102	15.4	0.028
d16	0.5	0.27	312	0.102	15.4	0.028
d17	0.5	0.27	312	0.102	15.4	0.028

The experimental campaign allowed us to highlight this behavior for almost all the investigated dwellings. However, for three residential buildings (d15, d16, d17) a completely different behavior was monitored, probably due to the influence of solar radiation and transparent surfaces during experimental campaigns. The indoor and outdoor air temperature trend for the three residential buildings d15, d16 and d17 is shown in Figure 1: these three dwellings were investigated in July in three different weeks (the first one 8th–15th of July, the second one 22nd–29th of July and the third during 15th–22nd of July). For that reason the real measurement period was not reported in abscissa, but as the number of acquired data collected every 10 minutes.

For these dwellings the indoor air temperature is strongly influenced by outdoor air temperature despite the efficiency thermal behavior of opaque surfaces, due to effects of transparent surfaces. In fact these dwellings present very large transparent surfaces that involved a higher value of indoor air temperature than the other residential buildings. For that reason, these buildings were neglected for the training of the Neural Network. The other building (d13) was neglected for the training of the Network due to little available data with respect to the other sample data. Therefore, all the remaining buildings were provided for the training, validation, and preliminary test of Network, while the others (d13, d15, d16 and d17) were used for a further test of the developed Network.

Figure 1. Indoor and outdoor air temperature monitored in three buildings: d15, d16 and d17.



2.2. Artificial Neural Network Pattern

The Neural Networks are mathematical models that allow the simulation of the biological neural network behavior. Their most important feature is that ANN is not programmed but it is trained on the basis of experimental data [28–30]; the theory on which the Neural Network based on is already described in a previous study [15].

In this work, a three-layer feed forward Neural Network was trained by using Matlab programming language; the training process of the Network automatically stops when the generalization of Network stops improving, *i.e.*, when the mean square error of validation process tends to increase.

The Network was trained by using the Back Error Propagation method, which allows us to minimize the error modifying the connections' weights of a small amount, step by step. This is the common method used for training the ANN and it allows us to calculate the correction to be applied to the weight of i-th connection from the gradient of the Error Function (defined as the mean square error between the real output and the one simulated by the Network). Therefore this method allows us to calculate the gradient of this function with respect to all the weights of the Network.

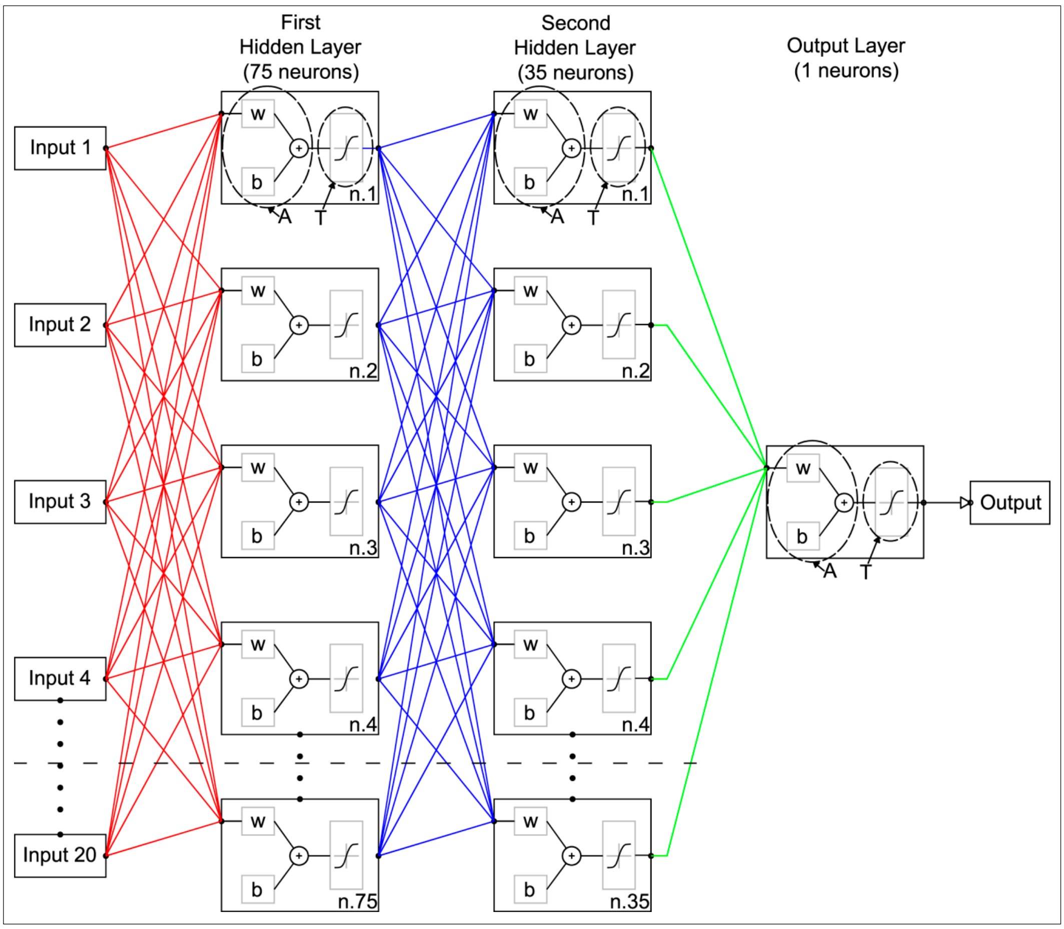
Both for the hidden layers and output one, a sigmoidal function was chosen as transfer function because it allows both to simplify the error's gradient calculation and to reduce the computational time required for the network training. The average error and the regression values of the training, validation, and testing were considered, in order to control the efficiency of the network.

For the two hidden layers, 75 and 35 neurons respectively were set; the neurons number was chosen based on many preliminary simulations in which the number of neurons was varied.

Specifically, two different analyses were carried out: in the first one, the neurons number of the second hidden layer was fixed while the one of the first hidden layer was varied. In this case, the best simulation was obtained with 75 neurons in the first hidden layer.

The next analysis was carried out by fixing 75 neurons in the first layer and by varying the ones in the second one. In this case, the best regression was obtained with 35 neurons in the second hidden layer. The ANN with 75 and 35 neurons in the first and in the second layers respectively provided the higher Global Regression value (0.9625) and lowest average error, despite a higher computational time for the training being required; the implemented ANN pattern is shown in Figure 2.

Figure 2. The implemented network pattern (A = activation function, T = transfer function, b = bias value, w = connection weight).



2.3. Input Data

The aim of the paper is to implement a feed forward Network in order to simulate the thermal behavior of the building's envelope during cooling period, considering the human interaction within the environments and the influence of transparent surfaces on indoor air temperature.

For this reason several input parameters were chosen to provide for the training of the network; specifically, the solar radiation, the thermal characteristics of buildings' envelope, the surface of investigated environment (A_{floor}), the mean transparent surface (A_g), and the thermal transmittance both of the frame (U_f) and of the transparent surfaces (U_g) were considered.

In order to properly train the network during the cooling period, the global (R_{gh}), direct (R_{dirh}) and diffuse (R_{difh}) solar radiation were provided on a horizontal surface; therefore, the orientation of the buildings (θ) was also set as input parameter. The environment floor level (f) was also provided for the training of network because it can be considerably influence the indoor air temperature during the cooling period; values equal to 0, 0.5 and 1 were considered for the ground, intermediate and attic floors respectively. All the input parameters provided to the Network were also normalized considering the maximum value for each parameter; this way, all the input data vary between 0 and 1. For the implementation of the Network the input data was split in different share for the three processes (training, validation and test); specifically, for the training, 70% of the input data was used, while the 15% of data for the validation and 15% for the test was provided.

The experimental data of the remaining buildings (d13, d15, d16 and d17) was used for a further test of the Network in order to evaluate the real efficiency of the implemented algorithm; specifically, the experimental data of the neglected dwellings (d15, d16 and d17) was influenced by solar radiation and by the large transparent surface. Therefore, an efficient Neural Network should simulate a lower indoor air temperature than the monitored one. In Table 2 the range of each input parameter provided for the training, validation, and test of the network are shown; this range represents the values' interval in which the reliability of the Network is very high.

Table 2. Range values of each training parameter provided for the training of Network.

Training parameter	Minimum value	Maximum value	u.m.
day	1	31	-
month	1	12	-
f	0	1	-
hour	0	23	h
R_{difh}	0	117.6	W/m^2
R_{dirh}	0	833.5	W/m^2
R_{gh}	0	940.4	W/m^2
θ	0	3.9	rad
outdoor air temperature	8	44.57	°C
s	0.42	0.53	m
U	0.231	0.437	W/m^{2}K
Ms	300	450	kg/m^2
f_d	0.028	0.145	-

Table 2. *Cont.*

Training parameter	Minimum value	Maximum value	u.m.
φ	13.67	20.37	h
ψ	0.008	0.063	W/m^2K
A_g	1.30	6.74	m^2
A_g/A_o	0.14	0.31	%
U_f	1.9	2.2	W/m^2K
U_g	1.3	2.8	W/m^2K
A_f	9.19	32.08	m^2
indoor air temperature	21.32	28.85	°C

3. Results

3.1. Training of the Artificial Neural Network

For the training of the network an average hourly value for each parameter was considered so that 1999 data for each input parameter was provided for the training of Neural Network. As a target parameter, the monitored indoor air temperature was chosen.

In order to evaluate the real efficiency of the Network and if it is well trained, several checks are necessary: the first one is to verify the trend of the air temperature simulated by the Network with respect to the monitored one, because it allows to control if the Network simulates correctly the indoor air temperature when solar radiation is present. The second one is to verify the mean error returned by the Network; specifically, it is important to check in how many cases the mean error is greater than a fixed value and what is its order of magnitude in each Network process (training, validation and test) and for each dwelling.

Figure 3 shows the comparison between the monitored indoor air temperature and the results of Neural Network training; for all the considered dwellings the average error between outputs of Neural Network and monitored air temperature is very low. For the dwelling d12, the average error is about of 1 °C. However, the network correctly simulates the main trend of the monitored indoor air temperature. The efficiency of the training of the network can be also shown by two control parameters: the first one is the mean error returned from the network, which is the difference between the monitored indoor air temperature (target) and the simulated one (output). Figure 4 shows the mean error returned from Network in the training, validation, and test; specifically, it highlights that the most likely error returned from the Network varies between −0.25 °C and 0 °C during training and validation, while during test it is in the range −0.5 °C–0.25 °C. This means that if new and different data is provided to the Network, the most likely returned error will be in the range −0.5 °C–0.25 °C, if the order of magnitude of data is the same of the ones provided for the training (Table 2). Figure 4 also highlights how, in only a few cases (about 0.7% of examined data), the error is greater than 1.5 °C and that in 97.3% of cases the error is less than 1 °C.

The mean error and the standard deviation of the air temperature simulated by the Network were also evaluated for each dwelling; specifically Table 3 shows the mean error and its standard deviation returned by the Network for each building and for each Network process (training, validation and test).

Considering all the processes, the mean error is always lower than 0.4 °C for all buildings, while the standard deviation is about ±0.4–0.5 °C, except for d12 (±0.7–0.8 °C).

However the mean errors returned by the Network are always lower than 1 °C, except in very few cases (lower than 1 %); so the Network can be considered well trained.

Figure 3. Comparison between monitored indoor air temperature and training results of Neural Network.

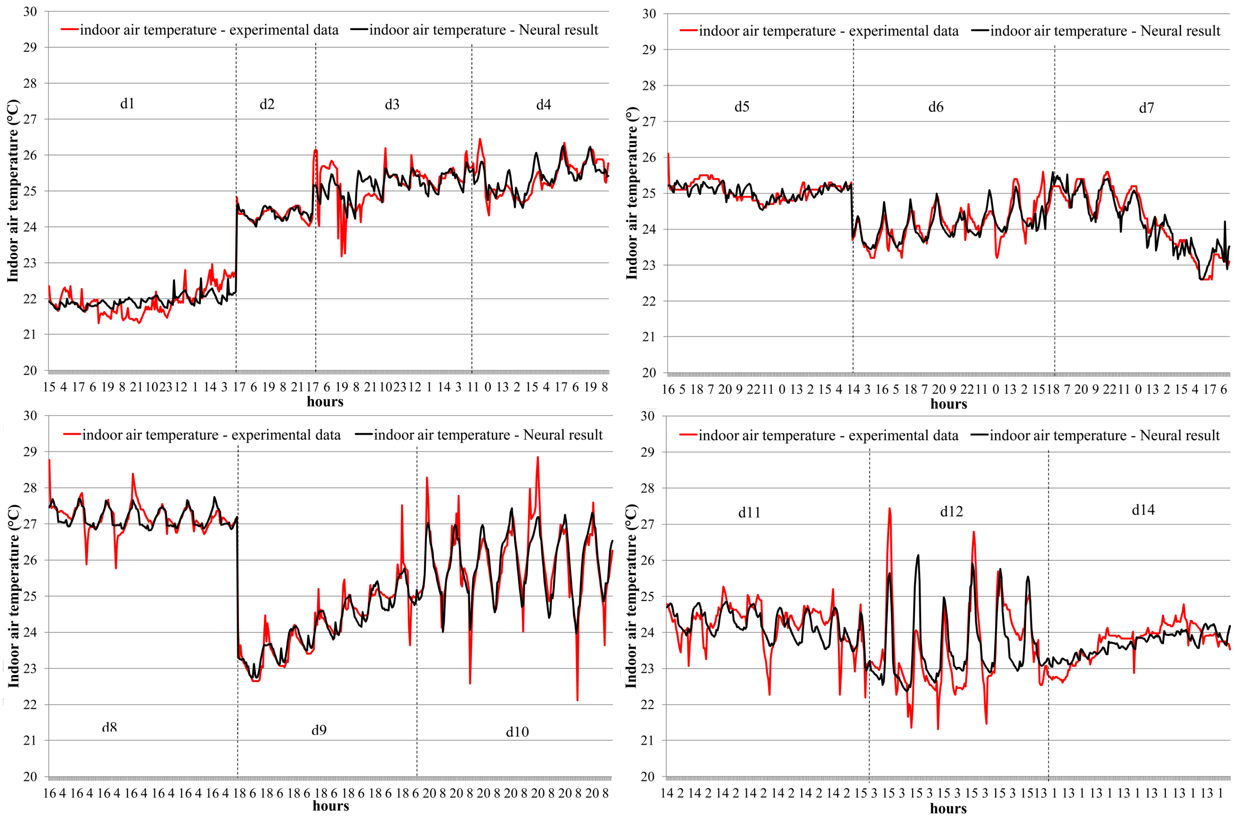


Figure 4. Histogram of errors returned from the Network for training, validation and test.

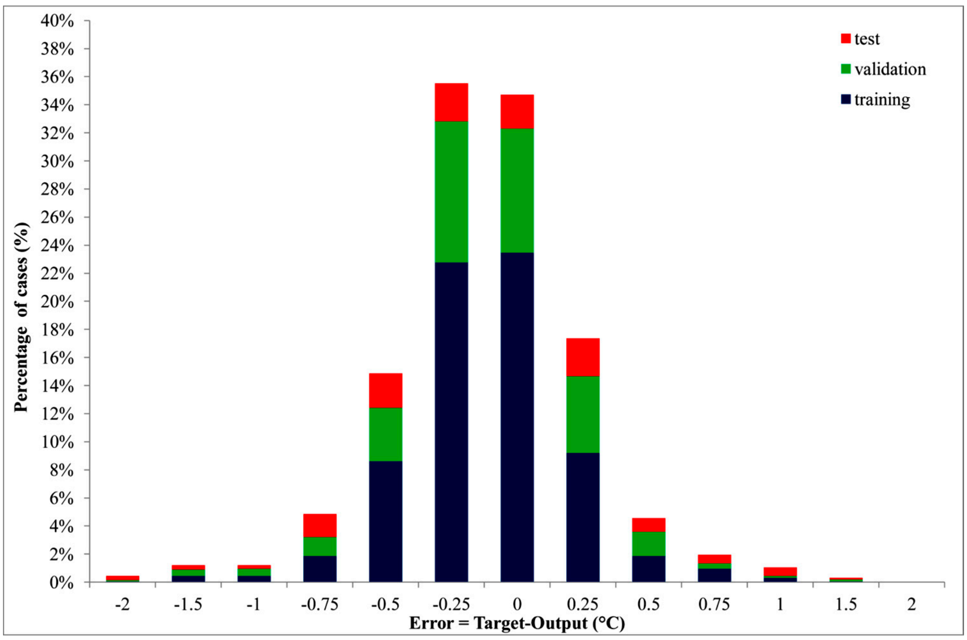


Table 3. Mean error and standard deviation of the simulated air temperature for each Network process and for each dwelling.

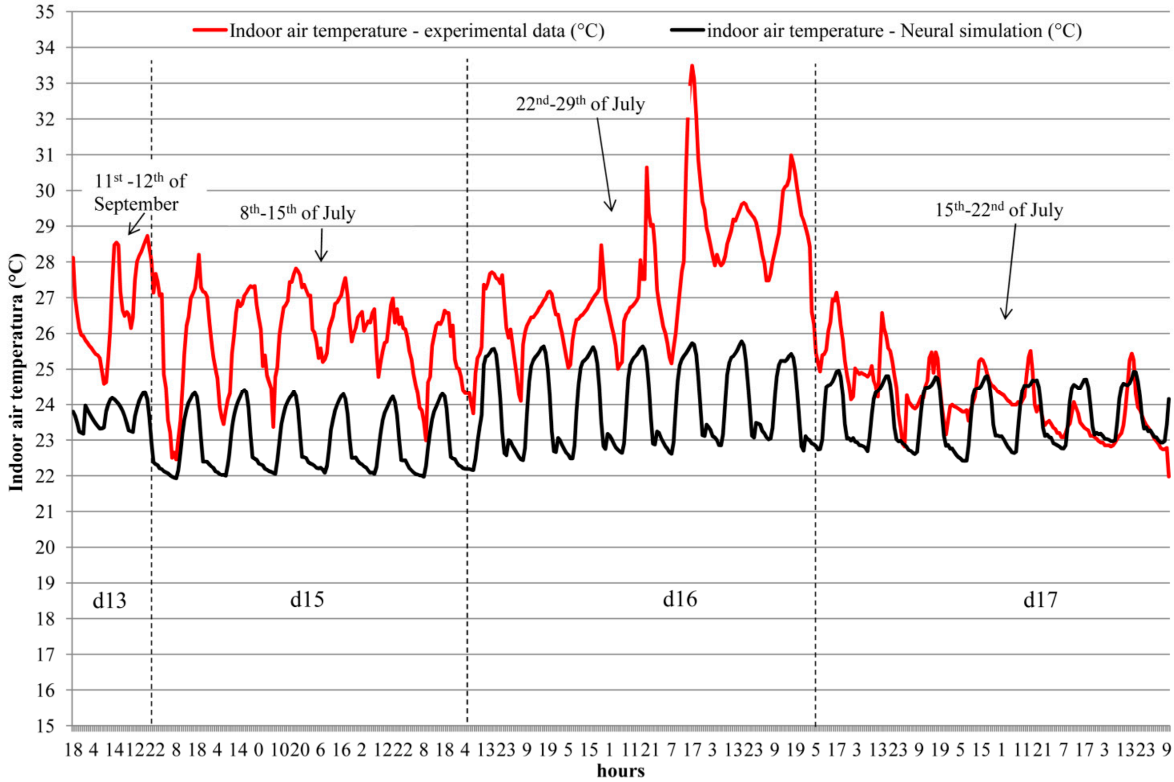
Dwellings	Mean error (°C)			Standard deviation (°C)		
	Training	Validation	Test	Training	Validation	Test
d1	−0.034	0.164	−0.010	±0.296	±0.351	±0.437
d2	0.010	−0.030	−0.071	±0.094	±0.113	±0.206
d3	0.022	0.284	−0.322	±0.322	±0.421	±0.590
d4	−0.056	0.064	0.004	±0.187	±0.249	±0.431
d5	0.035	−0.078	0.029	±0.192	±0.135	±0.205
d6	0.084	−0.057	−0.125	±0.283	±0.210	±0.431
d7	0.063	−0.139	−0.199	±0.274	±0.302	±0.305
d8	−0.006	0.069	0.063	±0.229	±0.162	±0.456
d9	−0.049	0.007	0.280	±0.226	±0.241	±0.514
d10	−0.049	0.366	−0.151	±0.458	±0.564	±0.410
d11	0.025	0.097	−0.055	±0.420	±0.494	±0.495
d12	−0.088	0.294	0.051	±0.787	±0.276	±0.693
d14	0.054	0.063	−0.153	±0.309	±0.283	±0.409

The second control parameter is the Regression value which measures the correlation between outputs and targets: more the value is close to 1 more a close relationship will be found. All the values obtained for these two control parameters are shown in Table 4. The implemented Network presents a very small average error (about 0.007 °C), with standard deviation of about ±0.387; besides, the Regression values obtained for the training, validation, and test are very high and about 0.96. A further test was carried out by using the ANN to evaluate the indoor air temperature in the remaining part of the investigated dwellings not used in the training step. The simulated temperature must be less than the monitored one because the monitored data was influenced by direct and diffuse solar radiation. In Figure 5 the simulated indoor air temperature of d13, d15, d16 and d17 is shown; the simulated trend is in agreement with the attendance of Network. A similar air temperature was obtained only for d17, but it depends on the particular external climatic conditions monitored during the experimental campaign.

Table 4. Evaluation of efficiency of Neural Network by using control parameters.

Control parameters	Values
Average error (°C)	0.007
Standard deviation	±0.387
$R_{training}$	0.9635
$R_{validation}$	0.9685
R_{test}	0.9511
R_{global}	0.9625

Figure 5. Comparison between monitored and simulated air temperature of d13, d15, d16 and d17 buildings.



3.2. Simulations of Innovative Solution Systems

Considering the thermal characteristics of the building envelope, innovative solutions were tested by using the implemented Neural Network, with the aim of improving the indoor air temperature and of reducing energy consumptions. Almost all the investigate dwellings present a higher value of thermal transmittance of the transparent surface. Therefore, with reference to previous works [6,24–26], two innovative glazing systems with aerogel in interspace were considered. The same thickness of 0.022 m for both glazing systems were considered and the thermal transmittance values for each transparent surface was calculated:

- DGG: double glazing with granular aerogel in interspace (Ug = 0.91 W/m^{2}K);
- DGM: double glazing with monolithic aerogel in interspace (Ug = 0.63 W/m^{2}K).

In Figure 6, the comparison between the monitored indoor air temperature, the simulated temperature with ANN considering the real transparent surface and these two new innovative solutions are shown.

In all dwellings, the new innovative solutions allowed to decrease the indoor air temperature of about 1–2 °C, in agreement with previous a work [6] in which the energy performance of a residential buildings was simulated using two different dynamics software; the agreement of the results with two different dynamic software types also proves the real efficiency of the training and especially the generalization of the Network that, therefore, can be used for the test of new engineering solutions on buildings' envelopes.

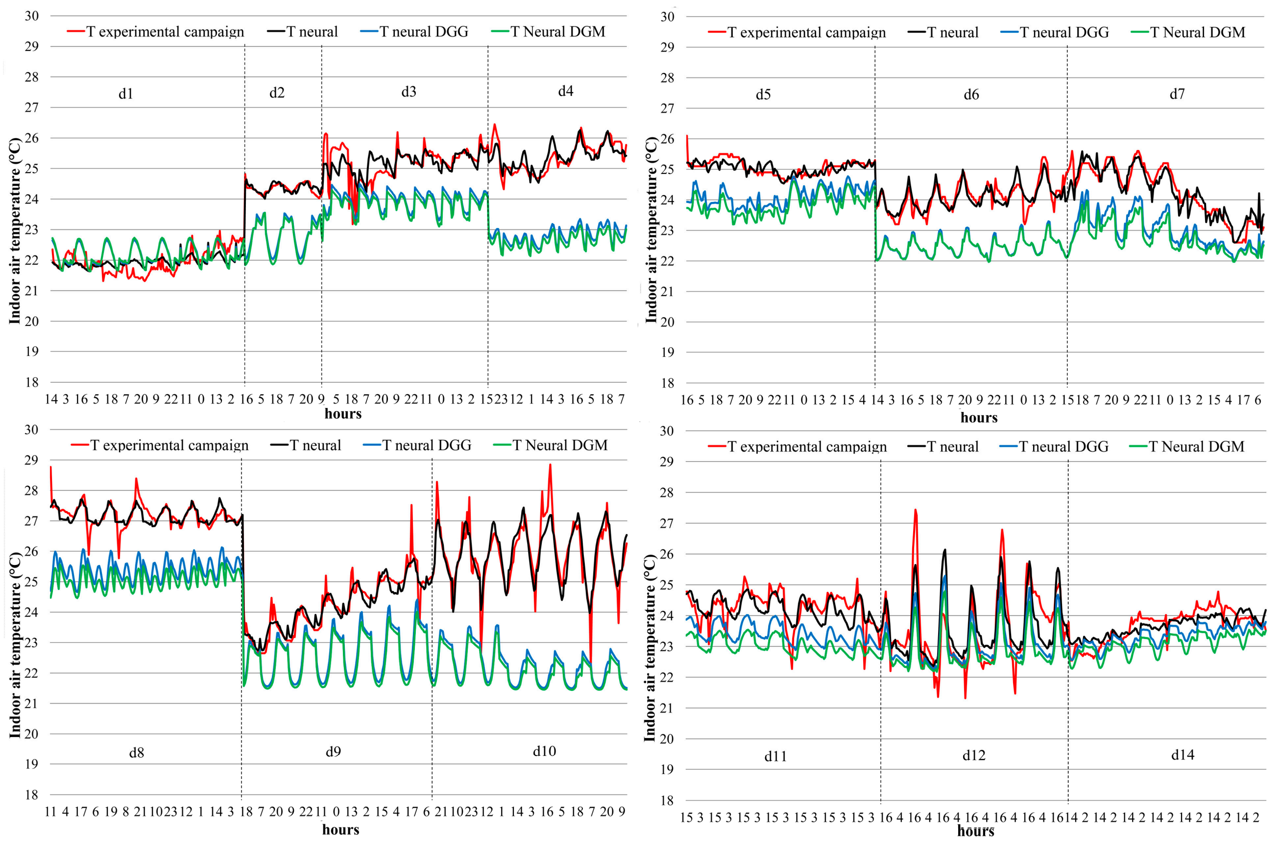
The comparison between the monitored temperature and the simulated one is also shown in Table 5; in particular, the mean values and the standard deviations are reported for each solution and dwelling.

The two innovative glazing systems allow us to decrease the mean temperature value in almost all the investigated dwellings of an average value of 1.5 °C. The temperature range is also decreased ensuring a more uniform temperature field within the environments.

Table 5. Mean indoor air temperature and standard deviation for different kind of glazing systems.

Dwellings	Mean temperature (°C)			Standard deviation		
	Existing glazing	DGG	DGM	Existing glazing	DGG	DGM
d1	21.9	22.2	22.2	±0.4	±0.3	±0.3
d2	24.3	22.8	22.7	±0.2	±0.5	±0.5
d3	25.2	24.0	23.8	±0.5	±0.3	±0.3
d4	25.4	22.8	22.6	±0.5	±0.3	±0.2
d5	25.1	24.1	23.8	±0.2	±0.3	±0.4
d6	24.1	22.5	22.4	±0.5	±0.3	±0.3
d7	24.3	23.0	22.8	±0.9	±0.6	±0.5
d8	27.2	25.4	25.1	±0.4	±0.3	±0.3
d9	24.2	22.6	22.5	±0.9	±0.8	±0.7
d10	25.9	22.2	22.1	±1.0	±0.6	±0.5
d11	24.2	23.4	23.0	±0.5	±0.3	±0.3
d12	23.6	23.1	22.9	±1.2	±0.7	±0.6
d14	23.7	23.3	23.1	±0.5	±0.3	±0.3

Figure 6. Comparison of monitored indoor air temperature with the ones simulated with Neural Network using innovative glazing systems.



4. Conclusions

In the present paper, many different residential buildings were investigated in order to evaluate the envelope performance; the dwellings are recently built and have very low energy consumptions.

All the thermal characteristics of the building envelope and the outdoor and indoor climate conditions were available in each dwelling for at least one week [27]. Based on these data sets, a Multilayer feed forward Network was trained in order to simulate the thermal performance of buildings envelope and to test new glazing solutions [6,24–26].

In order to evaluate the efficiency of the network, two different parameters were considered: the regression value and the mean error. A good training of Network was obtained, with a very small average error (about 0.007 °C) and a high regression value (about 0.96). Considering data used for the test and the results returned by the Network, the efficiency of the trained network is also highlighted: this case the error returned by the network is very small, in the −0.5 °C–0.25 °C range.

The implemented Neural Network was used to evaluate the indoor air temperature in the dwellings not used for the training; the simulated temperature from the Network was lower than the monitored one but it is in agreement with the attendance of the Network, considering that the experimental data was influenced by solar radiation and by large transparent surfaces.

Whereas the transparent surfaces represent the weakness of buildings envelope of almost all dwellings, the trained Network was also used to test new and innovative glazing systems, such as double glazing systems with monolithic and granular aerogel in interspace were considered (DGM, DGG).

The two innovative glazing systems allow to decrease the mean indoor temperature values in almost all the investigated dwellings of an average of 1.5 °C and to obtain a more uniform temperature field within the environments.

The results obtained in this work highlight how the ANN could be an alternative, interesting, speedy, simple, and useful tool for evaluating the thermal performance of building envelope and to evaluate the performance of new engineering solutions. The tool should be used for the preliminary or for renovation designs of buildings in order to test the efficiency of innovative solutions.

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Author Contributions

Authors equally contributed to the experimental campaigns, the Neural Network implementation, and the writing of the paper.

Conflict of Interest

The authors declare no conflict of interest.

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