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Artificial Neural Network for the Thermal Comfort Index Prediction: Development of a New Simplified Algorithm

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Abstract: A simplified algorithm using an artificial neural network (ANN, a feed-forward neural network) for the assessment of the predicted mean vote (PMV) index in summertime was developed, using solely three input variables (namely the indoor air temperature, relative humidity, and clothing insulation), whilst low air speed (<0.1 m/s), a minimal variation of radiant temperature (25.1 °C ± 2 °C) and steady metabolism (1.2 Met) were considered. Sensitivity analysis to the number of variables and to the number of neurons were performed. The developed ANN was then compared with three proven methods used for thermal comfort prediction: (i) the International Standard; (ii) the Rohles model; (iii) the modified Rohles model. Finally, another network able to predict the indoor thermal conditions was considered: the combined calculation of the two networks was tested for the PMV prediction. The proposed algorithm allows one to better approximate the PMV index than the other models (mean error of ANN predominantly in ±0.10–±0.20 range). The accuracy of the network in PMV prediction increases when air temperature and relative humidity values fall into 21–28 °C and 30–75% ranges. When the PMV is predicted by using the combined calculation (i.e., by using the two networks), the same order of magnitude of error was found, confirming the reliability of the networks. The developed ANN could be considered as an alternative method for the simplified prediction of PMV; moreover, the new simplified algorithm can be useful in buildings' design phase, i.e., in those cases where experimental data are not available.

Keywords: artificial neural networks; thermal comfort; predicted mean vote calculation; indoor thermal conditions; clothing insulation

1. Introduction

Buildings' design or energy retrofit interventions face two challenges: low energy consumption and thermal comfort conditions, both requiring a deep analysis of the building features and of the installed heating, ventilation and air conditioning (HVAC) system.

While buildings' energy consumption can be evaluated by using different approaches and methods, which can lead to very close results, the available methodologies for thermal comfort evaluation can lead to greatly different results, since it depends on the people and on their subjective thermal perception of the environment.

Is it possible to apply artificial intelligence to thermal comfort problems? If so, does it allow one to accurately predict the thermal comfort indexes, compared to common methodologies? In this case, is it possible to reduce the input variables needed to estimate the indexes? Is this kind of artificial neural network (ANN) able to predict the thermal comfort inside a building before its realization, i.e., in the building design phase? These are the research questions that motivated this work and have been answered by developing an ANN for the predicted mean vote (PMV) assessment in summertime, using solely three input variables which can be derived from in-situ monitoring campaign or from another ANN. Results have been compared with those from common methods used in this field.

The novelty of this work relies in the possibility of PMV calculation inside a building both before and after its realization. The paper is organized as follows: Section 2 describes the research background; Section 3 presents the employed methodology; Section 4 presents the experimental campaign; Section 5 is devoted to the ANN description (development and generalization processes); results are shown and discussed in Section 6; finally, conclusions are highlighted in Section 7.

2. Research Background

According to the ISO 7730 regulation [1], based on Fanger's thermal comfort static model, the comfort conditions can be evaluated by calculating two empirical indexes: the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD). While the PPD depends solely on PMV value, the PMV index requires the resolution of complex Equation (1) with several input variables. The PMV depends in fact on: the metabolism (M), the effective mechanical power (W), the water vapor partial pressure (p_a), the indoor air temperature (Ta), the clothing area coefficient (f_{cl}), the clothing surface temperature (T_{cl}), the mean radiant temperature (T_{mr}), and the convective heat transfer coefficient (h_c). The expression for PMV is shown in Equation (1):

$$\begin{aligned} \mathrm{PMV} = {} & [0.303 \cdot \exp(-0.036 \cdot \mathrm{M}) + 0.028] \cdot \{(\mathrm{M}-\mathrm{W}) - 3.05 \cdot 10^{-3} \cdot [5733 - 6.99 \cdot \\ & (\mathrm{M}-\mathrm{W}) - \mathrm{p_a}] - 0.42 \cdot [(\mathrm{M}-\mathrm{W}) - 58.15] - 1.7 \cdot 10^{-5} \cdot \mathrm{M} \cdot (5867 - \mathrm{p_a}) - 0.0014 \cdot \mathrm{M} \cdot (34 - \\ & \mathrm{t_a}) - 3.96 \cdot 10^{-8} \cdot \mathrm{f_{cl}} \cdot [(\mathrm{T_{cl}} + 273)^4 - (\mathrm{T_{mr}} + 273)^4] - \mathrm{f_{cl}} \cdot \mathrm{h_c} \cdot (-\mathrm{T_a})\}, \end{aligned} \tag{1}$$

The international ISO 7730 standard [1] allows the PMV calculation through a step by step procedure [1]. The PMV index requires the monitoring and acquisition of the following variables: indoor air temperature, air velocity, relative humidity, and globe thermometer temperature. Besides, other values should be fixed according to both the kind and the level of people's activity carried out within the investigated environment (metabolism, clothing insulation, and effective mechanical power).

ISO 7730 [1] can be used with both experimental and simulated data, but, as shown in [2–5], the PMV calculated using experimental data can differ from the simulated one due to the calculation approximations of the main variables (such as the mean radiant temperature, indoor air velocity, and so on).

Many authors have developed other methods for PMV prediction based on the adaptive approach [5–13], and shown that the thermal comfort sensation evaluated in this way (which requires for instance questionnaire compilation by the building occupants) could lead to thermal comfort values varying in a much wider range than the ones obtained according to ISO 7730 [1]. However, when energy retrofit or energy design of a building is carried out, this kind of approach cannot be used.

An interesting method was proposed by Rohles in [14], (in the following is referred to as Rohles model—A), where the PMV index was evaluated by using a simplified equation starting from the indoor air temperature, the water vapor partial pressure, and by considering three constant coefficients, as shown in Equation (2) [14]:

$$\mathrm{PMV} = \mathrm{a} \cdot \mathrm{T_a} + \mathrm{b} \cdot \mathrm{p_a} - \mathrm{c} \qquad \text{valid only for } \mathrm{I_{cl}} = 0.60 \text{ clo} \tag{2}$$

The method provided results very close to the ones returned by [1], but it was developed and valid only for a fixed value of the clothing insulation (I_{cl}), equal to 0.6 clo. Therefore, its application for different I_{cl} values was not recommended.

Starting from this issue, in [15] a modified Rohles model was proposed (from hereinafter called Rohles model—B) where simplified equations and different values of the three coefficients (see Table 1 [14,15]) were proposed, in order to extend the Rohles model for different I_{cl} values.

Table 1. Coefficients a, b, and c for the application of the Rohles models for different range value of I_{cl} [14,15].

	Rohles Model—A			**Rohles Model—B**								
	I_{cl} = 0.60 clo			**I_{cl} = 0.25–0.50 clo**			**I_{cl} = 0.51–1.00 clo**			**I_{cl} = 1.01–1.65 clo**		
	a	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**
Male	0.220	0.233	5.673	0.263	0.266	0.280	0.116	0.242	0.138	0.15	−0.167	2.512
Female	0.272	0.248	7.245	0.303	0.107	0.172	−0.134	0.061	0.027	0.149	−0.106	2.641
Both	0.245	0.248	6.475	6.807	6.723	7.138	2.201	5.587	3.019	0.148	−0.137	2.524

The main advantages of both Rohles models—A and B is the possibility of using them with both experimental and simulated data. They only require knowledge of the indoor air temperature and water vapor partial pressure (the latter depending on relative humidity and indoor air temperature [1]), that can be easily measured or simulated with a good approximation by simulation software (such as TRNSYS [4], Energy Plus [4], and so on).

Other simplified methods were developed by using different approaches such as the artificial neural networks (ANNs) which are very useful and common in engineering applications and in many different fields [16]. The main issue of the ANN is related to the generalization of networks which are not always possible [16]; for instance, the thermal comfort is strongly linked to the thermal sensation perceived by the occupants that, being subjective, is difficult to be predicted. In that case, a very good accuracy of network is not always reached [16].

Many works [17–47] related to thermal comfort propose a feed-forward neural network. Specifically, a fitting neural network (FNN) is considered, allowing the prediction of one specific variable (output) on the basis of thousands of input data. In these papers, the ANNs were trained by using experimental or simulated data, such as in [21] and in [34].

In [21] a radial basis network for calculating the PMV index was trained by providing three variables (air temperature, the mean radiant temperature and the relative humidity) whose values were randomly generated into specific ranges. In [26] a lot of input variables were instead provided for the implementation of network (minute, hour, day, month, occupancy, relative humidity, pool water temperature, room temperature, air temperature and supplied air flow rate) while PMV index was the output. In [29] the following input variables were provided as input: sol-air temperature (°C), wind speed (km/h), outdoor relative humidity (%) and the time of day (0–23). The measured indoor dry-bulb temperatures were instead the output. Obtained RMSE was equal to 1.76 °C meaning that 75% and 92% of the predicted indoor dry-bulb temperatures had the error less than ±2 °C and ±3 °C, respectively. In [33] an ANN able to simulate the energy consumptions as a function of the ambient air temperature (Ta), and three operating frequencies of the ACMV system was trained. The regression values were higher than 0.999 in each process with a mean error in −0.0068 and 0.0079 range. In [34] an ANN vas developed by using 18 input characteristic parameters (variables) for simulating the percentage of discomfort hours. A regression value of about 0.94 was obtained with a relative error mainly between in ±5% range with respect to the one calculated by Energy Plus. This error was found for a percentage of cases equal to 79% of the sample data, while, considering all the sample data this value increases up to ±25%. In [35], instead, an ANN was trained for predicting the thermal sensation by providing four input parameters (air temperature, relative humidity, clothing insulation and metabolic rate). In this case the regression value was of 0.74. In [36] a feed forward neural network model was trained by using all the variables needed for the calculation of PMV index [1]. In [38] the air temperature, relative humidity, mean radiant temperature, air velocity, metabolic rate and clothing index were used as the input of neural network and PMV as the output of the neural network.

The results show that this prediction approach was very effective and had higher accuracy with an absolute error below 5%.

It is worth noting that good regression values were always found in the training and validation processes (i.e., when both the input and target data were provided to the network). Besides, in these papers, the networks were implemented by providing a lot of input variables, especially the ones trained for predicting only the PMV index (except for [21] where another kind of network was trained). On the other hand, considering the number of variables required for the use of ANN developed in all the other works, such methods lack of ease of use.

Research Gap

Based on these premises, it is evident that the artificial neural networks could be an interesting method for the thermal comfort prediction, but they could be as much useful to elaborate a simplified procedure to be used as alternative method to the one provided by the International Standard [1].

Therefore, this work is proposed starting from the following considerations:

- the PMV calculation follows a quite complex procedure, requiring a lot of monitored data inputs;
- the Rohles model—A is recommended only for a specific I_{cl};
- the Rohles model—B was tested only for thermal comfort in school buildings;
- works implementing a Fitting Neural Network able to predict only the PMV index used the same parameters required by ISO 7730 [1] or as much variables as possible, as in [26,34,35], so the ANN lacks the ease of use.

Hence, in this paper a new algorithm able to predict the PMV starting from only three input variables is presented. Regarding the other variables, a low air speed (<0.1m/s), minimal variation of radiant temperature (25.1 °C ± 2 °C) and steady metabolism (1.2 Met) were considered.

Such an algorithm could be an alternative to the method proposed in ISO 7730 [1], so it can be used in building design or energy retrofit of existing buildings, when experimental data are not yet available.

Particularly, the simplification adopted does not aim to ease the mathematical expression of the phenomenon, but to simplify the number and type of variables to be monitored for this application. This implies that the monitoring campaign can be carried out without the need of complex or expensive equipment, and without specific expertise. Therefore, the algorithm relies on some hypotheses, allowing an easier design phase for engineers and technicians.

Moreover, it is reasonable to suppose that, in the near future, evaluations and considerations on the PMV will be requested in the design phase by Italian law. Therefore, tools and methods able to predict, with good accuracy, this index could be of help.

The research procedure was elaborated to maximize the accuracy of the algorithm in training, validation, and testing processes. In order to test the accuracy of the new algorithm, it was compared to:

(1) the method proposed by ISO 7730 [1]: it represented the valid standard method;
(2) the Rohles model—A [14]: it was as good and simplified method which could be applied for I_{cl} values equal to 0.6 clo;
(3) the Rohles model—B [15]: it was the modified Rohles model—A which could be applied for different values of I_{cl}.

The choice of comparing the ANN results to the Rohles models (A and B) lies in the fact that these methods allow to calculate the PMV index by using only three input variables. Therefore, this comparison would have the aims to verify the reliability of the simplified algorithms, i.e., Rohles model—A, Rohles model—B, and the proposed ANN, in the PMV prediction with respect to the common method [1].

Finally, it is possible to combine the ANN proposed in the present paper with the ANN implemented in a previous work [31], with the aim of predicting both the indoor thermal conditions and the thermal comfort sensation without using experimental data but providing only design data.

The developed ANN could be considered as an alternative method for the simplified prediction of PMV and it can be useful in buildings' design phase, i.e., in those cases where experimental data are not available.

The novelties of the paper consist in:

(1) PMV prediction by providing only three variables: indoor air temperature, relative humidity and insulation of clothing;
(2) Combined calculation: the developed ANN can be combined with another one able to predict the indoor environmental conditions within the rooms. This other network was studied and trained in [31], and it is able to predict the indoor thermal conditions within the room by considering the outdoor conditions and the thermal characteristics of the building envelope [31]. Therefore, the combined calculation with the newly developed ANN would allow to calculate both indoor thermal conditions and the PMV index in buildings' design phase.

3. Methodology

The aim of the paper is to develop a new algorithm able to predict the main thermal comfort index (PMV) during the summertime, by implementing a new Artificial Neural Network (referred to as $ANN_{comfort}$). The algorithm should be able to:

- predict the PMV index by providing only few input variables;
- predict the PMV index by using the output simulated by another ANN developed in a previous work [31] (the use of the two networks together is called combined calculation).

The research procedure elaborated and adopted in this work is described below and shown in Figure 1:

(1) Experimental Campaign (on the top of the Figure 1): during the experimental campaign lasting at least one week for each apartment, both indoor and outdoor data were monitored and acquired
(2) PMV calculation (left side of the Figure 1—black arrows): indoor data from 18 apartments was used for the PMV calculation, according to Standard [1], and according to the Rohles models (both Rohles model—A and Rohles model—B). The I_{cl} values were established according to the monitored period, as already described in [40]. Specifically, two different configurations for men and women were chosen, taking into account the outdoor and indoor thermal conditions of each apartment:
    (1) for the ones investigated at the end of springtime or at the beginning of summertime:
        (a) men configuration: slip, t-shirt, sleeves, normal trousers, socks and shoes;
        (b) women configuration: panties and bra, normal sleeves, normal skirts, socks and shoes;
    (2) for the ones investigated in the mid of summertime:
        (a) men configuration: slip, light-weight sleeves, light-weight trousers, socks and shoes;
        (b) women configuration: panties and bra, light-weight sleeves, light-weight skirts, socks and shoes.
(3) Artificial Neural Network implementation (central box of Figure 1—dashed blue line): as described, the purpose of the paper is the implementation of a new simplified method for the PMV calculation. This section represents the core of the work, where the experimental data was used for the $ANN_{comfort}$ development. The needed variables were chosen amongst those required for the PMV calculation (see Equation (1) according to [1]). Those chosen ones were:
    (a) indoor air temperature;

(b) air relative humidity;
(c) clothing insulation.

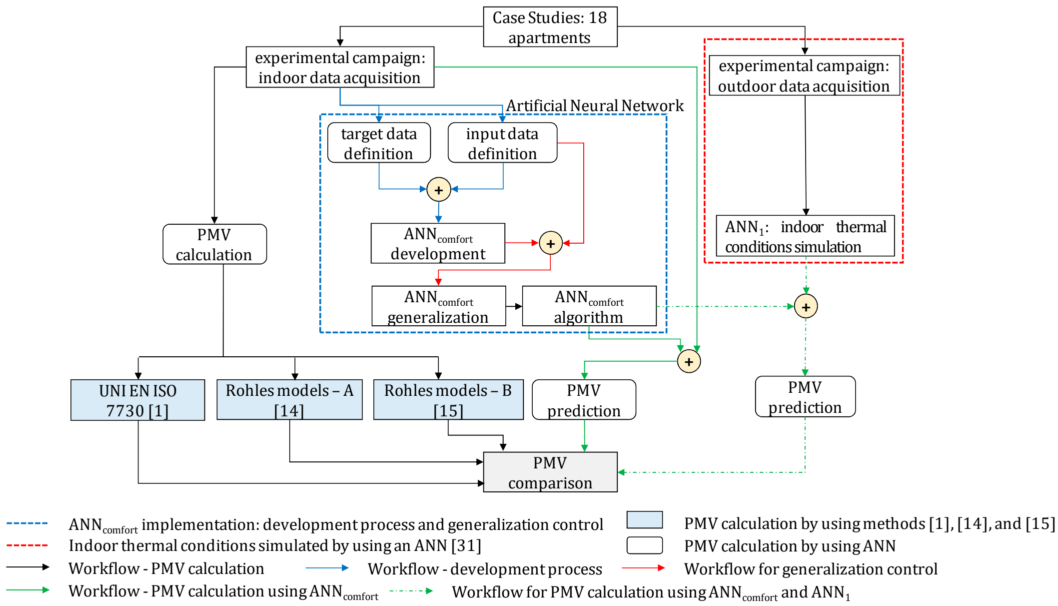

Figure 1. Research procedure adopted for the development of Artificial Neural Network able to simulate the main thermal comfort index (PMV).

Considering that:

(i) indoor air temperature and its relative humidity can be easily measured and logged, whilst clothing insulation should be evaluated based on the performed activity within the room and on the investigated period;
(ii) in [14,15] it was proven that the thermal comfort sensation can be evaluated with a very good approximation by monitoring less variables than the ones required by International Standard 1 (in [14,15] the PMV values was evaluated by providing only the indoor air temperature and the water vapor partial pressure, while the other boundary conditions were set to constant values);
(iii) the values of air velocity varied in such a small range, predominantly between 0.00 and 0.10 m/s (more than 98% of air velocity data falls in this range) that this variable, if considered, could lead to a poor ANN development as also stated in [28,30,31] therefore, it has been neglected for the implementation of ANN;
(iv) the metabolism was established according to the activity level and to previous paper [40], and it was assumed for all the apartments equal to 1.2 met. The lack of variation of this variable could lead to a poor development of ANN, too. Therefore, also the metabolism, has been neglected for the implementation of ANN; only three variables (indoor air temperature, air relative humidity, and clothing insulation) were chosen as input parameters to be provided for the development process of network.

With reference to Figure 1, the ANN implementation consisted in two main processes, namely:

- ANN development (blue arrows): it includes the training, validation, and test of the ANN$_{comfort}$ starting from indoor experimental data of 13 apartments;
- ANN generalization (red arrows): reliability assessment of the developed network by using data of the remaining five apartments.

In detail, the ANN$_{comfort}$ implementation entailed:

- Development process (divided in training, validation and testing processes as described in the Theory [48]), that was carried out as follows:
  - A multilayer perceptron (MLP) neural network was adopted as pattern of the ANN with only one hidden layer, as in other previous works [16–39];
  - Input and target data were provided for its implementation, particularly:

  (i) indoor air temperature and relative humidity data monitored in 13 apartments (the same used for the same process in [31]) were provided as input variables (70% for training, 15% for validation, and 15% for testing processes) [31];
  (ii) I_{cl} values were varied between 0.25 clo to 1.6 clo with step of 0.15 clo and they were provided as input variables: this choice was due to the aim of the paper, that is to develop an alternative method, therefore it is important to train the network with different I_{cl} values in order to obtain a good generalization of network;
  (iii) the PMV index, calculated according to [1] and by setting the I_{cl} values considered in step (ii), was provided as target;

  - A sensitivity analysis was also performed in order to establish the best number of neurons to be used within the hidden layers of the network.
  - The best artificial neural network was chosen considering the highest regression value and the lowest mean error.

- Generalization process [48]: the reliability of the best ANN was checked by providing data not used in the development process (i.e., data of the remaining 5 apartments). Only the input variables were supplied to the network; $ANN_{comfort}$ results were then compared with those from [1] for calculating the error and, therefore, the ANN reliability. Particularly:
  - indoor air temperature and relative humidity data monitored in the remaining 5 apartments were provided as first and second input variables;
  - Icl values were varied between 0.25 clo to 1.6 clo with step of 0.15 clo, and were provided as third input variable;
  - the PMV index, calculated according to [1] and by setting the Icl values considered in step (ii), was used for comparison with the one simulated by the network;

In order to give the same weight to each input variables in the implementation process, both input and target data (X) were normalized ($x_{normalized\text{-}value}$) by applying the Equation (3):

$$x_{normalized-value} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

(4) PMV prediction (central and right side of the Figure 1): once fully implemented, the term $ANN_{comfort}$ was used for the PMV calculation starting from:

  (i) indoor experimental data and I_{cl} values (solid green arrows in Figure 1);
  (ii) indoor thermal conditions simulated by means of the ANN_1 developed in [31] by using the outdoor experimental data (dashed red box—dashed green arrows in Figure 1). Outdoor monitored data, together with design data (i.e., solar radiation, apartments floor, thermal characteristics and thickness of opaque and semitransparent surfaces, and so on [40]), was input into an artificial neural network (ANN_1) developed in a previous work [31] for the indoor thermal condition prediction. The indoor thermal conditions resulting from ANN_1 were then used into the $ANN_{comfort}$ algorithm to calculate the PMV. In this way, the two networks have been coupled.

(5) PMV comparison (bottom of the Figure 1): finally, the PMV comparison was carried out to assess the differences between results from $ANN_{comfort}$ with respect to the other available approaches. Therefore, the comparison involved the PMV index calculated by applying:

(a) the calculation equation provided by the international standard ISO 7730 [1];
(b) the Rohles model defined in [14] (Rohles model—A);
(c) the modified Rohles model defined in [15] (Rohles model—B);
(d) the trained $ANN_{comfort}$ having respectively as input data:

(i) the indoor thermal conditions monitored during the experimental campaigns;
(ii) the indoor thermal conditions simulated by applying the ANN_1 trained in [31].

It is worth specifying at this point that information on the building features does not compromise nor influence the results of the proposed PMV algorithm. Particularly, results from $ANN_{comfort}$ do not depend on geographical data, building and HVAC characteristics, etc. Therefore, results can be considered "scalable". On the contrary, results derived from the application of ANN_1 might be affected by those features. This depends on the specific development of ANN_1, adopted in the previous work (where the same buildings were studied).

It is worth noting that the employed methodologies for the PMV calculation require different input data, which in turn might be derived quantities. Figure 2 shows the complexity of each method and the amount of data required for PMV calculation. As shown, the International Standard method—ISO 7730 [1] allows to calculate the PMV index from a big amount of data and equations resolution (continuous and dashed black lines). On the contrary, other models (Rohles model—A—solid orange line, Rohles model—B—solid red line, and $ANN_{comfort}$ algorithm—solid blue line) allow to simulate the PMV index with a good approximation but using a simplified method (two monitored input data plus the I_{cl} value). Finally, the combined method ($ANN_{comfort\_ANN1}$—solid green line) allows to simulate the PMV index starting from simulated input data (the outputs simulated by ANN_1 [31]), therefore it can be suitable for building design or energy retrofit evaluation when the experimental surveys are not available.

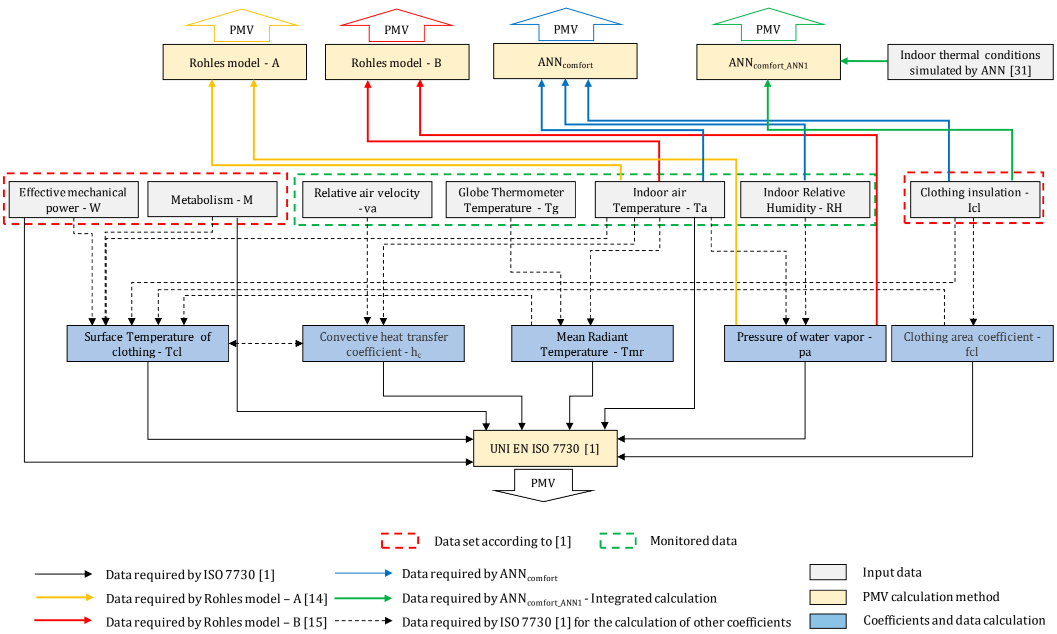

Figure 2. PMV calculation: comparison of the different approaches' calculation.

4. Experimental Campaign

For the experimental campaign, 18 different apartments in nine buildings, previously described and investigated in [31] and [40], were considered as case studies. All these buildings, located in the Umbria Region (Central Italy), were built with innovative materials and with new construction technologies, including green technologies and sustainable solutions. They were selected with the twofold aim of evaluating both the efficiency of new design solutions and the thermal comfort sensation. As seen before, the employed methodology does not depend on the building features nor on the construction technology, which however are available in [40]. The monitoring was carried out in summertime (2012), at least one week for each of the 18 apartments. Both indoor and outdoor data were monitored and acquired employing microclimatic probes linked to a BABUC C/M, 12-inputs acquisition system manufactured by LSI. Technical specification on the employed equipment is provided in Table 2.

Table 2. Technical specification of the equipment employed for the experimental campaigns.

Measurement Equipment	Measurement Range	Accuracy
Pressure probe mod. BSP002	800 hPa–1100 hPa	±1 hPa
Air temperature probe mod. BST101	−50 °C–80 °C	±0.15 °C
Anemometric probe mod. BSV105	Air velocity: 0–20 m/s Turbulence intensity: 0–100%	±5 cm/s for 0 < v < 0.5 m/s ±10 cm/s for 0,5 < v < 1.5 m/s ±4% for v >1.5 m/s:
Globe Thermometric probe mod. BST 131	−40 °C–80 °C	±0.17 °C
Psychrometric probe mod. BSU104	Temperature: −5 °C–60 °C Relative humidity: 0–100%	Temperature: ±0.13 °C Relative humidity: ±2%
TinyTag Ultra 2 TGU-4500	Temperature: −25 °C–85 °C Relative humidity: 0–95%	Temperature: ±0.4 °C Relative humidity: ±3.0%
TinyTag Plus 2 TGP-4500	Temperature: −25 °C–85 °C Relative humidity: 0–100%	Temperature: ±0.4 °C Relative humidity: ±3.0%

According to the methodology already described in the previous section, monitored variables were used to train all the networks and in order to predict only one output (PMV). For each variable, thousands of data were available; in fact, each apartment was investigated for at least one week and all the environmental conditions were acquired every 10 min. Therefore, for each apartment and for each variable about 10,080 data was available; in particular, the development process of ANN was carried out considering more than 98,000 data for each variable for the training process, about 20,000 for the validation and other 20,000 for the testing processes. The mean values and the standard deviation of the main monitored variables, including the I_{cl} values, are shown in Table 3 for each investigated apartment.

Table 3. Mean values and standard deviation (SD) of the main monitored variables and clothing insulation values.

Case Study	Indoor Air Temperature (°C)		Globe Thermometer Temperature (°C)		Indoor Air Velocity (m/s)		Relative Humidity (%)		Clothing Insulation (clo)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Men	Women
Ap. 1	21.85	±0.32	21.89	±0.35	0.01	±0.01	65.12	±4.04	0.65	0.60
Ap. 2	24.34	±0.16	24.36	±0.14	0.01	±0.01	55.08	±2.69	0.65	0.60
Ap. 3	25.12	±0.56	25.32	±0.87	0.02	±0.01	56.56	±4.97	0.45	0.40
Ap. 4	25.22	±0.48	25.33	±0.43	0.02	±0.01	43.76	±5.43	0.65	0.60
Ap. 5	24.93	±0.27	24.93	±0.27	0.01	±0.01	69.31	±7.63	0.45	0.40
Ap. 6	23.40	±1.02	23.40	±1.02	0.13	±0.01	59.39	±4.29	0.45	0.40
Ap. 7	23.02	±0.90	23.02	±0.90	0.01	±0.00	58.51	±6.05	0.45	0.40
Ap. 8	27.25	±0.46	27.66	±0.39	0.02	±0.01	46.94	±7.42	0.45	0.40
Ap. 9	23.79	±0.68	24.11	±0.68	0.03	±0.02	51.38	±5.22	0.65	0.60
Ap. 10	26.05	±1.02	26.48	±0.95	0.07	±0.01	52.49	±6.99	0.65	0.60
Ap. 11	24.31	±0.50	24.74	±0.50	0.03	±0.01	62.30	±3.65	0.65	0.60
Ap. 12	23.39	±1.42	24.03	±2.18	0.16	±0.02	52.42	±7.26	0.65	0.60
Ap. 13	26.28	±1.09	26.87	±1.34	0.19	±0.04	50.48	±4.90	0.65	0.40
Ap. 14	27.60	±1.78	27.64	±1.61	0.13	±0.02	58.75	±7.69	0.65	0.60
Ap. 15	26.90	±1.76	27.28	±1.61	0.07	±0.01	49.34	±7.32	0.45	0.40
Ap. 16	25.96	±1.35	26.14	±1.23	0.17	±0.05	54.97	±6.27	0.45	0.40
Ap. 17	24.47	±0.84	24.81	±0.81	0.23	±0.03	54.91	±5.49	0.45	0.40
Ap. 18	26.25	±2.25	26.71	±1.99	0.12	±0.21	38.26	±8.80	0.45	0.40
Mean values	24.84	±1.93	25.05	±1.98	0.02	±0.05	56.21	±9.31	0.54	0.50

5. Artificial Neural Network Implementation

5.1. Artificial Neural Network: Development Process

Neural networks are mathematical models that simulate the learning process of the biological neural system. Their most important feature is that they are not programmed as a code but are trained, based on experimental data [38,46]; the theory of neural networks is described in [46] more in detail.

In this paper, for the $ANN_{comfort}$ development a three-layer feed forward neural network (Figure 3) was trained by using Matlab programming language. The Levenberg-Marquardt backpropagation algorithm was adopted: this is a variation of Newton's method that was designed for minimizing functions that are sums of squares of other nonlinear functions. The key step in the Levenberg-Marquardt algorithm is the computation of the Jacobian matrix, specifically it allows to approximate the Hessian matrix and the error gradient using the matrix of first derivatives of the error function. The training process of the network automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. For each ANN development, the number of epochs was varied in 0–1000 range.

Firstly, a sensitivity analysis by varying the number of variables to be provided for the development process of the network was carried out in order to evaluate if the three input variables approach can have higher, lower or the same accuracy.

The first ANN was implemented by using all the data required by ISO 7730 [1], afterwards one variable at time was removed. As stated in the description of the research procedure (Figure 1), for the implementation process the clothing insulation has been varied in 0.25–1.6 clo range. The mean values of the variables provided as input to networks step by step and the PMV index provided as reference data and calculated according to 1 for each clothing insulation value (in 0.25–1.6 clo range) are shown in Table 4 for each investigated apartment. It is worth nothing that the values of metabolism and of effective mechanical power are not reported in the table because of their constant values and equal to 1.2 met and 0 W/m^2 respectively.

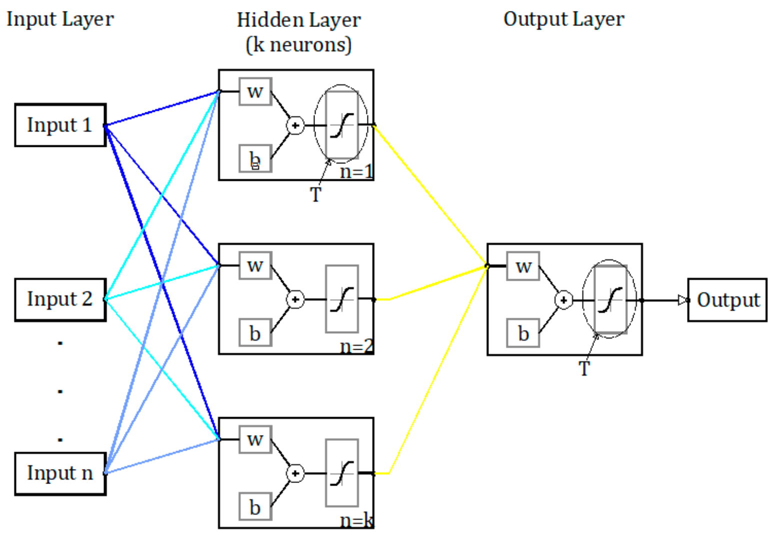

Figure 3. Neural Network Pattern: one input layer, one hidden layer and one output layer (T = transfer function, b = bias value, w = connection weight).

For the sake of clarity, the three sub-processes are briefly described:

- Training: it is the process that allows to calculate and to modify the weight matrix of the connections of the network according to the Levenberg-Marquardt backpropagation algorithm;
- Validation: it is the process able to measure the generalization of the network, in which the datasets is also used for halting the training process when the generalization stopped improving;
- Testing: it is the last process which does not have an influence on the training and validation processes, but it allows to provide an independent measure of the network performance. In general, it allows to understand the potential error of the network once developed.

For both the hidden and output layers, a sigmoidal function was chosen as transfer function, allowing to simplify the error's gradient calculation and to reduce the computational time required for the network training.

A sensitivity analysis was also performed, in order to establish the best neurons number to be set in the hidden layer. According to [31,38,45,46,49,50], the efficiency of a feed-forward neural network also depends on the number of the neurons used in the hidden layer; in particular, a higher number of neurons does not mean a higher efficiency or better accuracy of the network. In [31,45] a sensitivity analysis by varying the number of neurons was carried out in order to evaluate the best number of neurons to be used. Results shown that after reaching the optimal number of neurons, the efficiency of the networks tends to decrease with increasing of number of neurons. So once reached the optimal number of neurons the accuracy tends to decrease with the increasing of number of neurons. Therefore, the analysis was carried out taking into account the mean error and the regression values related to the training, validation, testing and global processes (it represents the overall result of the three described sub-processes) when the neurons number varies from 1 to 100.

For each ANN and for each set of variables, a sensitivity analysis of number of neurons to be used in the hidden layer was also performed. The best ANN was chosen as the one with the lowest mean square error (MSE) and the highest regression (R) values. As an example, Figure 4 shows the trend obtained of R by varying the number of neurons within the hidden layer for the network trained by using only three input variables. Therefore, R-training (blue dots of Figure 4) refer to the training phase, R-validation (green triangles of Figure 4) is for the validation phase as well as R-testing (red square) for testing phase, whilst black rhombus are related to the global process.

Table 4. Mean values of the variables provided as input or target data from apartment 1 to 13 used for the training, validation and testing sub-processes, data from apartment 14 to 18 for the generalization process of the ANN.

Apartments	T_g	V	T	RH	Icl (clo)									
	(°C)	(m/s)	(°C)	(%)	0.25	0.4	0.55	0.7	0.85	1	1.15	1.3	1.45	1.6
Ap. 1	21.89	0.01	21.85	65.12	−1.3	−0.8	−0.4	−0.1	0.2	0.4	0.6	0.7	0.8	1
Ap. 2	24.36	0.01	24.34	55.08	−0.3	0.1	0.4	0.7	0.8	1	1.1	1.2	1.3	1.4
Ap. 3	25.32	0.02	25.12	56.56	0.2	0.5	0.8	1	1.1	1.3	1.4	1.5	1.5	1.6
Ap. 4	25.33	0.02	25.22	43.76	−0.7	−0.3	0.1	0.4	0.6	0.8	0.9	1	1.2	1.3
Ap. 5	24.93	0.01	24.93	69.31	−1.2	−0.7	−0.3	0	0.3	0.5	0.7	0.8	0.9	1
Ap. 6	23.4	0.13	23.4	59.39	−2.2	−1.5	−1	−0.6	−0.3	−0.1	0.2	0.3	0.5	0.6
Ap. 7	23.02	0.01	23.02	58.51	−0.7	−0.3	0	0.3	0.5	0.7	0.8	1	1.1	1.2
Ap. 8	27.66	0.02	27.25	46.94	−1	−0.5	−0.1	0.2	0.4	0.6	0.8	0.9	1	1.2
Ap. 9	24.11	0.03	23.79	51.38	−1.4	−0.8	−0.4	−0.1	0.1	0.4	0.5	0.7	0.8	0.9
Ap. 10	26.48	0.07	26.05	52.49	−0.1	0.2	0.5	0.7	0.9	1.1	1.2	1.3	1.4	1.5
Ap. 11	24.74	0.03	24.31	62.3	−1.5	−1	−0.5	−0.2	0.1	0.3	0.5	0.7	0.8	0.9
Ap. 12	24.03	0.16	23.39	52.42	−1.7	−1.1	−0.7	−0.3	0	0.2	0.4	0.6	0.7	0.8
Ap. 13	26.87	0.19	26.28	50.48	−0.4	0	0.3	0.6	0.8	1	1.1	1.2	1.3	1.4
Ap. 14	27.64	0.13	27.6	58.75	0	0.4	0.6	0.8	1	1.2	1.3	1.4	1.5	1.5
Ap. 15	27.28	0.07	26.9	49.34	0.3	0.7	0.9	1.1	1.3	1.4	1.5	1.6	1.7	1.7
Ap. 16	26.14	0.17	25.96	54.97	−0.7	−0.3	0.1	0.4	0.6	0.8	0.9	1.1	1.2	1.3
Ap. 17	24.81	0.23	24.47	54.91	−1	−0.5	−0.1	0.1	0.4	0.6	0.7	0.9	1	1.1
Ap. 18	26.71	0.12	26.25	38.26	−0.6	−0.2	0.2	0.4	0.6	0.8	1	1.1	1.2	1.3
mean values	25.05	0.02	24.84	56.21	−0.9	−0.4	0	0.3	0.5	0.7	0.8	1	1.1	1.2

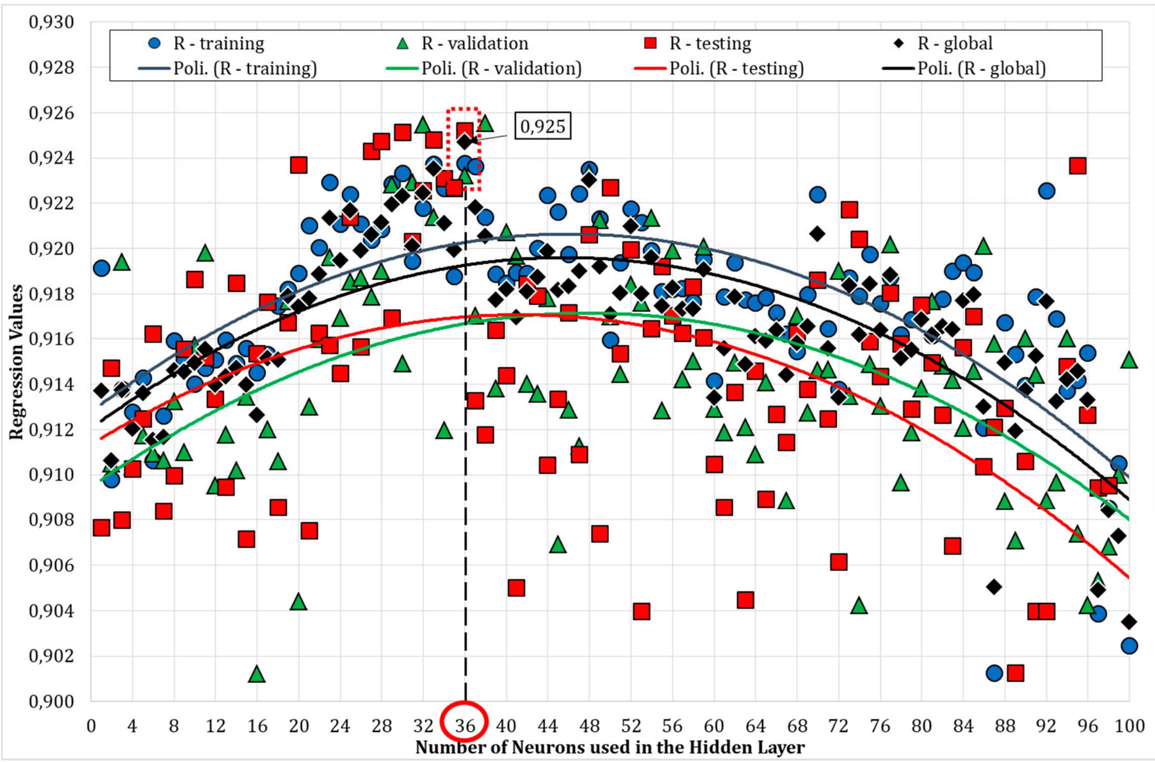

Figure 4. Neural Network Implementation: sensitivity analysis results (R = regression value for each development process: training, validation, testing and global).

These values (R) of each process versus the neuron number show a parabolic trend. They tend to increase when the number of neurons increases up to 40, then they reach the maximum value, while from 50 neurons onwards R tends to decrease. All the networks trained providing three input variables and with a number of neurons from 26 up to 38 neurons have regression values related to the testing process higher than 0.922, but for the other processes a wider variation is found (varied in 0.912–0.925 range). The network trained with 36 neurons is the one which has the regression values closer to each other in all the processes (0.924 for the training, 0.923 for the validation, and 0.925 for the testing).

Considering all the processes (global), the highest values of regression is found for the network with 36 neurons in the hidden layer; therefore, it was considered as the best trained network.

Based on the results in Figure 4, the network with 36 neurons in the hidden layer was chosen for the network trained with three input variables, since it has the highest regression values in each process (training, validation, and test) and the highest global regression value (0.925).

The same selection criterion was adopted for all the other network trained by providing more input variables.

Thus, the first ANN was implemented by using all the data required by ISO 7730 [1], afterwards the variables indicated in the Table 5 with ✘ were removed step by step. For each implemented ANN a sensitivity analysis of number of neurons was performed and the best networks, the one with the highest values of R and lowest of MSE, were chosen as the best networks. The comparison of the networks should be carried out considering the same control parameters (R and MSE), but only for MSE a significant variation was found while for all the best networks a global Regression close to 0.93 was always found. Therefore, MSE was considered as comparison parameter. The comparison of the best five ANNs obtained for each variable combination are shown in Table 5. As shown, the ANN developed with more variables (seven variables), named ANN_7, is the one with the lowest MSE in each development process (training, validation, and testing) with a global MSE of 2.3 10^{-5}. The MSE obtained for the ANN developed with the lowest number of variables (three variables), named ANN_3, is twice that of ANN_7. The order of magnitude of MSE of the other ANN varied in 3.2 10^{-5} and 4.9 10^{-5} range. According to the Table 5, the more the number of variables decreases, the more MSE tends to increase. However, it is worth nothing that the order of magnitude of MSE is always of 10^{-5} for all the network regardless of the number of variables provided for the development process.

Table 5. Sensitivity analysis by varying the number of variables to be provided for the implementation of ANN: Mean Square Error (MSE) comparison.

Variables Number	Variables							MSE (Values $\times 10^{-5}$)			
	W (W/m^2)	T_g (°C)	V (m/s)	M (W/m^2)	I_{cl} (clo)	UR (%)	T_{INT} (°C)	Training	Validation	Testing	Global
7	✓	✓	✓	✓	✓	✓	✓	2.3	2.3	2.5	2.3
6	✘	✓	✓	✓	✓	✓	✓	3.2	3.5	3.2	3.3
5	✘	✘	✓	✓	✓	✓	✓	3.6	3.7	3.9	3.7
4	✘	✘	✘	✓	✓	✓	✓	4.7	4.9	4.7	4.8
3	✘	✘	✘	✘	✓	✓	✓	4.8	6.3	5.3	5.1

Further comparison was done in order to highlight the accuracy of the three input variables approach; specifically, a comparison was performed of the mean errors returned by ANN_7 and ANN_3 having the higher and lowest MSE values (Table 5).

The mean and the standard deviation (SD) of relative and absolute errors between the PMV values calculated according to ISO 7730 [1] (namely $PMV_{standrad}$) and the PMV simulated by the two networks (ANN_7 and ANN_3) were calculated. Results are shown in Table 6 As shown, the lowest MSE of ANN_7 does not mean a significant and better accuracy in PMV index calculation of the network. In fact, the order of magnitude of both relative and absolute error is the same for both the networks. Only the percentage of cases, in which the error returned by the network is mainly in ±0.4 range, considering the ANN_7 was found higher (of about 2%).

Table 6. Mean error between PMV calculated according to ISO 7730 ($PMV_{standard}$) and the one simulated by ANN (ANN_7 and ANN_3).

Networks	Relative Error		Absolute Error		Percentage of Cases [Error is in ±0.4 Range]
	Mean	SD	Mean	SD	
ANN_7	−0.0016	±0.354	0.2347	±0.2656	85.6%
ANN_3	−0.0019	±0.355	0.2355	±0.2663	83.5%

According to these preliminary sensitivity analyses and considering the purpose of the paper, the ANN developed by using only three variables can be considered reliable because not significant differences or higher accuracy were found by using other networks developed with more variables.

5.2. *Artificial Neural Network: Accuracy Field Evaluation*

Once trained the network by providing only three input variables (indoor air temperature, relative humidity, and clothing insulation), the accuracy field of the network was evaluated.

Firstly the data set was analyzed in order to check the sample data available for the ANN implementation. In Table 7 the percentage distribution of the sample data in specific range of values of indoor air temperature and relative humidity is reported. The values shown in Table 7 (percentage distribution) were also highlighted with a different color tone based on the percentage value; specifically, it was varied from white to green according to this percentage (white for the vales close to 0 and green for the highest value).

Table 7. Percentage distribution of the sample of data available for the development of the network.

UR [%]	T_{INT} [°C]											
	[19–20]	[20–21]	[21–22]	[22–23]	[23–24]	[24–25]	[25–26]	[26–27]	[27–28]	[28–29]	[29–30]	[30–31]
[20–25]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
[25–30]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00
[30–35]	0.00	0.00	0.00	0.00	0.07	0.34	0.07	0.00	0.20	0.14	0.00	0.00
[35–40]	0.00	0.00	0.00	0.20	0.27	0.81	0.47	0.20	0.61	0.20	0.00	0.00
[40–45]	0.00	0.00	0.27	0.07	0.75	1.22	0.47	0.54	1.22	0.27	0.00	0.07
[45–50]	0.00	0.00	0.00	1.49	1.63	1.42	2.78	0.88	0.75	0.14	0.00	0.00
[50–55]	0.00	0.14	0.00	1.42	4.00	5.63	2.98	2.71	1.90	0.00	0.00	0.00
[55–60]	0.00	0.00	0.27	6.24	5.22	6.24	4.27	1.02	0.14	0.00	0.00	0.00
[60–65]	0.00	0.27	3.39	2.31	5.02	5.56	3.53	0.27	0.00	0.00	0.00	0.00
[65–70]	0.00	0.00	3.93	1.49	0.14	6.44	1.08	0.00	0.00	0.00	0.00	0.00
[70–75]	0.00	0.07	1.02	0.34	0.14	1.42	0.20	0.00	0.00	0.00	0.00	0.00
[75–80]	0.14	0.14	0.07	0.00	0.00	0.41	1.02	0.00	0.07	0.00	0.00	0.00
[80–85]	0.00	0.00	0.00	0.00	0.00	0.07	1.22	0.00	0.00	0.00	0.00	0.00
[>85]	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.07	0.00	0.00	0.00

As shown, all monitored data varied in 19–32 °C range of air temperature and in 20–85% range of relative humidity. However, the main sample data (more than 94% of sample) falls within the range 21–28 °C of air temperature and 35–75% of relative humidity. Therefore, outside these ranges is lawful to expect a lower accuracy of the network due to the poor available sample data.

In this context the accuracy of the network was checked considering:

(1) all the sample data available (in the following referred as δ_{SD1});
(2) only the range with the widest sample data (21–28 °C and 35–75%, in the following referred as δ_{SD2}).

Firstly, the accuracy occurred in development process was checked. Figure 5 shows the percentage of cases whose mean difference between PMV_{target} and $PMV_{ANNcomfort}$ ranges between the values detailed in the x-axis, considering both δ_{SD1} (histograms in blue, red and green) and δ_{SD2} (dashed histograms in blue, red and green).

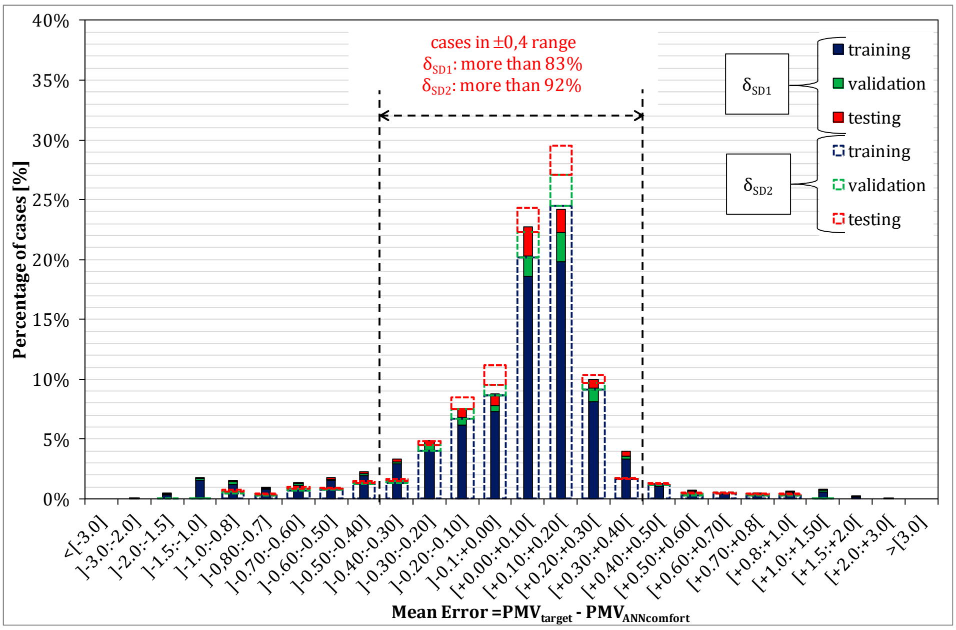

Figure 5. Neural Network Implementation: PMV mean error range returned by the ANN.

In particular, the blue histograms are for the training process, the green ones for the validation, while the red histograms are for the test process (all the data is related only to 13 apartments as described in the research procedure—Figure 1). Considering δ_{SD1} range, Figure 5 shows that in more than 83% of cases the $PMV_{ANNcomfort}$ differs from PMV_{target} (calculated according to 1) of a value in ±0.40 range, while in almost 90% of cases the mean error is in ±0.5 range. In δ_{SD2} the percentage of cases increases up to 92.2% in ±0.40 range of error, and up to 95% in ±0.5 range. It is worth noting that the percentage of cases in the ±0.30 range of error increases from 78% up to almost 90%. As shown, in δ_{SD2}, the accuracy of the network increases of almost 10%. According to the results, is lawful to assert that the lower accuracy of the network is due to the few data falling outside the 21–28 °C and 35–75% ranges.

The percentage of cases found in the testing phase is very close to that of the training and validation processes (86% vs. 84–83% respectively); this implies that the generalization of the network is possible and that the accuracy could be at least the same as the one obtained in the development process.

Compared to the other previous works [17–26], the implemented network ($ANN_{comfort}$) has the same accuracy in all the processes; this means that when it will be used with different input data without providing the target (generalization), it is very likely that the mean error will be in ±0.40 range.

In order to highlight the accuracy of the network in δ_{SD2} range, the following comparison is also done: the absolute error returned by the network in each development process are compared considering both δ_{SD1} and δ_{SD2} ranges of values. Results are shown in Figure 6. Considering δ_{SD2} range a mean absolute error equal to 0.076, 0.014, and 0.010 respectively in training, validation, and testing are found. According to the results, is lawful to assert that considering the δ_{SD1} range, the lower accuracy of network was due to the few data falling in 19–21 °C and 28–32 °C ranges of temperature, and in 20–35% and 75–100% ranges of relative humidity.

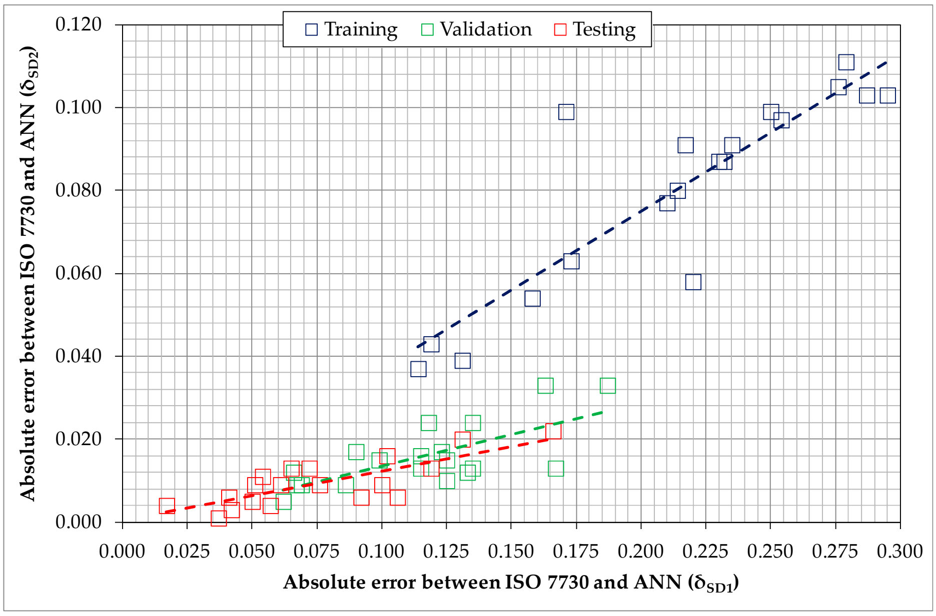

Figure 6. Absolute error returned by ANN in each development process considering all the sample of data (δ_{SD1}) and the ones fall in [21–28 °C] and [30–75%] ranges of temperature and relative humidity (δ_{SD2}).

5.3. Artificial Neural Network: Generalization Process

Once developed, the reliability of $ANN_{comfort}$ was checked by carrying out the generalization control (as shown in Figure 1), for which the indoor air temperature and the relative humidity of the remaining five apartments, and the I_{cl} range values showed in Table 4 were used as input variables. In this case, only these three input variables were provided to the network, while the PMV index calculated according to 1 was only used in the comparison and for testing the reliability of the network. The results of the generalization are shown in Figure 7 considering both cases:

- 100% of the sample data (δ_{SD1});
- only data within the range 21–28 °C of air temperature and 35–75% of relative humidity (δ_{SD2}).

As shown the trend is the same for both the cases, and specifically in more than 86% of cases the error (the difference between the PMV value calculated according to 1 and the one predicted by $ANN_{comfort}$) is in ±0.40 range, more than 75% in ±0.30 range, and more than 60% of cases in ±0.20 range. Furthermore, the trend of the error in the generalization process is very close to the one obtained during the development process. This confirms the accuracy of the implementation of $ANN_{comfort}$, and according to the Theory [49,50] it can be used for the PMV prediction for similar case studies (i.e., for the same intended use).

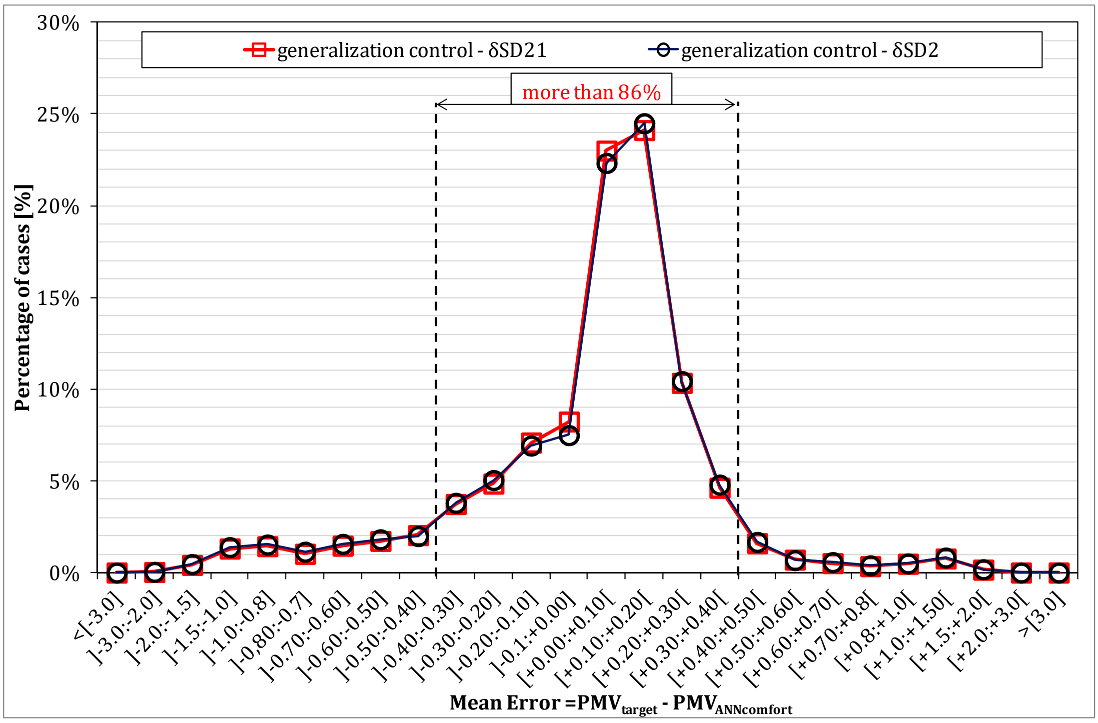

Figure 7. Neural Network generalization control: PMV mean error range returned by the ANN.

6. Results and Discussion

Once developed the $ANN_{comfort}$ algorithm and once identified its higher accuracy field (δ_{SD2}), the·comparison of the different available methods was carried out. For this analysis, the experimental data acquired during the experimental campaigns of 18 apartments and the real I_{cl} values established according to the activity level and monitored period were considered.

The first comparison was carried out considering all the methods that allowed to calculate the PMV index starting from monitored data considering δ_{SD1} and δ_{SD2}.

Figure 8 shows, for both men and women configurations (i.e., considering the defined I_{cl} values reported in Table 3 for men and for women, respectively) and for all the considered case studies the results of $PMV_{ANN\_comfort}$, $PMV_{Rohles\ A}$, and $PMV_{Rohles\text{-}B}$ vs. $PMV_{Standard}$. In particular, Figure 8a,b show the results considering the δ_{SD1} range, while Figure 8c,d refer to δ_{SD2}. Linear regression lines are also shown, together with the corresponding R^2 values.

As shown, the PMV values calculated according to ISO 7730 [1] ($PMV_{Standard}$) varied significantly between −2.5 (that corresponds to a thermal sensation between cold and very cold) and +2.8 (thermal sensation between warm and very warm), with a higher concentration of values in −1.0 (corresponds to slightly cold) and +1.0 (corresponds to slightly warm) range.

According to Figure 8, the following consideration can be done for each case:

(1) range δ_{SD1} (Figure 8a,b): the $ANN_{comfort}$ allowed to obtain a better correlation with $PMV_{Standard}$ (R^2 equal to 0.745 and 0.690 for men and women configurations respectively), followed by the Rohles model—A [14] (R^2 = 0.514 for men configuration and R^2 = 0.523 for women one), and then by Rohles model—B [15] (R^2 = 0.436–0.484 for the same configurations). It is worth noting that all the simplified methods are not able to correctly predict PMV values lower than −2.0 (that corresponds to cold sensation); however, this thermal sensation (between cold and very cold) represents only the 0.5% of cases.

(2) range δ_{SD2} (Figure 8c,d): the $ANN_{comfort}$ allowed to obtain a better correlation with $PMV_{Standard}$ (R^2 increase up to 0.909 and to 0.843 for men and women configurations respectively), followed by

the Rohles model—A [14] (R^2 = 0.488 for men configuration and R^2 = 0.501 for women one), and then by Rohles model—B [15] (R^2 = 0.411–0.473 for the same configurations).

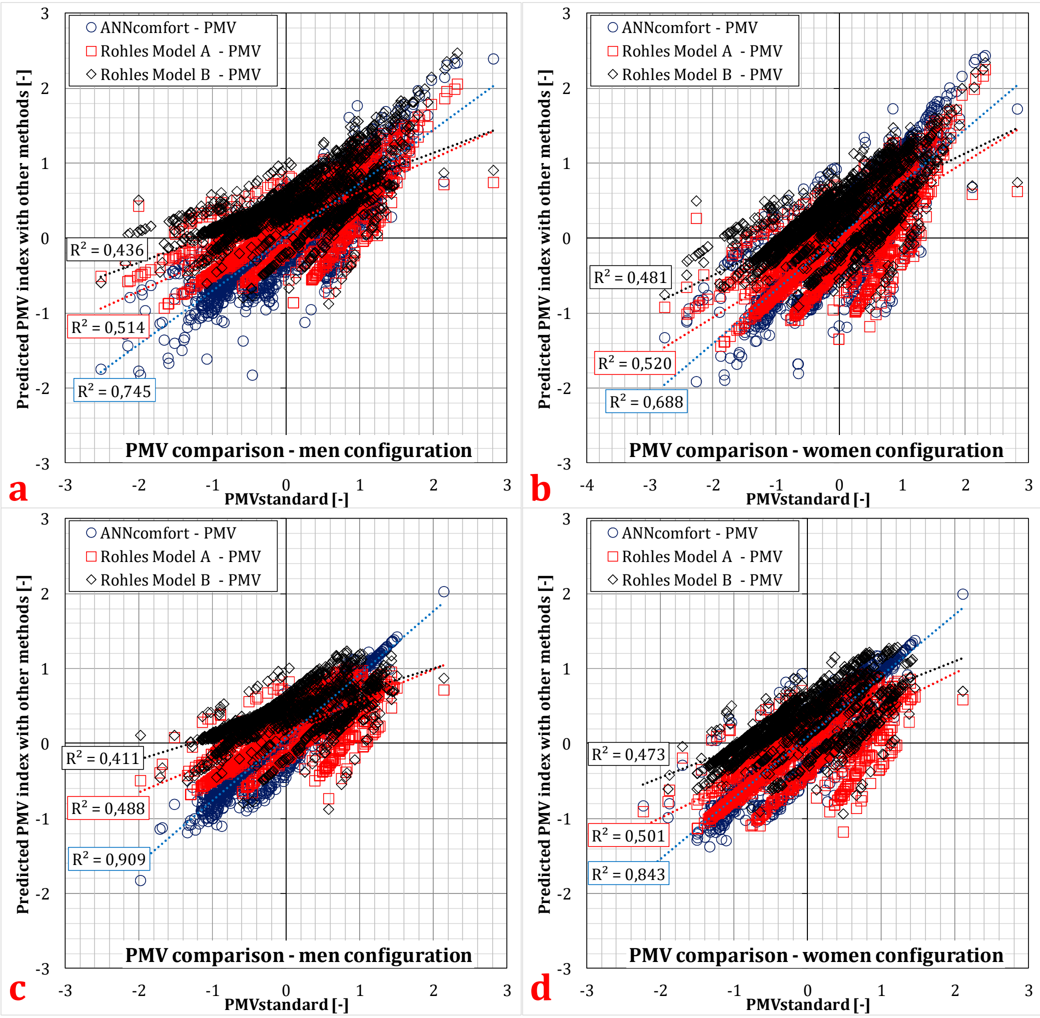

Figure 8. PMV index comparison for men and women configurations: (**a**,**b**) related to range δ_{SD1}, (**c**,**d**) related to range δ_{SD2}.

Therefore, it is clear that considering only the range of data where the ANN has higher accuracy (δ_{SD2}), the PMV prediction is closer to the one calculated according to ISO 7730 [1]. In fact, in this range the accuracy of the network has increased. The two new trend lines for both men and women configurations are closer to the bisector of the plane, confirming the higher accuracy of ANN in 21–28 °C range of temperature and 35–75% range of relative humidity.

Moreover, Figure 8 shows that the Rohles model—A, which can be considered valid only for the I_{cl} values equal to 0.6 clo, provided more reliable results than those of Rohles model—B. This result could depend on the I_{cl} values assumed in this work; in fact, they are in 0.40–0.65 range so very close to 0.60 clo. Therefore, it could be stated that for I_{cl} values close to 0.6 clo, the Rohles model—A, still provides reliable results.

The comparison of the different methods continued with the mean error analysis; specifically, the analysis of error calculated as the difference between the $PMV_{standard}$ and the one calculated using simplified methods was carried out. Figure 9 shows on the x-axis the mean error range (difference between the $PMV_{Standard}$ and the PMV from $ANN_{comfort}$, Rohles model—A and Rohles model—B), and on the y-axis the percentage of cases in which that error range occurred. Figure 9a shows the results considering δ_{SD1} range, while Figure 9b is the one considering δ_{SD2} range (the higher accuracy field of the network). The picture allows to confirm the reliability of the $ANN_{comfort}$ with respect the other simplified methods; specifically:

(1) range δ_{SD1} (Figure 9a): it is found that in more than 75% of cases the error between $PMV_{Standard}$ and $PMV_{ANN\_comfort}$ is in ±0.40 range and almost 90% is in ±0.50 range. It is worth noting that in more than 50% of cases the PMV error returned by $ANN_{comfort}$ is in +0.05-+0.4 range. A little lower accuracy was found for the other two proven models; by applying the Rohles model—A the calculated PMV error is in ±0.40 in only about 48% of cases, but in ±0.50 range this percentage increases up to about 71%. Applying the Rohles model—B, about 33% of cases are in ±0.40 error range, and about 46% in ±0.50 one.

(2) range δ_{SD2} (Figure 9b): a higher accuracy of $ANN_{comfort}$ can be found. In fact, in more than 94% of cases the error between $PMV_{Standard}$ and $PMV_{ANN\_comfort}$ is in ±0.40 range and almost 99% is in ±0.50 range. It is worth noting that in more than 81% of cases the PMV error returned by $ANN_{comfort}$ is in ±0.30 and about 71% in −0.10–+0.3 range. On the other hand, the accuracy of the other simplified methods slightly decreases. For the Rohles model—A the percentage of cases with an error in ±0.40 range is about 55% and of 65% in ±0.50 range. By applying the Rohles model—B, these percentage decreases up to 31% and 40%, respectively.

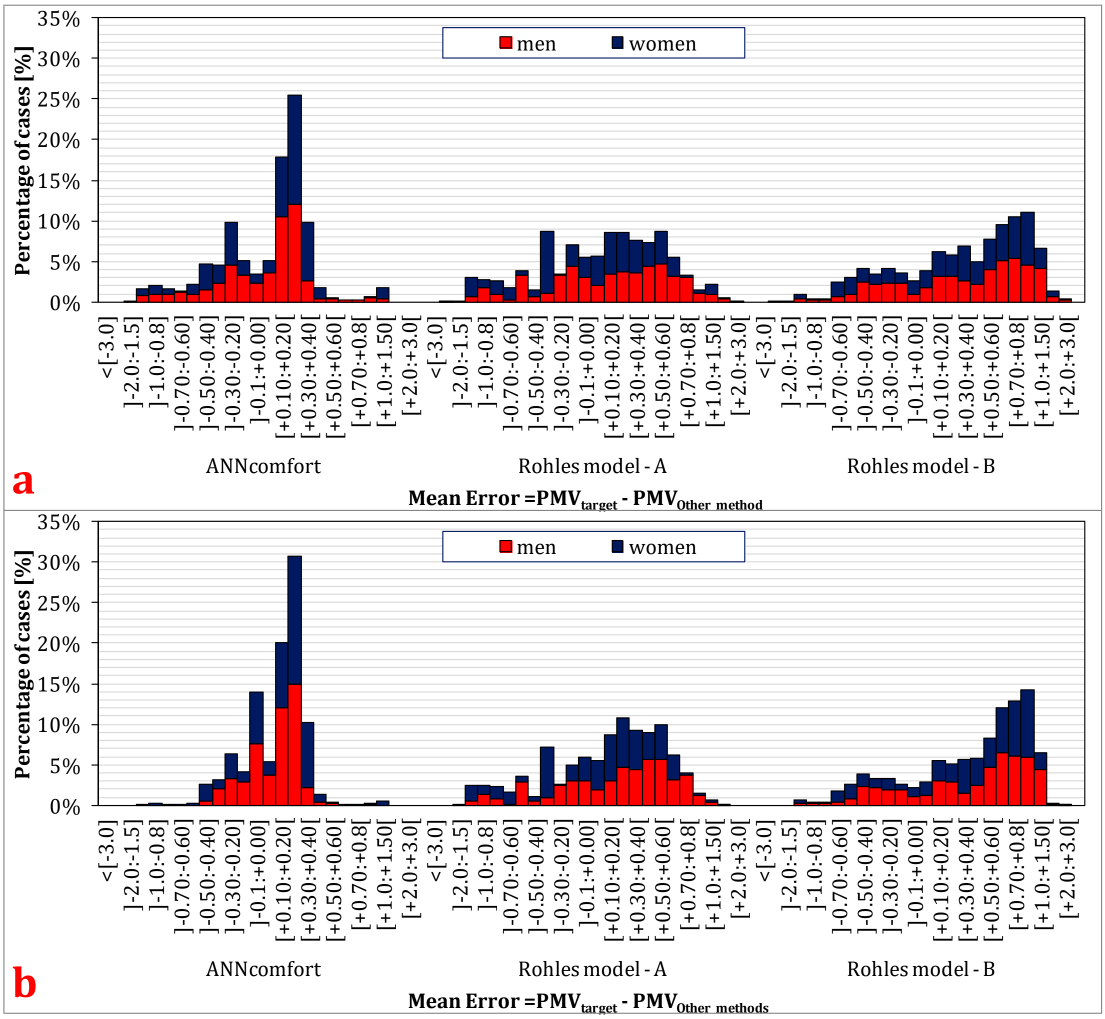

Figure 9. Mean error range comparison: (**a**) related to range δ_{SD1} and (**b**) related to range δ_{SD2}.

Therefore, the PMV index calculated using the $ANN_{comfort}$ algorithm seems to be more accurate and able to predict a closer thermal sensation to the one related to $PMV_{standard}$ than the other two proposed methods, especially in the range δ_{SD2}.

It is also worth noting that in only about 10% of cases the PMV value calculated with $ANN_{comfort}$ can involve a complete different thermal sensation (for instances when the mean error is higher than ±0.5). However, by applying the other two methods, this percentage increase from 35% (Rohles model—A) up to 53% (Rohles model—B).

A further analysis was then carried out in order to check if the error returned by the network can lead a complete different thermal sensation of the environment. Firstly, the mean error and the absolute error between $PMV_{standard}$ and $PMV_{ANNcomfort}$ was calculated and compared for each case study considering δ_{SD1} and δ_{SD2} ranges.

The mean error and the mean absolute error calculated for both the adopted configurations (men and women) are shown in Figure 10. Considering δ_{SD1}, a very small mean error (mean values of 0.004) can be found between $PMV_{standard}$ and $PMV_{ANNcomfort}$; however, in this case the mean absolute error is about 0.34–0.39. On the other hand, in δ_{SD2} range the differences decrease until to 0.0002–0.0003 for the mean relative error and to 0.11 and 0.16 for the mean absolute error for men and women respectively. This result confirmed the higher accuracy of the network in this specific range (δ_{SD2}).

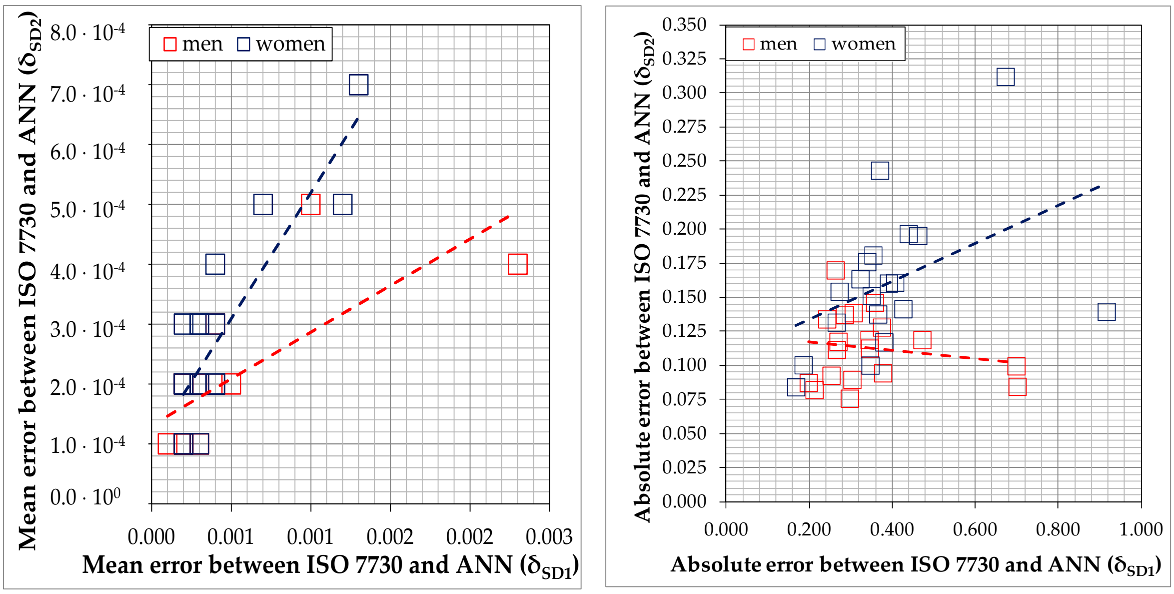

Figure 10. Mean relative and mean absolute errors between $PMV_{standard}$ and $PMV_{ANNcomfort}$ for men and women configurations: comparison considering δ_{SD1} and δ_{SD2} ranges.

Starting from these results, the thermal comfort class was then evaluated in order to evaluate if this order of magnitude of error can lead to completely different thermal comfort class. According to previous work [40] and to ISO 7730 [1], when the analysis is extended to a long time period, the thermal comfort class can be evaluated by considering the mean values of the indices PMV and PPD. In particular, based on the values of PPD, PMV, and on other local discomfort indices (draft risk—DR, Percentage of dissatisfied because of vertical difference of temperature—PD_{TDV}, hot or cold floor temperature—PD_{FT}, and radiant asymmetry—PD_{RA}), four different category are possible:

(1) Class A: when PMV is in ±0.2 range and the other indices are lower than 6% (PPD), 10% (DR), 3% (PD_{TDV}), 10% (PD_{FT}), and 5% (PD_{RA});

(2) Class B: when PMV is in ±0.5 range and the other indices are lower than 10% (PPD), 20% (DR), 5% (PD_{TDV}), 10% (PD_{FT}), and 5% (PD_{RA});

(3) Class C: when PMV is in ±0.7 range and the other indices are lower than 15% (PPD), 30% (DR), 10% (PD_{TDV}), 15% (PD_{FT}), and10% (PD_{RA});

(4) out of the class: in all the other cases.

In this case, only PPD and PMV varied applying ISO 7730 and ANN; therefore, the comparison was performed by considering only the PMV, PPD, and the resulting thermal comfort class. Results are shown below: Figure 11 shows the comparison of PMV and PPD indices considering δ_{SD1} and δ_{SD2}, while Table 8 shown the comparison of the thermal comfort class assigned considering the same range of data.

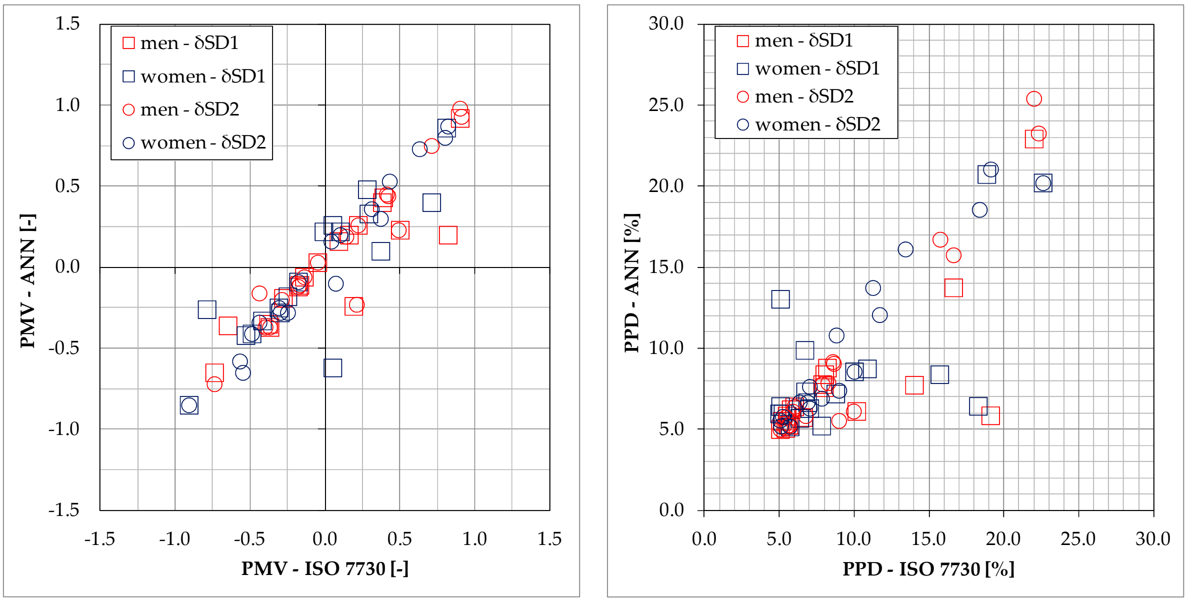

Figure 11. Comparison between the mean values of PMV and PPD indices for men and women configurations (□ referred to δ_{SD1} and ○ referred to δ_{SD2}).

Table 8. Thermal comfort class Comparison assigned for each case study.

Case Studies	MEN				WOMEN			
	δ_{SD1}		δ_{SD2}		δ_{SD1}		δ_{SD2}	
	ISO 7730	ANN	ISO 7730	ANN	ISO 7730	ANN	ISO 7730	ANN
1	x	C	x	x	x	x	x	x
2	A	A	A	A	A	A	A	A
3	A	A	A	A	B	A	B	B
4	B	B	B	B	A	B	A	A
5	B	B	x	x	B	B	C	x
6	A	B	B	B	A	B	B	C
7	A	A	A	A	A	B	A	A
8	A	A	A	A	B	B	B	B
9	B	A	B	B	B	B	B	B
10	B	B	B	B	C	B	C	C
11	x	x	x	x	x	x	x	x
12	A	A	A	A	B	B	B	B
13	B	B	B	B	B	B	B	B
14	C	B	B	B	B	A	B	B
15	A	B	B	B	A	C	A	A
16	x	B	x	x	x	B	x	x
17	B	B	B	B	C	B	B	B
18	C	B	B	A	x	B	C	C

According to Figure 11 and Table 8 the error returned by the network can lead to a different thermal comfort class despite the mean PMV index differs by few values. Considering the δ_{SD1} range, for men configuration in 8 case studies a different thermal comfort class is found, while for women one in 10 case studies.

On the other hand, in δ_{SD2} range a higher correlation can be found. In this case the thermal comfort class calculated by ANN for the men configuration is always in agreement with the one returned by ISO 7730. For the women configuration, instead only in two case studies (case studies 5 and 6) a higher thermal comfort class was found.

Therefore, δ_{SD2} range the error returned by applying the ANN seems to not lead to neither a significantly variation of the thermal sensation perceived within the environment nor to a different thermal comfort class.

According to these results, the following considerations can be proposed:

(1) the accuracy of the new proposed algorithm is higher than the one obtained by using other two methodologies;
(2) in δ_{SD2} range, the error returned by ANN does not involve a significant variation neither of the thermal sensation nor of thermal comfort class.

Therefore, the new algorithm can be considered an accurate and reliable simplified PMV calculation method especially when the stating data falls in 21–28 °C range of air temperature and in 30–75% of relative humidity (δ_{SD2}).

Finally, the combined calculation by using two different ANNs was also tested. Specifically, the outputs simulated in [31] by using an ANN (hereinafter referred to as ANN_1) were provided as input data to the new algorithm $ANN_{comfort}$. The benefits of this combined calculation by using both the networks could be the possibility to predict the indoor thermal conditions by using ANN_1 [31] and the PMV index by using $ANN_{comfort}$ without having indoor monitored data. ANN_1 can predict the indoor thermal conditions starting from both experimental and design data as well as $ANN_{comfort}$. This peculiarity can be very useful in new building design or in energy retrofit of existing buildings when, generally, experimental data are not yet available. Only the outdoor weather conditions and characteristics of the building (such as geometry, external opaque surface, windows surface, thermal characteristics of the building envelope, internal useful surface, and so on [31]) are necessary.

The PMV indexes calculated by using the combined calculation of the two networks are shown in Figure 12. In Figure 12a,b the results obtained by using data in δ_{SD1} range while in Figure 12c,d the ones related to δ_{SD2} range are reported. On the abscissas the $PMV_{standard}$ (calculated according to ISO 7730 [1]) while in the ordinates the PMV calculated with ANN were reported. Specifically, $ANN_{comfort}$–PMV indicates the PMV indexes calculated using the $ANN_{comfort}$ starting from experimental data, while $ANN_{comfort\_ANN1}$ indicated the PMV indexes calculated using the combined calculation, i.e., by using the two networks. It is worth noting that, according to [31], the ANN_1 has a very high accuracy in indoor thermal conditions; for instance, in only 1% of cases an error higher than 1 °C between the monitored indoor air temperature and the simulated one was found (for more detail, please refer to [31]). Therefore, it is reasonable to expect very close results between the two approaches, as also proved in Figure 12, where R^2 values of the two methods are very close each other (considering data in δ_{SD1} range, equal to 0.745 for men and 0.690 for women considering the $ANN_{comfort}$–PMV and equal 0.740 for men and 0.689 for women considering $ANN_{comfort\_ANN1}$). As already shown in the previous Figures, also in this case the accuracy of the network significantly increases when it is used with data falls in δ_{SD2} range. R^2 of the two trend lines related to the two approaches are also in this case very close each other, and they increase up to 0.909 and 0.906 for men configuration and up to 0.843 and 0.844 for women.

Thanks to this further result, it is possible to foresee that the $ANN_{comfort}$ algorithm can be employed also in building design, allowing to predict with good approximation the PMV index within the room without having experimental data. Moreover, the accuracy of the PMV prediction by applying only the ANNs seems to be very high especially when the data falls into δ_{SD2} ranges.

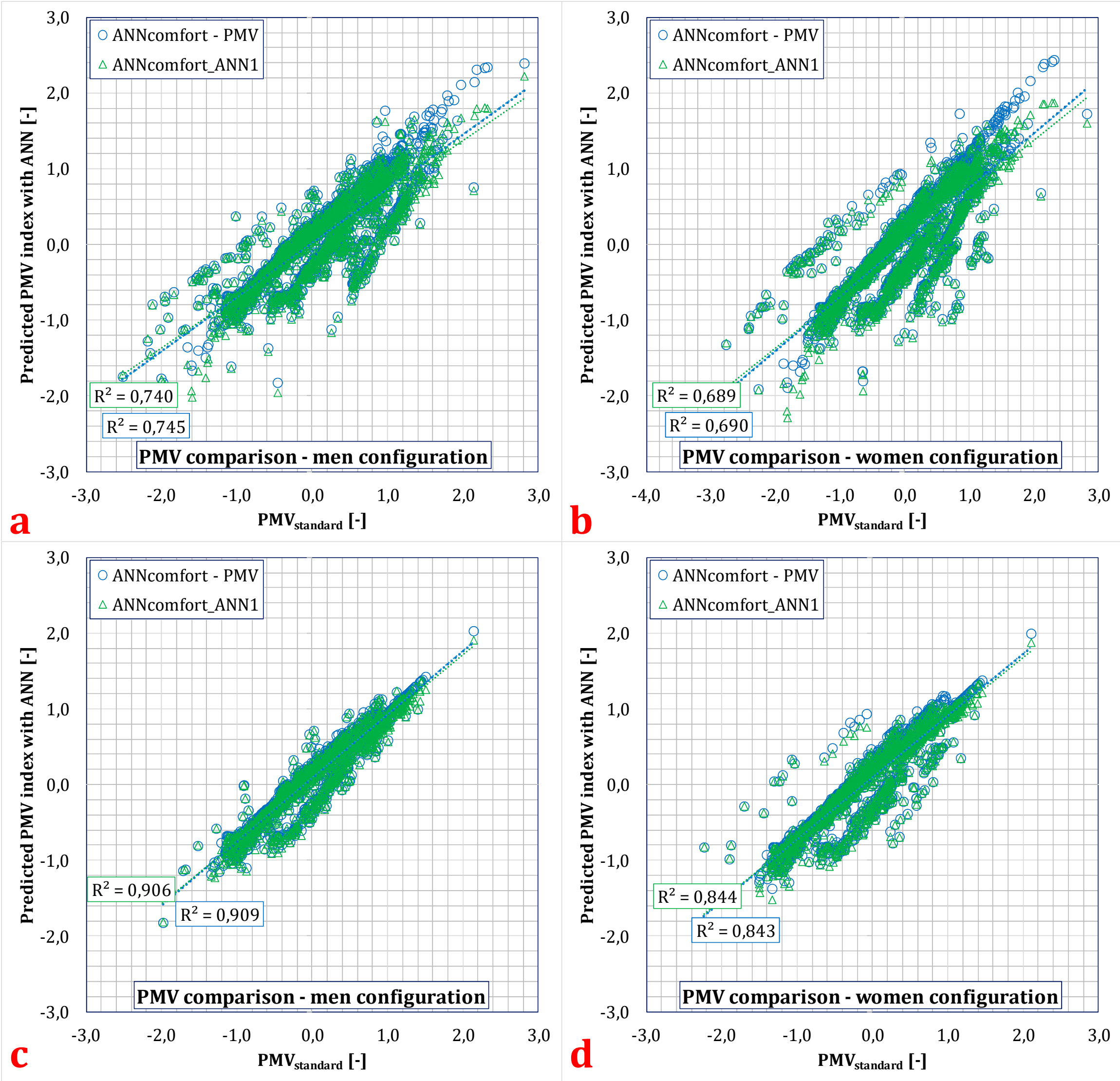

Figure 12. PMV comparison from ANNcomfort and ANNcomfort_ANN1 for men and women configurations: (**a**,**b**) related to range δ_{SD1}, (**c**,**d**) related to range δ_{SD2}.

7. Conclusions

In the present paper, a new artificial neural network (ANN) was developed able to predict the predicted mean vote (PMV) index within the rooms, being feed by the following input variables: the indoor air temperature, the relative humidity, and the thermal insulation of clothing.

Two sensitivity analysis were performed; the first one allowed to confirm the reliability of the ANN trained by using only three input variables with respect to the other ANNs trained by using more input variables, while the second one allowed to choose the ANN trained with 36 neurons in the hidden layer as the best trained ANN with the highest global regression value, equal to 0.925. Further analysis were carried out allowing to highlight the greater accuracy field of the network; in fact, the results shown that the network is significantly more accurate when data of air temperature and of relative humidity falls into 21–28 °C and 30–75% ranges respectively. Considering the development process, in this range of values the following results were obtained:

(1) the mean absolute error was equal to 0.08, 0.016, and 0.009 for the training, validation and testing respectively;

(2) the mean error between the PMV predicted by ANN and the one calculated according to ISO 7730 is in ±0.40 range in more than 92% of cases.

Once developed, the ANN was tested and compared with two Rohles models, i.e., two proven methods for PMV calculation by using only three input variables.

The PMV comparison between the common methods or those available in literature highlighted that the new proposed ANN allowed to better approximate the PMV index with respect to the two Rohles models (Rohles model—A and Rohles model—B). In particular, the comparison was carried out considering two ranges of values, i.e., considering the whole sample of data (δ_{SD1}) and only the data falls into 21–28 °C and 30–75% ranges (where a higher accuracy of network was found—δ_{SD2}). Results shown a higher accuracy of network than the two Rohles models, specifically:

(1) δ_{SD1} range: in almost 90% of cases the PMV error is in ±0.50 range, while adopting the other methods this percentage decreases until 71% for Rohles model—A and to 46% for Rohles model—B. Considering men and women configurations, the R^2 of the trend lines of ANN were equal to 0.745 and 0.690 respectively, while for the Rohles model—A they decrease until to 0.514 and 0.523. Lower values of R^2 were found for the Rohles model—B (0.436 and 0.484 for men and women configurations).
(2) δ_{SD2} range: the error is in almost 99% of cases in ±0.50 range, and specifically in more than 81% of cases in ±0.30 range. On the other hand, for the Rohles model—A the percentage of cases with an error in ±0.40 range was of about 55% and of 65% in ±0.50 range. These percentage decreases up to 31% and 40% respectively for the Rohles model—B. The R^2 obtained for ANN increase up to 0.909 and to 0.843 for men and women configurations respectively, while the ones of Rohles models decrease until to 0.488 and 0.501 (Rohles model—A) and to 0.411 and 0.473 (Rohles model—B)

The accuracy of the network was also checked; firstly, the relative and the absolute errors were analyzed and then the thermal comfort class, calculated according to ISO 7730, was checked. In this case, results show a strong dependence on considered the sample data, in particular:

(1) δ_{SD1} range: the mean error was about 0.0004 while the absolute error varied from 0.34 to 0.39 for men and women configurations. This error can lead to a variation of the thermal comfort class calculated by ANN, in fact in 8–10 case studies a different thermal comfort class was calculated;
(2) δ_{SD2} range: the relative mean error was about 0.0003 while the absolute error decrease until to 0.11 and 0.16 for men and women configurations. In this range of values, the error did not involve a significant variation of the thermal sensation and of thermal comfort class. In fact, only for the women configuration and in only two case studies (n. 5 and n. 6) a higher thermal comfort class was calculated.

According to results, the developed network has a higher accuracy than the other proven methods, especially when data falls into 21–28 °C and 30–75% ranges (δ_{SD2}).

Thanks to the good training process of ANN and to the goodness of the PMV results, the combined calculation by using two different ANNs was also tested. Specifically, the indoor thermal conditions simulated by using ANN_1 trained in a previous work [31] were provided as input data to the new developed algorithm $ANN_{comfort}$. According to the results, the PMV now evaluated is very close to $PMV_{Standard}$, with the same range error returned by using experimental data. The benefits of this combined calculation could be the possibility to predict the indoor thermal conditions by using ANN_1 and the PMV index by using $ANN_{comfort}$ without having monitored data inside the room. The first network (trained in previous work [31]) could in fact predict the indoor thermal conditions starting from both experimental and design data, as well as $ANN_{comfort}$. This peculiarity can be very useful in new building design or in energy retrofit of existing buildings when, generally, experimental data are not yet available.

According to the results, the new $ANN_{comfort}$, can be considered a good model to be used for the simplified calculation of PMV, especially when the air temperature and the relative humidity data fall into 21–28 °C and 30–75% ranges. Besides, the peculiarity of the network to predict the PMV by providing only the indoor air temperature, the relative humidity, and the clothing insulation allowed to use the ANN as alternative method to the ones available in the literature.

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Nomenclature

ANN:	Artificial Neural Network (-)
b:	bias value (-)
DR:	draft risk (%)
f:	clothing area coefficient (m^2K/W—clo)
h_c:	convective heat transfer coefficient (W/ m^2K)
I_{cl}:	clothing insulation (m^2K/W—clo)
M:	metabolism (met)
pa:	water vapor partial pressure (Pa)
PMV:	Predicted Mean Vote (-)
PPD:	Percentage of dissatisfied people (%)
PDTDV:	Percentage of dissatisfied because of vertical difference of temperature
PDFT:	Percentage of dissatisfied because of hot or cold floor temperature
PDRA:	Percentage of dissatisfied because of radiant asymmetry
RH:	relative humidity (%)
T:	transfer function (-)
T_a:	indoor air temperature (°C)
T_{cl}:	surface temperature of clothing (°C)
T_{gl}:	globe thermometer temperature (°C)
T_{mr}:	mean radiant temperature (°C)
v_a:	relative air velocity (m/s)
W:	effective mechanical power (W)
w:	connection weight (-)
X:	generic data (-)
$x_{normalized\text{-}value}$:	normalized generic data (-)

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