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Comparison of the energy performance of existing buildings by means of dynamic simulations and Artificial Neural Networks

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Abstract

The energy efficiency of buildings can be evaluated by using the methodology provided by European regulations; however, this method required a lot of information which is generally not available for the existing buildings. In this paper an alternative method for the energy efficiency investigation of buildings is proposed and tested by means of Artificial Neural Networks (ANNs); an existing building built in 1990 and located in Perugia was chosen as case study and it was investigated by adopting both the mentioned approaches. An experimental campaign was also carried out in order to implement and validate the 3D model developed in TRNSYS. Results showed that the indoor air temperature trend simulated with ANN is closer to the measured data than the one simulated with TRNSYS, with lower mean error and MSE values. The energy consumption simulated with ANN is slightly higher than the one returned by using TRNSYS code of about 20 kWh/m^{2}year (difference lower than 7%). In agreement with the results, the proposed method can be considered as an alternative tool that can be used for the thermal-energy investigation of existing buildings, with important money and time saving.

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Keywords: Energy consumptions simulation; dynamic simulations; Artificial Neural Network; ANN and TRNSYS comparison

1. Introduction

Energy efficiency in buildings is one of the most important targets of European countries for reducing the greenhouse gas emissions and limiting the global warming. Many international reports [1-3] highlighted that the

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building sector is responsible for about 40% of the total energy consumptions, manly due both to poor building envelope characteristics and inefficient heating systems.

In order to check and to improve the energy performance of buildings, a common European methodology was provided [4, 5]; on the basis of these regulations each European country have to develop its national standards [6-8].

The European methodology [5] provides not only a common method for the energy performance evaluation of buildings but also a common tool for its checking. However, it requires a lot of data related to the buildings and HVAC systems as inputs which are often not easy to find or to establish uniquely.

Many studies were carried out in order to improve and to evaluate the energy performance of buildings; some of them were based on statistical data provided by European reports or by Municipalities [9], other one evaluated the efficiency of European methodology by using a survey questionnaire carried out in all European countries [10]. Other works evaluated the energy performance of buildings based on database in which different parameters related to the existing buildings were included [11-12]. Other works applied the methodology proposed by the European regulations by using dynamic software for different purposes; Al-Saadi et al. [13] developed a new TRNSYS type and it was validated for simulating PCM-enhanced walls, while Cornaro et al. [14] used both dynamic simulations and measurements for evaluating refurbishment solutions of Villa Mondragone located in the Colli Albani. Buratti et al. [15] also used dynamic simulation for the refurbishment of existing buildings, by applying aerogel materials on the interspace of semi-transparent surfaces in compliance with national regulations.

In the Literature interesting papers about the application of ANN algorithm to many different purposes can be found: Li et al. [16] developed an ANN for simulating the building's electricity consumption prediction, Fisher et al. [17] carried out a comparison between ANN and state-of-the-art for investigating conventional flat plate collectors and evacuated tubular collectors. Buratti et al. [18, 19] also carried out different studies in order to check the efficiency and the effectiveness of the ANN implementation in engineering application: in [18], an ANN was trained for checking energy certificates in accordance with European regulations; in [19] a Fitting Neural Network was implemented for the evaluation of thermal behavior of building envelope in summer conditions.

On the basis of the methodologies adopted in the Literature [9-19] and considering the European and Italian standards [3-8], in this paper an alternative method for the energy performance evaluation of buildings is proposed and tested. In particular, two Artificial Neural Networks implemented and validated in previous works [18, 19] were used and updated for the thermal and energy investigation of a case study and results were compared to ones obtained using TRNSYS code. The first network was trained in [18] basing on more than 3000 energy certificates of buildings and it is able to predict the energy consumptions in compliance with national regulations, the second one was developed in [19] basing on more than 2000 data acquired in several experimental campaigns in different buildings and it is able to simulate the indoor air temperature within the environment. Both the Networks were therefore validated using thousands of data of existing buildings different from the case study investigated in this work.

2. Methodology

2.1. Artificial Neural Network implementation

In [18] hundreds neural networks were trained varying the number of input parameters to be provided for the learning process; the best network was obtained using 21 input parameters but, because the goal of the paper [18] was to check the energy certificates drafted in the Umbria Region, some information about HVAC systems were neglected and did not provided for the learning process of ANN because not always available. Moreover, some energy indicators were also used as input parameters [18]. In the present paper, the best ANN found in [18] was updated for the energy consumptions prediction by providing the following 21 input parameters:

- data related to the building: category, year of construction, heated volume, heat transmission surface, use of the building, heat transmission surface/heated volume ratio, and Heating Degree Days;
- data related to the plant system: year of installation, type of system, fuel, and power of heating, cooling, and hot water production plants;
- data related to the renewable plants: type of system and year of installation.

Therefore, unlike [18], all the information available about building and HVAC systems and no energy indicators were provided for the learning process of the ANN. Data about cooling, ventilation, and illumination plants were neglected due to the small sample of data available with this kind of information; therefore, the ANN will be able to simulate only the heating and hot water energy demand. As in [18], the ANN was updated using more than 3000 data of more than 3000 different buildings; all the data was converted in numerical format; for no quantitative information a numerical format was adopted and it is shown in Table 1. A normalization of the data to be supplied for the training process was also carried out, considering the maximum value of each one [18, 19]; this way all the input parameters varied in the 0-1 range.

A two-layers feed forward Neural Network was trained by using Matlab programming language; a sigmoidal function for the hidden layer and a linear function for the output one were chosen as transfer function (T). The choice of the sigmoidal function for the hidden layer allows to simplify the gradient calculation of the error function and to reduce the computational time of the training process [20, 21]. The training process was carried out using the Levenberg-Marquardt backpropagation algorithm and the supervised method; therefore, the global energy performance index (G.E.P.I.) reported in EPC was supplied as target.

As in [18, 19], the number of neurons to be used in the hidden layer was established by carrying out a sensitivity analysis; in particular it was varied in the 1-120 range. The maximum number of neurons was established in order to avoid the overfitting problem of ANN which occurs when a high number of neurons is used. The Regression Value for each process (training, validation, test, and global) and the mean error, defined as the average difference between outputs and targets were used for checking the efficiency of the training process. The best ANN was found by using 79 neurons in the hidden layer; the related control parameters are shown in Figure 1 (regression values for each process) and in Figure 2 (mean error). Figure 1 shows that a very high Regression value for each process was obtained, and a Global Regression value equal to 0.989 which means that a very good correlation between the Neural Global Energy Performance Index (N.G.E.P.I) simulated with ANN and the one declared in EPC (G.E.P.I.) was found. The efficiency of the training of the network can be also highlighted by the mean error (the difference between the G.E.P.I. declared in the EPC and the one simulated with ANN). Figure 2 shows that the most likely error returned by the Network in all the process varies in ±5 kWh/m^2, with a relative mean error lower than 2%.

Table 1. Format number assigned to some input parameters chosen for the training process of ANN.

Input parameters	Type of parameters	Format number
Category	undeclared	0
	new buildings	1
	existing buildings	2
	refurbishment buildings	3
Fuel	undeclared	0
	methane	1
	liquefied petroleum gas (LPG)	2
	diesel	3
	electricity	4
	other	5
Renewable systems	undeclared	0
	photovoltaic	1
	solar thermal	2
	photovoltaic and solar thermal	3
	biomass	4
	other	5

Input parameters	Type of parameters	Format number
Use of building	undeclared	0
	residential building	1
	non residential building	2
Plant systems	undeclared	0
	traditional boiler	1
	boiler with sealed chamber	2
	condensing boiler	3
	electrical boiler	4
	centralized heating plant	5
	heat pump	6
	heater	7
	traditional boiler with tank	8
	condensing boiler with tank	9
	electrical water heater	10
	gas water heater	11
	other	12

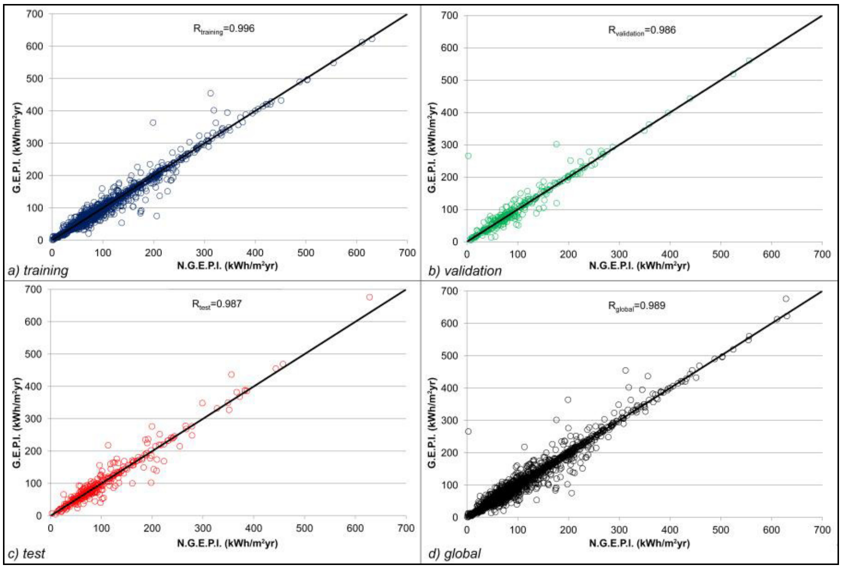

Fig. 1. Regression values obtained for each process (training, validation, test, global) of the best implemented ANN.

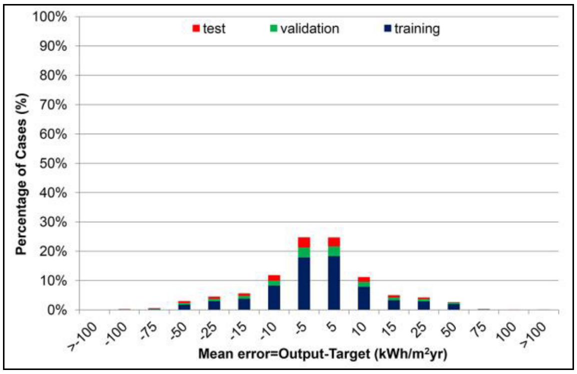

Fig. 2. Mean error returned by the best implemented ANN for each process (training, validation, test).

The network developed in [19] is able to simulate the indoor air temperature within the room starting from outdoor climate conditions and the thermal characteristics of the building envelope; for the implementation of the ANN thousands of experimental data monitored during spring-summer period in about twenty dwellings was used [19]. A very high Regression value (higher than 0.95) and a very small mean error (about -0.25°C) were obtained for this network, therefore, it was not considered necessary to improve it.

2.2. Case Study

A case study was chosen for testing the efficiency of the proposed method; in particular, results returned by applying the two ANNs were compared to the ones obtained by using the TRNSYS code. The case study (Figure 3) is a residential building built in 1990 and it is located in Perugia. It consists in five floors; in the first one are located four offices and in the other floors 16 dwellings of about 110 m^2. The data related to this building was not used for the implementation of the network, therefore it can be an interesting case for testing the generalization of the two networks. An experimental campaign was carried out in order to acquire all the data necessary for the validation of the simulation model implemented in TRNSYS; in particular, a survey was carried out in one dwelling (the one exposed to South-West in the last floor, and framed in red of Figure 3) from 14 to 24 of May 2015 and the following data was monitored: thermal transmittance of the external wall, indoor air temperature, and geometrical characteristics of buildings.

The indoor air temperature was monitored in different rooms by using TinyTag Ultra 2 TGU-4500, with an acquisition rate of 10 minutes, and using a DeltaOhm HD32.7 acquisition system with probes for air temperature (HP3217R) with the same acquisition rate located in the most important room (living room). A ThermoZig was also used for the measurement of the thermal transmittance of the external wall; in particular it allows to monitor the surface temperature and the heat flux through the external wall. The position of the adopted instrumentation is reported in Figure 3.During the experimental campaign, the thermal characteristics of the building envelope (Table 2), and the boundary conditions were checked. Windows are characterized by wooden frames and double glazing (4/8/4) with air in interspace (U = 2.2 W/m^{2}K). The thermal transmittance of the external wall was checked by using data monitored with ThermoZig: the values measured in compliance with ISO 6946 are very close to the ones calculated (0.723 vs 0.735 W/m^{2}K), therefore the chosen stratigraphy was considered proper. Moreover, a natural gas boiler of 32 kW is used in the examined dwelling for heating and hot water production.

A 3D simulation model (Fig. 3 below) was implemented using Google SketchUp program and imported in TRNSYS; the mean indoor air temperature value monitored during the experimental campaign was used for the validation of the 3D simulation model. The heating period, infiltration, and ventilation values defined in TRNSYS were chosen in agreement with European and Italian regulation.During the validation process, a MSE equal to 0.91°C was obtained between the monitored indoor air temperature and the simulated one, with a mean error of 0.13°C. In agreement with previous works [15], the 3D simulation model was considered validated.

Fig. 3. Case Study: existing building and 3D simulation model.

Table 2. Thermal characteristics of the building envelope: external wall, roof, and ceiling.

Layer/Materials		s (m)	c_p (J/kgK)	λ (W/mk)	ρ (kg/m^3)	R (m^{2}K/W)	U (W/m^{2}K)
Roof	plaster	0.010	1800	0.900	910	0.01	0.960
	hollow clay filler blocks	0.200	920	0.660	840	0.30	
	screed	0.200	1000	2.300	2400	0.08	
	insulating	0.010	1200	0.150	30	0.07	
	brick	0.050	840	0.160	700	0.31	
	bituminous	0.005	160	0.040	1360	0.13	
External Wall	plaster	0.010	1800	0.900	910	0.01	0.723
	brick	0.080	1400	0.400	800	0.20	
	air	0.100	1005	/	/	0.18	
	insulating	0.020	1200	0.040	30	0.50	
	brick	0.120	1400	0.387	800	0.31	
	plaster	0.010	1800	0.900	910	0.01	
Ceiling	plaster	0.015	1000	0.900	910	0.02	1.300
	hollow clay filler blocks	0.200	920	0.660	840	0.30	
	screed	0.100	1000	2.300	2400	0.04	
	insulating	0.010	1400	0.045	200	0.22	
	bedding screed	0.040	1000	1.300	2150	0.03	
	flooring	0.015	800	1.00	2000	0.02	

3. Results and discussion

Energy performance and indoor thermal conditions were simulated using both the described methods. Table 3 shows all the information and steps required for the application of the two ANNs and the ones necessary to set the 3D simulation model implemented in TRNSYS; it highlights that all the information required by ANNs is also necessary for the simulation model, moreover, all data is readily available or calculable with respect to the other ones required for the 3D model implementation, such as opaque wall stratigraphy or distribution, emission, and regulation information about heating and hot water production systems, which may be difficult to assess, especially for existing buildings. Table 3, therefore, highlights that ANNs require in general lower number of input parameters than TRNSYS dynamic model for the prediction of indoor air temperature and energy consumption of buildings.

All the data necessary for the application of the two ANNs and for TRNSYS code were provided and set, and the indoor air temperature and the energy consumptions of the investigated dwelling were calculated. The mean value of the air temperatures acquired in different rooms of the dwelling was considered for the comparison between the simulated values and the experimental ones.

In Figure 4 the comparisons for indoor air temperature and energy consumptions are shown; Figure 4 (a) shows that both the methodologies allowed to correctly simulate the indoor air temperature, with a very small difference with respect to the mean value of the monitored data. The mean differences are about 0.13°C for TRNSYS and 0.06°C for ANN, while the MSE values are respectively equal to 0.91 and 0.20°C.

The energy consumptions of the examined dwelling are shown in Figure 4 (b); it can be seen that the energy demand simulated by using TRNSYS and the ANNs is very similar. The G.E.P.I. (Global Energy Performance Index) returned by the ANN is higher than the one obtained using TRNSYS of about 20 kWh/m^{2}year, but this difference consists in a relative error of about 6%, lower than the maximum error expected from the calculation codes conforming to European methodology (10%), therefore it can be considered acceptable.

Table 3. Input data required for the application of two methods.

ANN Energy consumptions	 Indoor air temperature	TRNSYS
1. Heating Degree Day (HDD) and place 2. category of building (new, existing or refurbishment building) 3. geometric survey (year of construction of building, heated volume, floor area, heat transmission surface, heat transmission surface and heated volume ratio, use of buildings) 4. heating and hot water plant information (year of construction, type, power, and fuel) 5. renewable plant information (year of construction and type)	1. Outdoor climate conditions (day, month, hour, air temperature, diffuse solar radiation on horizontal surface, direct solar radiation on horizontal surface, global solar radiation on horizontal surface, orientation) 2. building envelope characteristics (thickness, thermal transmittance, surface mass, attenuation factor, phase shift factor, periodic thermal transmittance, and surface of the external wall, area of windows and frame, floor area)	1. Climate file (modified with experimental data) 2. heating period (in agreement with Italian regulation) 3. geometric survey (heated volume, floor area, heat transmission surface, heat transmission surface and heated volume ratio, window characteristics) 4. heating and hot water production system (power, fuel, efficiency and type of the generation, distribution, emission, and regulations systems) 5. renewable energy plant data (power, fuel, efficiency and type of the generation, distribution, emission, and regulations systems) 6. 3D simulation model implementation 7. heat load definition in agreement with Italian regulations 8. opaque and semi-transparent surfaces definition (thermal characteristics) 9. 3D model validation

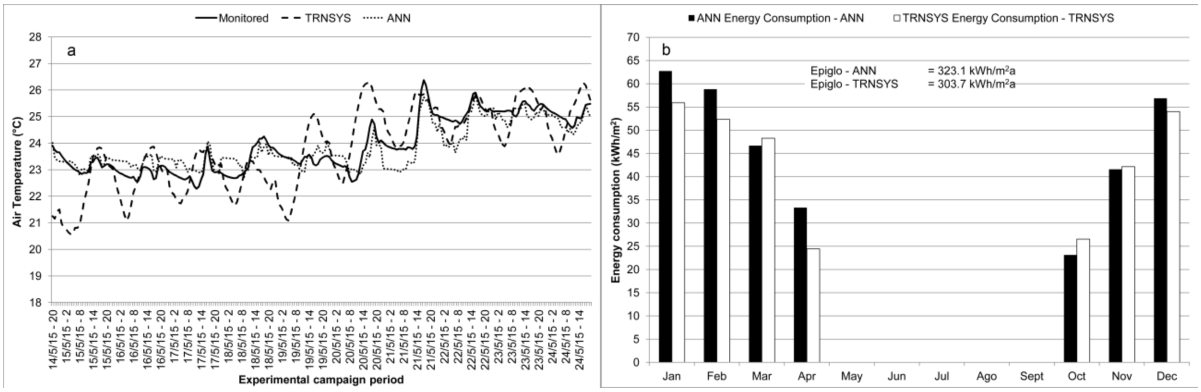

Fig. 4. Indoor air temperature and energy consumptions comparison: TRNSYS and ANN data.

Results shown in Figure 4 allow to confirm the effectiveness of the trained Network. In particular, it highlights that ANN allows to better approximate the monitored trend of indoor air temperature with respect to the one simulated with TRNSYS. Results confirmed the effectiveness of using ANNs for the thermal and energy investigation of existing buildings; in particular the advantages of the ANN application with respect to TRNSYS code were highlighted. In fact, the two ANNs used in this work allowed to simulate the indoor air temperature within the dwelling and its energy demand in less time and with less and more available input parameters, getting results very close to experimental evidence.

4. Conclusion

In this study the application of two ANNs to a new case study was tested in order to check the effectiveness of the implemented algorithms with respect to the TRNSYS code. Both networks were developed and validated in previous works [19, 20], however the first one [19] was updated using more information about HVAC systems. The two networks are able to simulate the indoor air temperature and the energy consumptions of buildings, and the results were compared to the ones obtained using 3D simulation model implemented in TRNSYS, by applying the two methods on a case study.

An existing building not used for the implementation of the two ANNs was considered as case study and then investigated by applying both ANNs and TRNSYS. An experimental campaign was carried out from 14 to 24 of May 2015 for the measurement of the thermal characteristics of the building envelope and of the indoor air temperature in order to validate the 3D simulation model implemented in TRNSYS.

Results showed that the ANN allows to simulate the indoor air temperature trend with a very small mean difference of about 0.06°C and a very small MSE (0.20°C) with respect to experimental data. The energy consumptions simulated with ANN are slightly higher than the ones obtained with TRNSYS (20 kWh/m^{2}year). However the difference between the results obtained with the two methodologies is about 6%, lower than the one acceptable and returned by certificated software (acceptable error 10%).

In accordance with results, the two implemented ANNs allow to obtain results very close to the experimental data, furthermore they have the advantage of requiring lower and more available input parameters and no 3D simulation models and no model validations are required. Therefore, it can be an alternative tool for predicting the indoor thermal conditions and the energy consumptions of buildings with an important time and money saving.

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