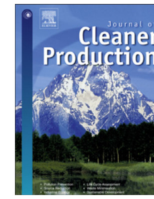
Journal of Cleaner Production 239 (2019) 117993

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro



Artificial Neural Networks to assess energy and environmental performance of buildings: An Italian case study

A. D'Amico [a, b, *], G. Ciulla [a, b], M. Traverso [c], V. Lo Brano [a, b], E. Palumbo [c]

[a] *University of Palermo, Italy*
[b] *Department of Engineering (DI), Italy*
[c] *Institute of Sustainability in Civil Engineering, RWTH Aachen University, Germany*

A R T I C L E I N F O

Article history:
Received 5 March 2019
Received in revised form
1 July 2019
Accepted 9 August 2019
Available online 11 August 2019

Handling editor. Zhen Leng

Keywords:
Building energy demand
Artificial neural network
Energy balance
Life cycle assessment
Environmental impacts
Decision support tool

A B S T R A C T

Approximately 40% of the European energy consumption and a large proportion of environmental impacts are related to the building sector. However, the selection of adequate and correct designs can provide considerable energy savings and reduce environmental impacts. To achieve this objective, a simultaneous energy and environmental assessment of a building's life cycle is necessary. To date, the resolution of this complex problem is entrusted to numerous software and calculation algorithms that are often complex to use. They involve long diagnosis phases and are characterised by the lack of a common language. Despite the efforts by the scientific community in the building sector, there is no simple and reliable tool that simultaneously solves the energy and environmental balance of buildings. In this work, the authors address this challenge by proposing the application of an Artificial Neural Network. Due to the high reliability of learning algorithms in the resolution of complex and non-linear problems, it was possible to simultaneously solve two different but strongly dependent aspects after a deep training phase. In previous researches, the authors applied several topologies of neural networks, which were trained on a large and representative database and developed for the Italian building stock. The database, characterised by several building models simulated in different climatic conditions, collects 29 inputs (13 energy data and 16 environmental data) and provides 7 outputs, 1 for heating energy demand and 6 of the most used indicators in life cycle assessment of buildings. A statistical analysis of the results confirmed that the proposed method is appropriate to achieve the goal of the study. The best artificial neural network for each output presented low Root Mean Square Error, Mean Absolute Error lower than 5%, and determination coefficient close to 1. The excellent results confirmed that this methodology can be extended in any context and to any condition (other countries and building stocks). Furthermore, the implementation of this solution algorithm in a software program can enable the development of a suitable decision support tool, which is simple, reliable, and easy to use even for a non-expert user. The possibility to use an instrument to predict a building's performance in its design and planning phase, represent an important result to support decision-making processes toward more sustainable choices.

1. Introduction

Energy transition to a low-carbon economy is one of the European Commission priorities. This transition should be in line with the Paris Climate Agreement and with the goals of climate action and sustainable production and consumption (12 and 13th SDG, 2012) concerning environmental pollution, waste, management, and reduction of raw materials and natural, resources.

Moreover, Europe's economic dependence on fossil fuels and on non-European resources increases the need for meticulous assessments regarding future energy consumption, raw material demand, and environmental impacts. In this context the building sector is essential and presents a significant potential. It consumes up to 40% of the world's energy, contributing to 36% of the global

* Corresponding author. Department of Engineering, University of Palermo, Italy.
E-mail addresses: antonio.damico@deim.unipa.it (A. D'Amico), giuseppina.ciulla@unipa.it (G. Ciulla), marzia.traverso@inab.rwth-aachen.de (M. Traverso), valerio.lobrano@unipa.it (V. Lo Brano), elisabetta.palumbo@inab.rwth-aachen.de (E. Palumbo).

https://doi.org/10.1016/j.jclepro.2019.117993
0959-6526/

Nomenclature

Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modelling
BP	Back-propagation algorithm
BPS	Building Performance Simulation
EPD	Environmental Product Declaration
GD	Gradient Descendent algorithm
LCA	Life Cycle Assessment
MLP	Multi-Layer perceptron

Error and performance parameters

MAPE	Mean Absolute Percentage Error [%]
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R^2	Determination coefficient
StD	Standard Deviation

Other parameters

C_T	Total thermal capacity [kWh/(m^3·K)]
EI_{EC}	Environmental Impact of the energy carrier
EI_{glazed}	Environmental Impact of the glazed surface
EI_{global}	Global Environmental Impact of the building
EI_{opaque}	Environmental Impact of the opaque surface
h	Operating heating hour [h]
$H_d{}^*$	Annual heating energy demand [kWh/year]
HDD	Heating Degree Days [K day]
M_i	Mass of opaque layer [kg]
Q_G	Internal gains [kWh/year]
Q_S	solar gains [kWh/year]
S	Losses surface [m^2]
S_H	Heat surface[m^2]
S_{op}	Opaque surface [m^2]
S_w	Surface of the glazed component [m^2]
S/V	Shape factor [m^{-1}]
U_0	Overall U-value [W/(m^2·K)]
U_{op}	Opaque thermal transmittance [W/(m^2·K)])
U_w	Glazed thermal transmittance [W/(m^2·K)])
V	Heated volume [m^3]
v	wind speed [m/s]

Outputs of the model

ADP_{Fossil}	Abiotic Depletion Potential-Fossil [MJ]
AP	Acidification Potential kg [SO_2 eq]
EP	Eutrophication Potential kg [PO_4^{3-} eq]
GWP	Global Worming Potential [kg CO_2 eq]
H_d	Heating energy demand [kWh/(m^2 ·year)]
ODP	Ozone Depletion Potential [kg CFC11 eq]
POCP	Photochemical Ozone Creation Potential [kg C_2H_4 eq]

greenhouse gases (Peltokorpi et al., 2019), and it is responsible for 25%–30% of all waste generated in the EU. The building sector should be designed, constructed, used, and rebuilt considering all mentioned priority areas.

1.1. State of the art review

From an energy consumption perspective, there have been significant efforts to improve the efficiency of buildings and reduce energy consumption through the development of various energy saving policies worldwide. A building's energy performance is a function of several variables such as: thermo-physical properties of opaque and glazed envelope surfaces, geometry, weather conditions, intended use, occupant behaviour, control strategies, and several other parameters. To solve the building energy balance, several numerical approaches were developed, and most of them were tested and implemented using specialised software tools for Building Performance Simulation (BPS) such as: TRNSYS, Energy Plus, ESP-r, and DOE-2. These software programs are characterised by the lack of a common language. They describe the thermal balance by exploiting different numerical methods. These characteristics complicate the selection of the most suitable solution (Ciulla et al., 2017; Ferrari et al., 2019).

To accelerate the preliminary assessment, it is more convenient to analyse simplified methods and models, e.g. those characterised by a steady state approach (De Rosa et al., 2014). However, certain phenomena are completely neglected by those software (Ciulla et al., 2016), creating limitations and rendering these software unsuitable. In contrast, the use of BPS tools or complete procedures (ASHRAE, 1980; EN ISO 13790, 2008) are characterised by excessive computational costs and high complexity. The results are reliable if the model is correctly calibrated and the data inserted in the model is obtained from a long and careful data collection phase. In all cases, it is necessary to be an expert user to implement, solve, evaluate the results, and correct any possible mistakes.

From the environmental point of view, the most appropriate scientific method to measure the environmental impacts of the entire building's life (raw material supply, manufacture of construction products, construction process, usage, demolition, and/or recycling) is the Life Cycle Assessment (LCA) (EN ISO 14040, 2006; Proietti et al., 2013; Stephan and Athanassiadis, 2017). LCA aims to assess the environmental impacts of a product along its life cycle according to the (EN ISO 14040, 2006; EN ISO 14044, 2006), and for buildings according to the (ISO 15686, 2011).

Several studies describe the LCA of a building from a theoretical point of view, whereas other papers used this methodology in analytical manner and through case studies (Asdrubali et al., 2013; Azari and Abbasabadi, 2018; Buyle et al., 2013; De Lassio et al., 2016; Roh et al., 2016). LCA has been implemented in residential, commercial, and office buildings for at least two decades (Bovea et al., 2014; Gervasio et al., 2018). Several databases and software programs, such as GaBi© and Simapro©, were developed to support LCA implementation in the building sector. Moreover, a type III ecolabel scheme, the Environmental Product Declaration (EPD) (ISO 14025, 2006), was developed and widely applied to assess buildings and their components. In this context, the first database developed based on LCA results from EPD of building materials was the Ökobaudat. The Ökobaudat platform is a standardised database for environmental evaluations of buildings provided by the Federal Ministry of the Interior, Building and Community ("ÖKOBAUDAT," 2019).

However, although LCA is standardised by the ISO 14040/44 (2006), its implementation in the building sector still presents several challenges.

Recently, several researchers are working on the development of a comprehensive life cycle energy analysis tool. For example (Stephan et al., 2012) describe a framework which considers energy requirements at the building and city scales. This framework has been implemented through the development of a software tool which analyses the life cycle energy demand of buildings (D'Amico and Pomponi, 2018).present a computational tool to help practitioners in the design of material-efficient structures for multi-storey buildings frames. In all cases, not only the energy consumption of the building is considered, but also embodied energy, and energy within the LCA phases (Dixit, 2019).

Based on these considerations and on the difficulties that characterize the energy performance analysis of buildings, a comprehensive energy and environmental building assessment is difficult to implement. To analyse the energy and environmental performance of buildings, certification schemes such as LEED, DGNB, etc. have been developed. All of them include a sustainability assessment in their evaluation, but not all are based on a life cycle approach. Another possibility is the inclusion of LCA data on the Building Information Modelling (BIM). This solution facilitates the application of LCA in the building sector (Anand and Ben Amor, 2017) during the preliminary design phase (Peng, 2016; Shafiq et al., 2015), and it provides data required to evaluate the energy needs and environmental impacts of a building during its entire useful life (Anand and Ben Amor, 2017; Díaz and Antön, 2014). There are several works regarding the power of BIM (Krygiel et al., 2008; Najjar et al., 2017), whereas others underline the aims and potential of green BIM in the building sector (Volk et al., 2014; Wong and Zhou, 2015). However, there is a growing concern regarding BIM and LCA integration due to its high complexity (Jrade and Abdulla, 2012). In the construction sector, the implementation of a BIM tools requires evolved technologies to support sustainable construction and decision-making processes (Wong and Zhou, 2015; Wu and Issa, 2013). Furthermore, the lack of a harmonised methodology for BIM hinders the development of comprehensive building analyses from several points of view. No tool or methodology with low computational time is available for non-expert users (Attia et al., 2009). This situation can influence energy planning, slowing down the preliminary assessment of the energy and environmental performance of a building stock. Therefore, a model and tool that allow fora comprehensive assessment of environmental and energy performance with user-friendly interface, low computational cost, and high level of accuracy without losing meaningful parameters should be developed to represent the complex reality. This study aims to issue an alternative method to support the decision-making process during the planning and designing of high energy performance buildings (Beccali et al., 2017); the method should provide an estimation of the environmental and energy performances of a building's life cycle. Previous researches, such as (D'Amico and Pomponi, 2018) and (B. D'Amico et al., 2019), attempted to develop such method. However, significant lots efforts are still needed to meet this ambitious target. The present study aims to contribute to cover this research gap.

A solution for this complex problem can be developed based on the use of Artificial Intelligence (AI) algorithms. These algorithms exploit the correlation between large amounts of data to identify functional connections between input and output, which would be difficult or impossible in some other way (Ciulla et al., 2019b). As one of the most popular AIs, the Artificial Neural Network (ANN) is a mathematical paradigm that imitates the behaviour of biological neural networks. It is widely applied to solve complex problems in different fields (Ciulla et al., 2019a). In a neural network, the problem is decomposed into “elementary” information contained within each single neuron. The network is not previously programmed, but it is obtained through a “training” process with empirical data in which the network learns through input/output samples (Floreano and Mattiussi, 2002). The training process is performed regardless of any hypothesis concerning the statistical distribution of the data itself and the knowledge of the physical laws that regulate the studied phenomenon.

Unlike other statistical or parametric methods, ANNs are can derive non-explicit relationships from a large mass of correlated data by exploiting the high computing capabilities of current computers. In this manner, ANNs have become a successful approach to solve problems in different areas such as robotics, power systems, optimization, and manufacturing (Maren et al., 1990) of complex domains such as image processing (Jha et al., 2017; Zhang et al., 2018), industrial problems (Qin et al., 2017), and forecasting (Ruiz et al., 2018; Senjyu et al., 2002).

Furthermore, ANNs have also been developed to forecast the life cycle environmental impacts based on the energy inputs required for particular food processes. In (Khanali et al., 2017), ANN was applied for the production of black tea, green tea, and oolong tea in Iran. In (Nabavi-Pelesaraei et al., 2018), it described the forecast for energy output and environmental impacts of paddy production (Elhami et al., 2017). applied ANN to determine the environmental emissions from lentil cultivation (Li et al., 2015). used ANNs to estimate the missing data for an LCA of electronic products. The first approach combining ANN and LCA for the building sector is described by (Oduyemi et al., 2015), who include only an economic analysis.

As determined by (B. D'Amico et al., 2019), the possibilities of ANN applications to solve comprehensive building performance are endless. However, a large and reliable dataset of real and accurate building designs is needed.

To better understand the readability of the work, in Table 1 are collected the papers that assess the energy and environmental performance of building, distinguished in the following key finding:

- Building LCA: samples of papers that evaluate the environmental aspects of the building construction through the LCA application;
- LCA and BIM: samples of papers that evaluate the environmental and energy aspects of the building construction through the simultaneously LCA and BIM application;
- ANN and Building: samples of papers that solve the building energy balance with the ANN application;
- ANN and LCA: samples of papers that evaluate the environmental and energy aspects of the building construction through the simultaneously LCA and ANN application.

For each paper is indicated the key finding, the authors and year of publication, and a brief description of the main objectives:

1.2. Contribution of the work

Based on the previous considerations, the authors propose a methodology to support decision makers during the planning and design phases of a building. The method can be provide a valid estimation of the energy and environmental performance of a building along its life cycle. It can analyse different scenarios and identify the most sustainable one already in the strategic phase. Moreover, this tool can be used by non-experts on LCA and/or energy performance calculation, which is often the case in the administrations or stakeholders. The use of AI to solve this complex problem can represent a valid and attractive alternative. The implementation requires the presence of a suitable database set, so that the output data strongly relate to one or more input data.

To create a reliable database, the results obtained by dynamic models and LCA of an “ideal building” designed with high energy performance according to the minimum standard requirements of the European Community were used (EN ISO 13790, 2008). Starting from a recently validated energy database used to evaluate the heating energy demand of a non-residential building (Ciulla et al., 2017, 2019b), the model will be improved and developed by

Table 1
Key finding of papers to evaluate the energy and environmental building performance.

Key finding	Authors	Main objective
Building LCA	Asdrubali et al. (2013)	Proposes the LCA as a tool for the eco-friendly building design.
	Azari and Abbasabadi (2018)	A review on embodied energy use in buildings, indicating research gaps and major strategies to reduce embodied energy.
	Buyle et al. (2013)	An overview of the current situation of Life cycle assessment (LCA) in the construction industry.
	Dixit (2019)	An overview to identify key parameters affecting REE calculations in order to streamline the embodied energy calculation.
	Gervasio et al. (2018)	Part of a research project aiming for the development of a performance-based approach for sustainable design, focusing on the efficient use of natural resources over the lifetime of buildings.
	Proietti et al. (2013)	Results of a detailed LCA study of a low-energy consumption building, complying with the "Passive House" standard, located in Italy, according to European ISO 14040 and 14044.
	Roh et al. (2016)	Development of the Building Life Cycle Carbon Emissions Assessment Program (BEGAS 2.0) to support Korea's GBI certification system.
	Stephan and Athanassiadis (2017)	A bottom-up approach to spatially model building stocks and quantify their embodied environmental requirements; each building's geometry is modelled and used to derive a bill of quantities
	Stephan et al. (2012)	A framework which takes into account energy requirements at the building scale, the embodied and operational energy of the building and its refurbishment, implemented through the development of a software tool which allows the rapid analysis of the life cycle energy demand of buildings at different scales.
	D'Amico and Pomponi (2018)	A computational tool that aims to help practitioners to design material-efficient structures for buildings based on an optimization framework.
LCA and BIM	Anand and Ben Amor (2017)	A review to explore the application of LCA to the various areas in the buildings sector: the embodied energy and the building certification systems.
	Díaz and Antön (2014)	Description of the integration of LCA and BIM to create synergies to develop a tool for attaining higher efficiency and sustainable construction.
	Krygiel et al. (2008)	A book to the subject of sustainable design and of the use of building information models (BIMs).The first two chapters introduce both sustainable (or "green") design and BIM..
	Najjar et al. (2017)	Description of the integration of BIM with LCA, and presents the outcome of this integration in evaluating environmental impacts of building materials in the construction sector.
	Wong and Zhou (2015)	An overview and comparison of 84 green BIM papers.
	Jrade and Abdulla (2012)	An overview regarding LCA, BIM, and data exchange standards that could facilitate integrating; it is proposed a prototype, developed and validated, where a level 2 LCA tool is linked to a BIM model.
ANN and Building	Ciulla et al. (2019b)	The use of ANNs to predict the demand for thermal energy linked to the winter acclimatization of non-residential building at European level.
	Ruiz et al. (2018)	A method for energy consumption forecasting in public buildings, to achieve energy savings, and to improve the energy efficiency, without affecting the comfort and wellness.
	Senjyu et al. (2002)	A new 1-h-ahead load forecasting method using the correction of similar day data; the forecasted load power is obtained by adding a correction to the selected similar day data.
ANN and LCA in Building	Li et al. (2015)	A survey of the current Environment Impact Assessment (EIA) methodologies; an ANN approach is developed to estimate the missing data.
	Oduyemi et al. (2015)	An ANN model to estimate operating and maintenance costs of existing buildings; an Office Block, Penllergaer Business Park.
	(B. D'Amico et al., 2019)	A brief review of the current status of machine learning and neural network applications in structural and civil engineering, highlighting their potential use in research concerning sustainability related decisions concerned with building structures and structural materials..

adding other case studies.

Different transmittance values, construction materials, and energy carriers were chosen and simulated to represent representative building stocks of Italian cities for different climatic zones, weather conditions, and shape factors (A. D'Amico et al., 2019). In this manner, it was possible to develop a representative database where certain data identifying building conditions was input, creating a certain data output that described the energy and environmental performances. This database was used to train several ANNs to provide 1 energy output and 6 environmental outputs. For each building it is possible to have immediately knowledge on the heating energy demand and the values of representative environmental impacts such as: Global Warming Potential (GWP), Ozone Depletion Potential (ODP), Acidification Potential (AP), Eutrophication Potential (EP), Photochemical Ozone Creation Potential (POCP), and Abiotic Depletion Potential-Fossil (ADP_{Fossil}) (Thibodeau et al., 2019; Wijnants et al., 2019). The values of those indicators were acquired from the Environmental Product Declaration relative to the materials already inserted in the database.

In this work, the results of the best ANN solutions are presented. These networks are characterised by high determination coefficients (R^2), high Mean Absolute Percentage Error (MAPE), and low Root Mean Square Error (RMSE). The results confirm that the use of ANN is a reliable approach to simultaneously solve the energy and environmental aspects of a building. This work represents only the initial step towards an instrument that solves complex and different problems with a single informatics tool, unique language, and simple user interface.

2. Methodology

To reach the study's objective, the research can be divided in two main areas: the energy balance solution and the LCA of a building. The application of the main theoretical concepts and numerical solutions of these areas will enable a building analysis which simultaneously provides an energy and an environmental response. Fig. 1 represents the work's schema, where the main tasks are identified.

As indicated by (B. D'Amico et al., 2019), AI approaches such as machine learning algorithms and neural networks are good alternatives for this kind of problem. However, the single and biggest impediment of this approach is the lack of large datasets of actual building performances. To overcome this problem, the first step of this work is characterized by the implementation of a reliable energy and environmental building database.

The first main task is related to the development of a comprehensive database. The two actions of this task are:

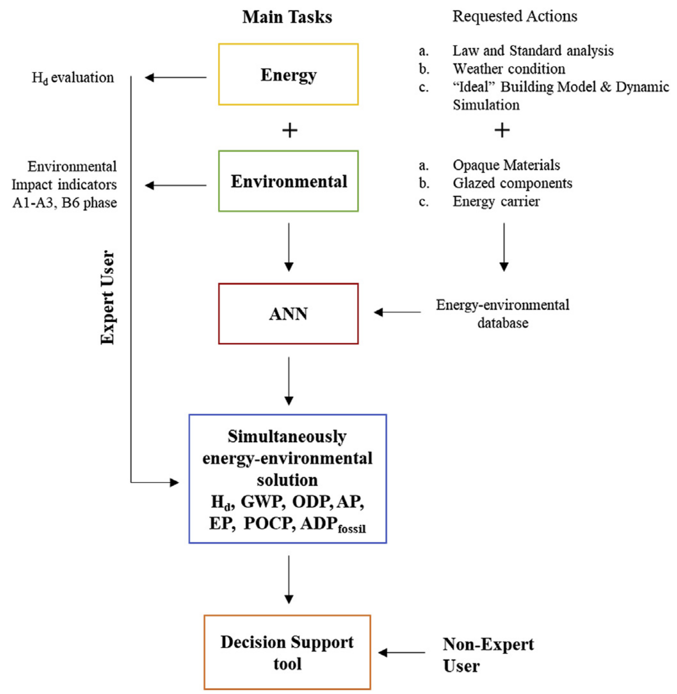


Fig. 1. Flowchart of the main tasks.

1. Implement a building energy database to determine the heating energy requirements (H_d);
2. Identify and select LCA results of building components, and introduce them into the database.

The second task contemplates the application of an ANN to simultaneously identify the energy and environmental performances of a generic building.

Finally, these results will be used to develop a decision support tool which allows, non-expert users to quickly and easily identify energy and environmental building performances.

2.1. Building energy database to determine heating energy requirements

To apply the ANN approach, it is necessary to implement a suitable database that represents the analysed problem in any general form or condition. However, European country autonomously legislate the field of energy efficiency according to their own heating or cooling needs. Each country is characterised by a different existing real estate asset and varied transmittance limit values for the envelope and efficiency limit and type of systems. For this reason, in this initial work, the authors decided to develop a representative database for typical high energy performance non-residential building stocks in the Italian context.

A deep examination of the national laws on Italian construction (Dlg. n° 192, 2005; DPR 412/93, 1993) and a careful analysis of the climatic context were performed. Climatic indices such as the Heating Degree Days (HDD) were used to classify the country into harsh, mild, or warm climate, and to select several cities that represent the entire climate conditions of each classification. The legal energy requirements of member states based on the Italian standard for energy consumption of buildings (EN ISO 13790, 2008) were collected. Based on these requirements, several representative building constructions were selected, and the most suitable and useable envelope configuration (shape, stratigraphy and materials), was identified. Specific information regarding the following items were collected:

- geometric characteristics of the building: width, depth, height, heated volume, and loss surfaces;
- thermo-physical characteristics: transmittance and thermal capacity of opaque and glazed surfaces;
- boundary conditions of the building envelope: weather conditions, climatic indexes, solar radiations, latitude, altitude, wind speed, and relative humidity;
- plants: heating periods and operating hours; lighting system;
- intended use: employment rate, air infiltration, air change, and internal gains.

In this stage, an "ideal building" model was developed in a dynamic software and the reliability of the data was ensured by calibrating the models with the energy performance dictated by reference data (Eurostat, n.d.). Due to the parametric simulation, the "ideal building" was varied with different shape factors, heated volumes, and building construction types to represent Italian building stocks. Each model was established under different Italian climates and designed with varying thermophysical features. The results were analysed and collected in a specific database, it is possible to identify the energy requirements of each building configuration. All main features are described in section 3.

2.2. Life cycle assessment of buildings to identify environmental impact indicators

In this phase the aim is to identify and gather information on the environmental impacts of building components along their life cycle, and estimate the environmental profile of a generic Italian building. The environmental impacts of building models and their components are analysed and inserted in the database to select certain indicators for the environmental profile estimation of a building. In this initial work, the authors decided to collect data with the use of an EPD according to the (EN 15804, 2014) considering A1 to A3 and B6 phases to determine the following environmental indices:

- GWP: contribution of a product to climate change; it measures the greenhouse gas emissions into the air over 100 years. The contribution to climate change by each greenhouse gas is compared to the CO_2 contribution. Hence, the indicator unit is kg of CO_2 per kg of emission;
- ODP: effect of an emitted gas in the reduction of the ozone layer that protects the earth from harmful UV-radiation. Each chemical effect is compared to CFC-11, and the unit used is kg of CFC-11 per kg of emission;
- AP: contribution to the acidification potential of each emitted air pollutant, such as SO_2 or NO_x,. The AP unit is kg of SO_2;
- EP: indicates the levels of macronutrients, such as N and P, in the environment, and measures the contribution of each emission. The unit is kg of $(PO_4{}^{2})$ equivalents per kg of emission;
- POCP: contribution to photochemical ozone formation of each substance emitted into the air. The unit is kg of ethylene (C_2H_4) equivalents per kg of emission;
- ADP_{Fossil}: refers to the use of abiotic natural resources. It is a relative measure of the depletion by a reference element considering the impacts derived from the extraction of minerals and fossil fuels. In this study, antimony is used as a reference element, and the unit is kg of antimony (Sb) equivalents per kg of extracted mineral (Pikoń, 2012).

These indexes are very common in the literature and were used in an LCA study implemented with the CML database of Leiden University (Bozorg Chenani et al., 2015).

The authors have considered only phases A1 to A3 and B6 because the main goal was to train the ANN and prove that could simultaneously provide energy and environmental profile data under changing building scenarios. The work will be complete in further studies.

2.3. Application of ANN to simultaneously identify the energy and environmental performance of a generic building

As previously indicated, a wide range of scientifically validated tools are available internationally. However, to analyse several aspects of the same problem, multiple software programs may be needed.

In the field of ANN, problem-solving and searching refer to a large body of core ideas that addresses: deduction, inference, planning, common sense reasoning, theorem proving, and related processes. These algorithms are not based on the knowledge of the system dynamics, but on the elaboration of a significant sample of input data, which represent the variables under study, and on the related output data. These models are very useful when the studied phenomenon is characterised by high complexity and interdependence of several factors. Particularly when the identification and calibration of an analytical and/or statistical deterministic model is quite complicated and often does not offer sufficient guarantees of reliability.

Based on these considerations, the exemplary database was used to identify, train and develop the optimal solutions and typologies of an ANN, which simultaneously represents and solves a traditional energy balance and LCA of a building.

3. Case study

To select and train an ANN to simultaneously solve the energy-environmental balance of a building, it was necessary to develop a comprehensive building database that simultaneously considers energy and environmental features. To guarantee the reliability of the results, it was necessary to use a large database based on well-known conditions: form of construction, weather, and typology of materials and components, including their thermophysical and environmental profiles. Focusing on Italian laws and standards on energy efficiency buildings, the authors implemented a representative building database of a non-residential building designed with high energy performance and representative environmental performance.

Regarding the accuracy of the energy analysis, the validity of this database was guaranteed by the calibration of the first model based on monitored internal temperatures in an actual building located in Palermo.

3.1. Energy database

For a correct energy planning a deep knowledge of the energy performance of a building stock is strategic. Several energy efficiency and sustainable growth scenarios should be define to:

- reduce energy consumption;
- reduce CO_2 emissions;
- increase the added value of the building stock.

As previously mentioned, to study the influence of various relevant parameters in the overall energy balance of a building, a dynamic model of a non-residential "ideal building" was developed. A dynamic model of an actual office building located in Palermo was built in the TRNSYS environment (Klein and others, 1996), which was carefully calibrated with monitored temperature data. Based on this model, the "ideal building" model was designed to have high energy performance according to the standard requirements.

Based on the Italian national guidelines for building energy certification (Decreto 26 giugno, 2015), the peninsula is characterised by 6 climatic zones that theoretically have the same climate. Hence, the Italian law imposes the transmittance limit values presented in Table 2.

From the thermophysical point of view, the main features of the building envelope, are collected in Table 3.

To achieve the required limit transmittance value (Table 2), a layer of rock wool with different thicknesses (conductivity of 0.039 W/mK and density of 30 kg/m^3) was added for each climatic zone.

Finally, to generalize the results, the "ideal building" was:

- simulated with varying shape factors ($0.24 < S/V < 0.9$) and heated volumes creating 13 building models (Table 4);
- simulated in 5 climate zones; for each zone, 3 cities were chosen to include the maximum, minimum, and mean HDD values (Table 5) (A. D'Amico et al., 2019);
- simulated 8 times varying the orientation by 45° to consider the average contribution of solar gains (Ciulla et al., 2016; Pacheco et al., 2012);
- characterised by specific internal gains (Ciulla et al., 2017).

Because in Italy there are only two cities that belong to the first zone, with very similar HDD values, climatic zone A was not simulated.

Based on a parametric simulation, 1560 "ideal building" models were simulated (Fig. 2).

As specified by (A. D'Amico et al., 2019), each model was characterised by the detailed schedules of equipment, lighting systems, attendance of office users, operating time of heating systems, heat gains, and ventilation losses. In Table 6, the results obtained from the dynamic simulations, characterised by an HDD, for each model and each city are summarized.

3.2. Environmental assessment

According to ISO 14040 LCA is defined as the environmental profile of a product from cradle to grave (from extraction of raw materials to manufacture, usage, recycling, and/or end of life) (Moncaster et al., 2018). The whole production process is analysed considering all inputs (raw materials and energy consumption) and their interactions (Lazzerini et al., 2016). LCA considers as environmental impacts all burdens caused by materials emitted into the air, soil, and water (McDougall et al., 2001). Based on (EN ISO 14040, 2006), every LCA methodology consists of 4 stages: goal and scope definition, life cycle inventory analysis of materials or processes, life cycle impact assessment and interpretation of results. The data on the environmental performance of building components and materials which are included in the ANN database were collected from LCAs in the literature (EPD) and the SimaPro© data. The ANN estimation of the environmental profile of different scenarios of a non-residential building in the design phase was done by changing shapes and geographical locations and consequently the thermophysical configurations of the buildings. For instance changes in the location and climate zone, induce changes in the thickness of the insulation components. At this point the authors considered the building LCA results related only to A1-A3 and B6 phases, and not the entire life cycle of buildings.

The functional unit is a generic non-residential building that

Table 2
Limit and model thermal transmittance values used in TRNSYS models.

Climatic zone	A-B		C		D		E		F	
U value	Limit	model	limit	model	Limit	model	limit	model	Limit	model
	[W/(m^2·K)]									
U_{wall}	0.45	0.444	0.38	0.379	0.34	0.336	0.30	0.297	0.28	0.276
U_{roof}	0.38	0.377	0.36	0.353	0.30	0.303	0.25	0.249	0.23	0.234
U_{floor}	0.46	0.445	0.40	0.385	0.32	0.307	0.30	0.287	0.28	0.268
U_{window}	3.2	2.76	2.40	2.26	2.00	1.76	1.80	1.76	1.50	1.40

Table 3
Envelope thermal features of the actual building model.

Components	Layers	Materials	Conductivity	Density	Thermal capacity
			[W/mK]	[kg/m^3]	[kJ/kgK]
External Wall	1	*External plaster*	1.00	1800	0.84
	2	*Cement lime plaster*	0.90	1800	0.96
	3	*Tuff block*	0.63	1500	0.70
	4	*Internal Plaster*	0.70	850	0.96
Floor	1	*Concrete Brick*	2.00	2500	0.88
	2	*Concrete Screed*	1.40	2000	1.20
	4	*Concrete slab*	1.91	1400	1.00
	5	*Internal Plaster 2*	0.70	800	0.837
Roof	1	*Floor tile*	1.10	2100	0.84
	2	*Bitumen*	0.17	1200	1.40
	3	*Cement lime plaster*	0.90	1800	0.96
	5	*Concreate slab*	1.91	1400	1.00
	6	*Internal Plaster 2*	0.70	800	0.84

Table 4
Geometric features of the 13 building models (A. D'Amico et al., 2019).

Case study	*S/V*	Width	Depth	Height	Loss surface	Heated surface	Heated volume
	[m^{-1}]	[m]	[m]	[m]	[m^2]	[m^2]	[m^3]
1	0.24	45	39	13.5	5797	7050	23793
2	0.50	106	50	4.5	11987	5293	23793
3	0.90	118	8	3.16	2673	940	2970
4	0.35	15	30	13.5	2115	1800	6075
5	0.62	25	20	4.5	1405	500	2248
6	0.76	40	25	3.16	2411	1000	3160
7	0.4	25	15	10.5	1590	1125	3938
8	0.32	40	40	9	4640	3200	14400
9	0.27	60	22	13.5	4854	5280	17820
10	0.69	90	20	3.5	4370	1800	6300
11	0.70	45	60	3.2	6072	2700	8640
12	0.58	50	50	4	5800	2500	10000
13	0.56	100	50	4	11200	5000	20000

Table 5
Selected Italian cities and DPR 412/94 HDD values (A. D'Amico et al., 2019).

Italian climatic zones									
B		C		D		E		F	
Location	HDD	Location	HDD	Location	HDD	Location	HDD	Location	HDD
Messina	707	Cagliari	990	Genova	1435	Trieste	2102	Cuneo	3012
Palermo	751	Bari	1185	Firenze	1821	Torino	2617	Cortina	4433
Crotone	899	Termoli	1350	Forlì	2087	Bolzano	2791	Sestriere	5165

changes position, shape, and characteristics within the Italian building stock in the database. To satisfy the heating energy demand 4 energy carrier scenarios were supposed: electricity, natural gas, Liquid Propane Gas (LPG) and biogas. To represent the LCA profile of the materials, the authors considered 6 well-known environmental indicators: GWP, ODP, AP, EP, POCP and ADP_{Fossil}.

First, based on the deep research and analysis of specific EPDs and on the selected construction materials for the "ideal building", the environmental impacts of materials were identified. Because perfect correspondence is difficult, the authors selected materials that were similar to those chosen in the model (Table 7).

Five types of windows were selected considering the thermal transmittance limit imposed by current legislation. For each climatic zone, a specific window characterised by diverse thermophysical characteristics was considered. Using Simapro©, a professional software that has several databases of life cycle impact

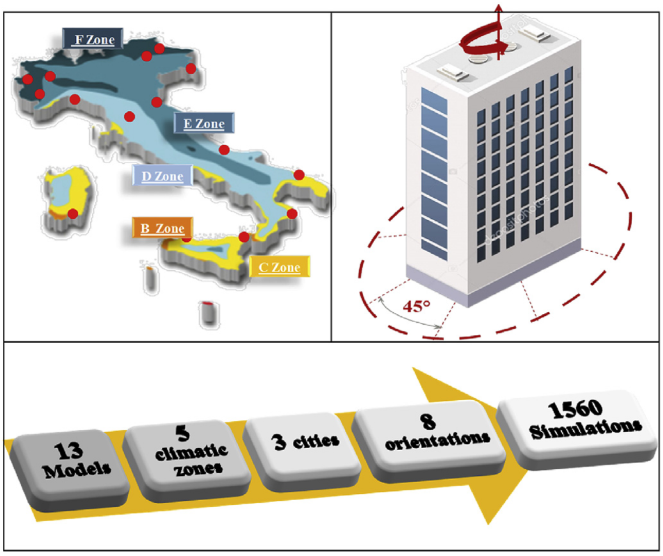


Fig. 2. Italian case study and parametric simulation.

assessment for different products and services, it was possible to identify and calculate the environmental impact indicators per square metre of glazed component (Table 8).

The environmental indicators for the single layer of a single model were calculated based on the mass of each single opaque layer and square metre of each glazed surface, the product between the value of the environmental indicator (Tables 7 and 8), and single mass (Eq. (1)) or square metre (Eq. (2)):

$$EI_{opaque} = \sum_{i=1}^{n} (M_i \cdot EI_i) \tag{1}$$

$$EI_{glazed} = \sum_{j=1}^{z} (S_{w,j} \cdot EI_j) \tag{2}$$

Where

M_i is the i-th mass of opaque layer [kg];
S_{wj} is the square metre of the j-th glazed component [m^2];
$EI_{i/j}$ is the i-th or j-th Environmental Impact.

The mass values of the opaque layers and the square metre of the glazed surface were calculated for each model. A specific stratigraphy for the opaque surfaces was designed for each model and a specific window that respects the transmittance limit values for each climatic zone was identified.

For a complete analysis, the impacts related to the thermal needs of the building must be considered. These impacts change with the energy carrier (EC) used to satisfy the heating energy demand. Therefore4 scenarios were investigated to obtain a

Table 6
Thermal heating energy demand in each location and for different S/V (A. D'Amico et al., 2019).

Climatic Zone	Location	HDD	H_d models [kWh/(m^2·year)]												
			1	2	3	4	5	6	7	8	9	10	11	12	13
B	***Messina***	**707**	1.60	11.66	10.83	3.49	12.43	8.80	4.68	6.06	1.75	9.92	10.06	10.11	9.90
	Palermo	**751**	1.42	11.04	9.78	2.98	11.37	8.13	4.01	5.35	1.53	9.18	9.47	9.51	9.37
	Crotone	**899**	4.16	16.27	15.73	7.00	18.02	12.74	8.57	10.35	4.30	14.27	14.24	14.39	13.98
C	***Cagliari***	**990**	0.70	11.16	6.95	1.36	8.93	6.99	2.01	4.00	0.69	7.82	8.90	9.10	9.48
	Bari	**1185**	1.97	15.35	10.54	3.05	13.33	10.12	4.03	7.14	1.85	11.44	12.57	12.88	13.17
	Termoli	**1350**	4.35	18.93	15.83	6.48	19.01	13.78	8.01	11.15	4.28	15.49	15.93	16.44	16.34
D	***Genova***	**1435**	2.42	14.76	11.14	4.01	14.23	9.62	5.12	7.67	2.35	11.11	11.34	12.35	12.36
	Firenze	**1821**	2.90	17.06	12.48	4.33	16.19	11.20	5.56	9.03	2.71	12.89	13.30	14.39	14.44
	Forlì	**2087**	7.48	24.02	22.29	11.07	26.88	17.88	13.29	16.52	7.54	20.31	19.38	21.14	20.60
E	***Trieste***	**2102**	4.10	17.71	14.52	6.30	18.42	11.94	7.74	10.64	4.09	13.85	13.48	15.07	14.85
	Torino	**2617**	8.52	25.74	22.05	11.84	27.53	18.38	13.79	17.70	8.47	20.90	20.20	22.41	21.98
	Bolzano	**2791**	8.53	25.71	20.86	11.35	26.39	18.15	13.07	17.53	8.30	20.48	20.33	22.32	22.08
F	***Cuneo***	**3012**	3.64	19.21	11.20	4.31	15.92	11.19	5.26	10.19	3.11	13.10	14.02	15.61	16.10
	Cortina	**4433**	16.43	43.24	32.43	19.55	41.52	29.19	22.10	30.28	15.76	33.32	33.28	36.92	37.11
	Sestriere	**5165**	16.97	50.37	29.42	16.96	40.18	30.61	19.01	31.90	15.13	35.06	37.92	41.56	43.40

Table 7
Environmental impact indicators per kg of each construction material.

Materials	GWP	ODP	AP	EP	POCP	ADP_{Fossil}
	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
External plaster	2.60E-01	3.12E-07	1.58E-03	8.04E-04	2.59E-04	8.07E+00
Cement lime plaster	4.49E-01	3.05E-09	8.15E-04	1.52E-04	8.37E-05	4.59E+00
Rock wool	1.08E+00	4.41E-08	7.93E-03	3.78E-04	5.59E-04	1.80E+01
Tuff block	1.47E-01	2.54E-09	1.59E-04	2.28E-05	1.23E-05	1.09E+00
Internal plaster 1	1.20E-01	2.00E-08	4.80E-04	6.60E-05	4.40E-05	2.20E+00
Concrete brick	1.31E-01	9.26E-10	2.37E-04	2.27E-05	7.06E-05	8.19E-01
Concrete screed	1.06E-01	3.54E-09	3.96E-04	1.25E-04	1.79E-05	5.29E-01
Concrete slab	1.12E-01	2.55E-12	1.81E-04	2.88E-05	4.11E-06	5.80E-01
Internal plaster 2	1.20E-01	2.00E-08	4.80E-04	6.60E-05	4.40E-05	2.20E+00
Floor tile	1.04E+00	1.53E-10	2.71E-03	2.14E-03	2.19E-04	1.47E+01
Bitumen	6.33E-03	2.83E-09	2.54E-05	4.15E-06	6.72E-06	3.76E-01
Brick	1.53E-01	3.08E-08	5.12E-04	5.60E-05	1.56E-04	2.43E+00

Table 8
Environmental impact indicators per m^2 of each glazed component.

Climatic Zone	GWP	ODP	AP	EP	POCP	ADP_{Fossi}
	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
B	8.27E+01	7.32E-06	5.53E-01	1.90E-01	4.19E-02	9.31E+02
C	7.33E+01	6.67E-06	4.82E-01	1.56E-01	3.40E-02	8.38E+02
D	7.86E+01	7.03E-06	5.21E-01	1.75E-01	3.84E-02	8.90E+02
E	7.86E+01	7.03E-06	5.21E-01	1.75E-01	3.84E-02	8.90E+02
F	7.45E+01	6.75E-06	4.91E-01	1.60E-01	3.50E-02	8.50E+02

significantly more heterogeneous and versatile database. The 4 scenarios are represented by: electricity, natural gas, LPG and biogas. Moreover, in this case, the environmental impacts of the energy carrier were obtained from Simapro© (Table 9).

For each energy carrier the respective environmental impact was calculated as (Eq. (3)):

$$EI_{EC} = \sum_{k=1}^{m} (H_d^{*} \cdot EI_{EC,k}) \tag{3}$$

Where

$H_d{}^*$ is the annual heating energy demand of the building [kWh/year]; and
$EI_{EC,k}$ is the environmental impact of the k-th energy carrier.

The sum of all indicators that compose the “ideal building” (Eq. (1), (2) and (3)) identify the global environmental indicator:

$$EI_{global} = EI_{opaque} + EI_{glazed} + EI_{EC} \tag{4}$$

In this manner, each building is characterised by 6 global environmental indicators. Table 10 illustrates the GWP indicators calculated for the electricity scenario, for the 13 models in 15 cities.

From Figs. 3–8 display the individual life cycle stages (A1-A3 and B6) and their contribution to environmental impacts over a 50-year building lifespan.

In general, for all environmental impacts, except ODP and ADP_{Fossil}, the A1-A3 phases are higher than the B6 phase. Furthermore, the electricity scenario for all environmental indicators is characterised by a prevalent B6 phase.

3.3. Summary database

The development of this approach allowed the implementation of an energy and environmental database. The database is composed by 36 columns and 780 rows for a total matrix composed of 28,080 cells. The columns are represented as follows:

1. Heating degree days [K day];
2. Shape factor [m^{-1}];
3. Heated surfaces [m^2];
4. Glazed surface [m^2];
5. Opaque losses surfaces [m^2];
6. Glazed surface transmittance [W/m^2K];
7. Opaque losses surface thermal transmittance [W/m^2K];
8. Overall thermal transmittance [W/m^2K];
9. Solar gains [kWh/year];
10. Heating operating hours [h];
11. Wind speed [m/s];
12. Thermal capacity [kWh/m^3K];
13. Internal gains [kWh/year];
14. Electricity energy carrier;
15. Natural gas energy carrier;
16. LPG energy carrier;
17. Biogas energy carrier;
18. External plaster mass [kg];
19. Cement lime plaster mass [kg];
20. Rock wool mass [kg];
21. Tuff block mass [kg];
22. Internal plaster 1 mass [kg];
23. Concrete brick mass [kg];
24. Concrete screed mass [kg];
25. Concrete slab mass [kg];
26. Internal plaster 2 mass [kg];
27. Floor tile mass [kg];
28. Bitumen mass [kg];
29. Brick mass [kg];
30. Heating energy demand [kWh/m^2year];
31. GWP [kg CO_2 eq];
32. ODP [kg CFC11 eq];
33. AP [kg SO_2 eq];
34. EP [kg PO_4^{-3} eq];
35. POCP [kg C_2H_4 eq];
36. ADP_{Fossil} [MJ].

In the rows, there are 13 building models located in three cities for 5 climatic zones, which were simulated for 4 energy carrier scenarios (780 cases were analyzed).

4. ANN application

Among many AI methods, ANNs are well-known computational algorithms that predict the output of complex systems and solve nonlinear problems even without prior information (Tohidi et al., 2012).

ANNs are inspired in the human brain functionality, and can be

Table 9
Environmental impact indicators per kWh of each energy carrier considered to satisfy the heating energy demand.

Energy Carrier	GWP	ODP	AP	EP	POCP	ADP_{Fossi}
	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
Electricity	4.16E-01	4.91E-08	2.10E-03	5.81E-04	8.65E-05	4.82E+00
Natural Gas	5.79E-02	2.45E-08	1.96E-04	1.99E-05	2.75E-05	4.13E+00
LPG	3.23E-02	2.33E-08	2.43E-04	3.12E-05	1.64E-05	1.86E+00
Biogas	7.97E-02	4.13E-09	2.16E-03	8.95E-04	2.76E-05	5.47E-01

Table 10
GWP indicator of all 13 case studies calculated for electricity scenario.

Climatic Zone	Location	GWP [kg CO_2 eq]												
		1	2	3	4	5	6	7	8	9	10	11	12	13
B	***Messina***	9.76E+05	6.03E+06	1.05E+06	3.55E+05	6.46E+05	9.18E+05	2.82E+05	8.98E+05	7.40E+05	1.83E+06	2.77E+06	2.56E+06	5.00E+06
	Palermo	9.50E+05	5.76E+06	9.71E+05	3.36E+05	6.01E+05	8.62E+05	2.66E+05	8.51E+05	7.16E+05	1.72E+06	2.64E+06	2.43E+06	4.78E+06
	Crotone	1.35E+06	8.06E+06	1.44E+06	4.87E+05	8.78E+05	1.25E+06	3.73E+05	1.18E+06	1.02E+06	2.48E+06	3.71E+06	3.45E+06	6.69E+06
C	***Cagliari***	8.67E+05	5.84E+06	7.52E+05	2.78E+05	4.85E+05	7.72E+05	2.23E+05	7.74E+05	6.38E+05	1.52E+06	2.52E+06	2.36E+06	4.85E+06
	Bari	1.05E+06	7.68E+06	1.03E+06	3.42E+05	6.68E+05	1.03E+06	2.70E+05	9.83E+05	7.65E+05	2.07E+06	3.35E+06	3.15E+06	6.38E+06
	Termoli	1.40E+06	9.26E+06	1.45E+06	4.70E+05	9.04E+05	1.34E+06	3.63E+05	1.25E+06	1.03E+06	2.67E+06	4.10E+06	3.89E+06	7.70E+06
D	***Genova***	1.22E+06	7.63E+06	1.12E+06	4.10E+05	7.28E+05	1.03E+06	3.21E+05	1.10E+06	9.03E+05	2.09E+06	3.18E+06	3.14E+06	6.25E+06
	Firenze	1.29E+06	8.65E+06	1.23E+06	4.22E+05	8.10E+05	1.16E+06	3.31E+05	1.19E+06	9.42E+05	2.36E+06	3.62E+06	3.56E+06	7.11E+06
	Forlì	1.96E+06	1.17E+07	1.99E+06	6.75E+05	1.25E+06	1.72E+06	5.12E+05	1.69E+06	1.47E+06	3.47E+06	4.99E+06	4.97E+06	9.67E+06
E	***Trieste***	1.39E+06	8.79E+06	1.36E+06	4.77E+05	8.90E+05	1.20E+06	3.66E+05	1.24E+06	1.04E+06	2.45E+06	3.59E+06	3.64E+06	7.15E+06
	Torino	2.04E+06	1.23E+07	1.95E+06	6.85E+05	1.27E+06	1.73E+06	5.08E+05	1.71E+06	1.52E+06	3.51E+06	5.10E+06	5.16E+06	1.01E+07
	Bolzano	2.04E+06	1.23E+07	1.86E+06	6.66E+05	1.22E+06	1.72E+06	4.91E+05	1.70E+06	1.50E+06	3.45E+06	5.13E+06	5.15E+06	1.02E+07
F	***Cuneo***	1.32E+06	9.46E+06	1.10E+06	4.01E+05	7.85E+05	1.14E+06	3.07E+05	1.21E+06	9.27E+05	2.34E+06	3.71E+06	3.75E+06	7.67E+06
	Cortina	3.20E+06	2.00E+07	2.76E+06	9.72E+05	1.85E+06	2.63E+06	7.01E+05	2.55E+06	2.32E+06	5.37E+06	8.04E+06	8.18E+06	1.64E+07
	Sestriere	3.28E+06	2.32E+07	2.53E+06	8.75E+05	1.79E+06	2.75E+06	6.29E+05	2.66E+06	2.25E+06	5.63E+06	9.08E+06	9.15E+06	1.90E+07

modelled as a network of interconnected elements called neurons (Zangeneh et al., 2011). These neurons or processing elements are connected to each other and form, such as an excellent nonlinear modelling tool. They can identify the existing relation between input and output variables through the composition of activation functions and weights (Pahlavan et al., 2012). Given a training dataset, one of the most impressive features of ANNs is their ability to learn and forecast solutions. (Czarnowski and Je,drzejowicz, 2006).

To obtain an optimal solution, the training process provides an iterative update of the synaptic connections (weights) after the presentation of all possible input/output pairs of the training database. The verse and intensity of the synaptic weights are guaranteed by minimizing the Mean Squared Error (MSE) between the provided output and the expected result. To model physical systems, a feed-forward Back-Propagation (BP) Multilayered Perceptron (MLP) structure is commonly applied (Omid et al., 2009). MLP is a feed-forward layered network with one input layer, one output layer, and certain hidden layers. The information flows only in the forward direction, from inputs to outputs (Elhami et al., 2017). The main advantages of MLP structures are that they are easy to use, fast, and require relatively little memory. Moreover, they can learn complex relationships between input and output, which would be difficult to model through standard methods (Azadeh et al., 2008). BP is the most popular learning algorithm and, in general, it updates the weights to bring the output response closer to the desired target. The knowledge obtained during the training phase, is not stored as equations or in a knowledge base, it is distributed throughout the network in the form of connection weights between neurons.

In this study, several feed-forward BP neural networks with one input layer, one or more hidden layers, and a single layer of output neurons were evaluated and trained using the data collected from the previous database (section 3.3). To simultaneously solve the energy and environmental balance of a building through ANN, the appropriate input parameters of the model were carefully selected. The performance of the ANN prediction was evaluated by comparing the network outputs with the target values. All networks were trained with 85% of the database, while the remaining 15% was used for validation. The criteria used to measure the network performance were RMSE, R^2, and MAPE (Kayfeci et al., 2014; Taki et al., 2018).

4.1. Input-output selection

Selection of appropriate input parameters for the ANN is essential for the model development. To ensure the suitability of this selection, a deep analysis of the relationship between description variables (inputs) and target variables (outputs) was done. The analysis was based on the evaluation of traditional building energy balance and building environmental indicators, linked to the envelope and the energy carriers. Hence, it was possible to simultaneously identify strong correlations between energy and environmental inputs and output.

As indicated in Fig. 9, 29 inputs and 7 outputs were identified; among the input data, 13 are related to energy parameters and 16 to the environment; among the output data 1 is related to energy and 6 to the environment.

4.2. ANN selection

Following the pre-processing phase, the authors explored several topologies of ANNs by changing the number of neurons, hidden layers, activation functions, and all parameters of the learning process to minimize the MSE and to identify the optimal

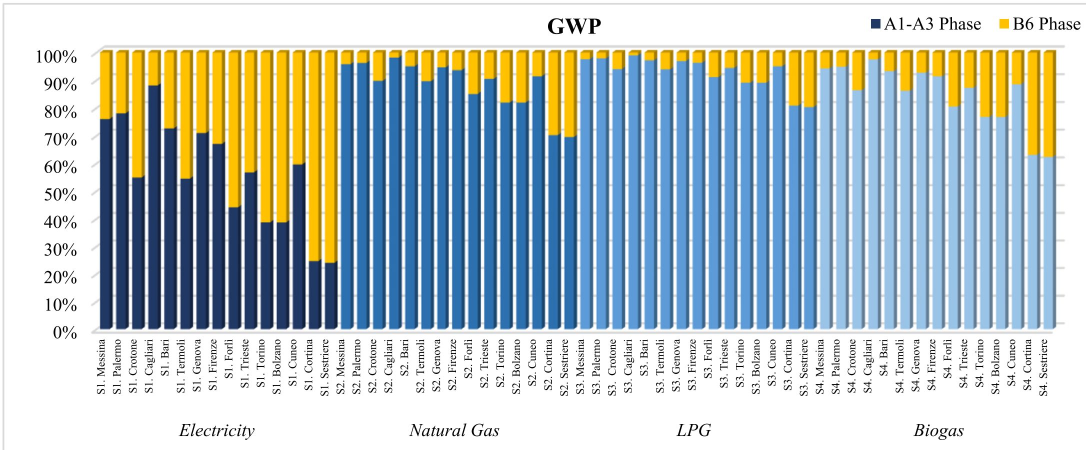


Fig. 3. Life cycle stages (A1-A3 and B6) contribute to GWP indicator.

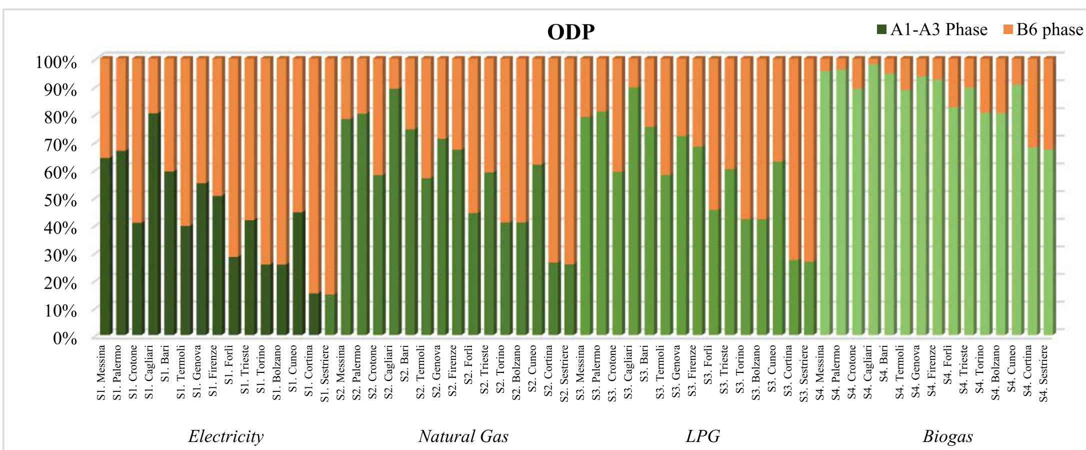


Fig. 4. Life cycle stages (A1-A3 and B6) contribute to ODP indicator.

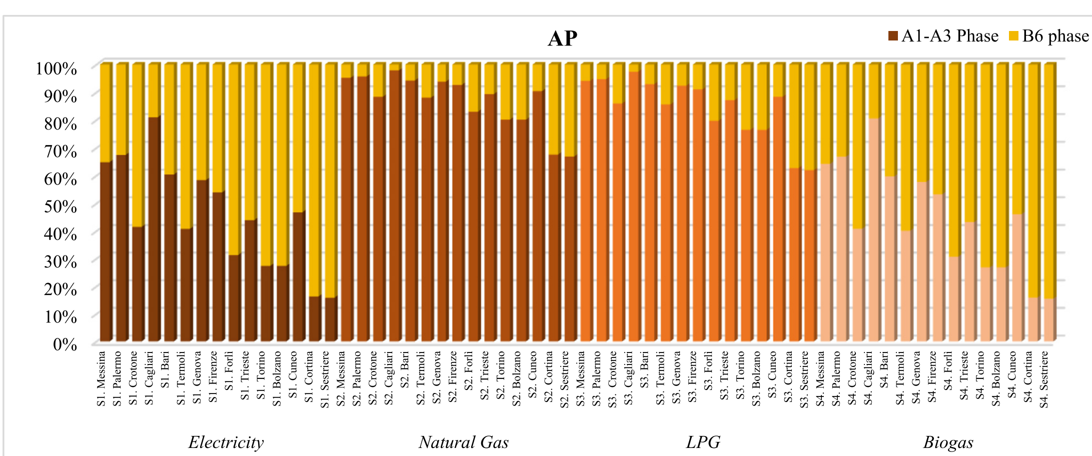


Fig. 5. Life cycle stages (A1-A3 and B6) contribute to AP indicator.

configuration. The basic ANN configuration investigated was the MLP (Taki et al., 2016). In this research, all configurations explored are characterised by two different activation functions: a tanh-sigmoid activation function for the hidden layers and a linear activation function for the output layer. The first is a nonlinear, continuous, and differentiable function with a bounded output, and it enables the ANN to learn non-linear correlations between the presented pattern (input-output samples) (Safa and Samarasinghe, 2011). The second performs a linearization of the input vector and allows the ANN to provide non-bounded outputs (Pahlavan et al.,

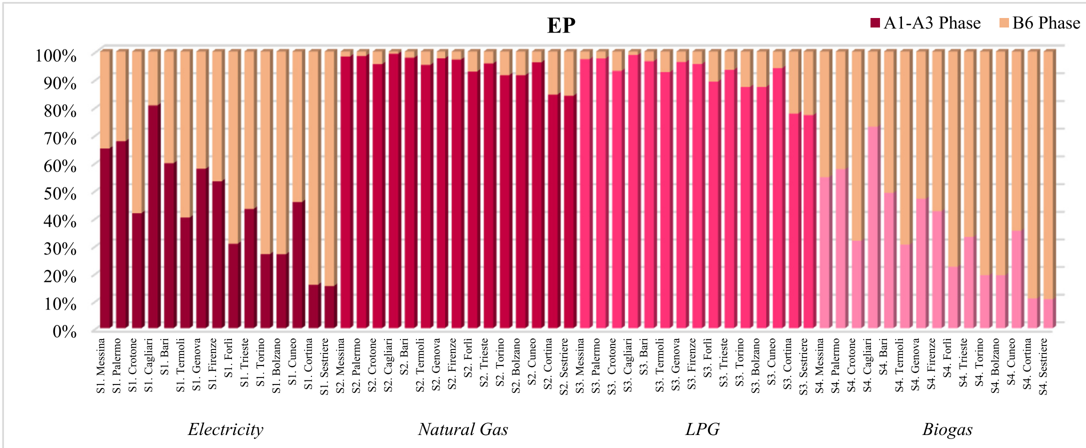


Fig. 6. Life cycle stages (A1-A3 and B6) contribute to EP indicator.

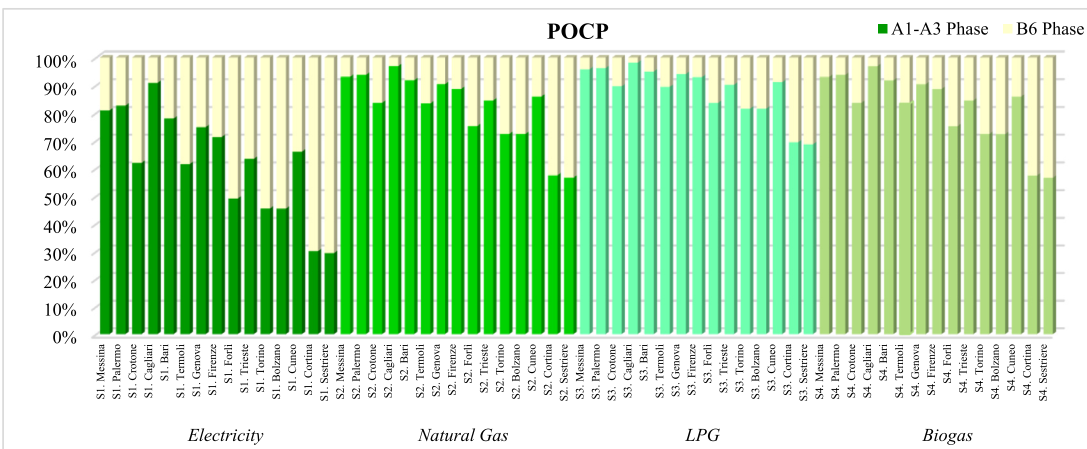


Fig. 7. Life cycle stages (A1-A3 and B6) contribute to POCP indicator.

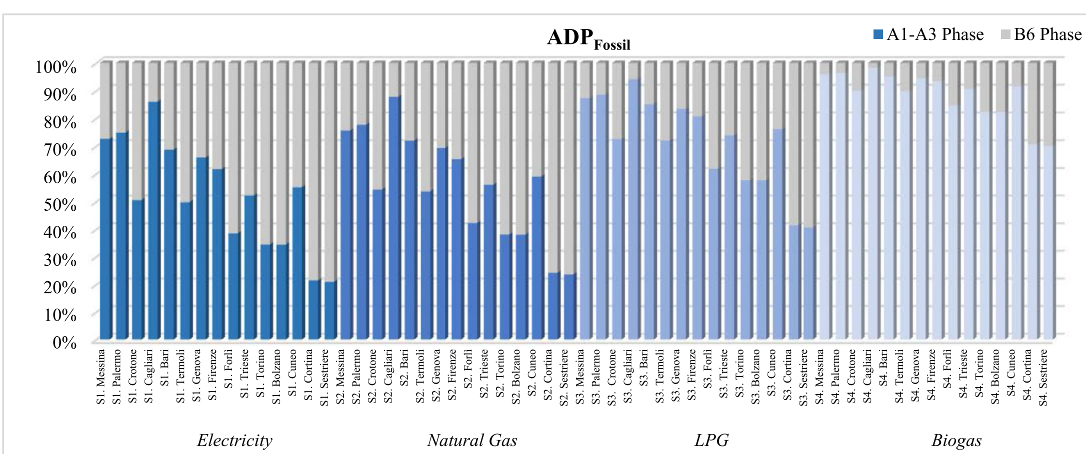


Fig. 8. Life cycle stages (A1-A3 and B6) contribute to ADP_{Fossil} indicator.

2012).

In this work, the authors used the Synapse environment, a component-based development created by Peltarion, for neural networks and adaptive systems, ("Peltarion," 2019).

To select the ANNs with the lowest MSE, the authors chosen the three best configurations to compare the results by varying the complexity degree of the network and the computational time. The main features (number of hidden layers and neurons) for each of them are summarized in Table 11.

To limit the poor generalization capacity, the training phase was

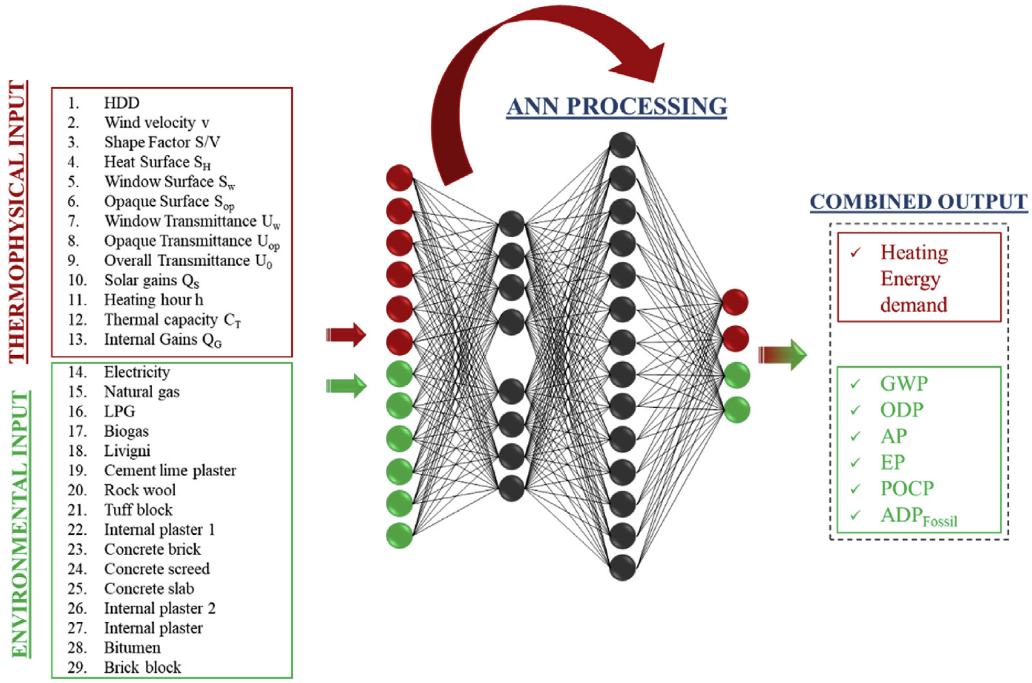


Fig. 9. Input and output of the ANNs.

interrupted before the overfitting phase. The training was stopped every time the error trend of the validation pattern and the training pattern began to diverge. Consequently, the epoch number for each ANN was identified.

For the learning process, a BP algorithm with the "step rule" was employed (Ciulla et al., 2019b). The "step rule" is an improved version of the standard Gradient Descendent (GD) algorithm with momentum and stabilization regularization, in which the network weights are moved along the negative gradient of the performance function (Ozbilen et al., 2013). This improved rule allows for local minima to be avoided, stabilizing and regularizing convergence, and speeding up the learning process of the ANN (Pahlavan et al., 2012).Furthermore, the learning speed is regulated by the learning rate, which acts on the percentage of change of the synaptic weights.

The first "ANN 1" (Fig. 10) is a linear feedforward MLP characterised by two hidden layers; the first with 200 neurons, and the second with 100 neurons.

The second "ANN 2" (Fig. 11) is a feedforward MLP with two hidden layers (50 and 25 neurons in the first and second layers, respectively) differently connected to each other. Particularly, these connections allow the input signal to follow three different paths (Line 1—3):

- Line 1. The input signal starts from the input layer, passes through the two hidden layers and reaches the output neurons (longest path);
- Line 2. The input layer is directly connected to the second hidden layer (25 neurons) bypassing the first one. The input signal, starts from the input layer, passes through one hidden layer, and reaches the output neurons (shortest path);
- Line 3. The input layer is normally connected to the first hidden layer (50 neurons) which is directly connected with the output layer bypassing the second hidden layer. The input signal follows a short path.

The third "ANN 3" (Fig. 12), is always a feedforward MLP, but there are 4 hidden layers: two with 8 neurons and two with 6

Table 11
Main features of the ANNs design.

MLP Models	ANN Design: N° of total hidden layers	Signal path	N° of hidden layers for each line	N° of Neurons: 1° hidden layer	N° of Neurons: 2° hidden layer	Activation function: Tanh-sigmoid	Activation function: Linear	Epoch number	Momentum	Learning rate
ANN 1	2	Line 1	2	200	100	2	1	8 106	0.7	0.1
ANN 2	2	Line 1	2	50	25	2	1	1 10^6	0.7	0.1
		Line 2	1	25	–	1	1			
		Line 3	1	50	–	1	1			
ANN 3	4	Line 1	2	8	6	2	1	8 10^6	0.7	0.1
		Line 2	1	6	–	1	1			
		Line 3	1	8	–	1	1			
		Line 4	2	6	8	2	1			
		Line 5	–	–	–	–	1			

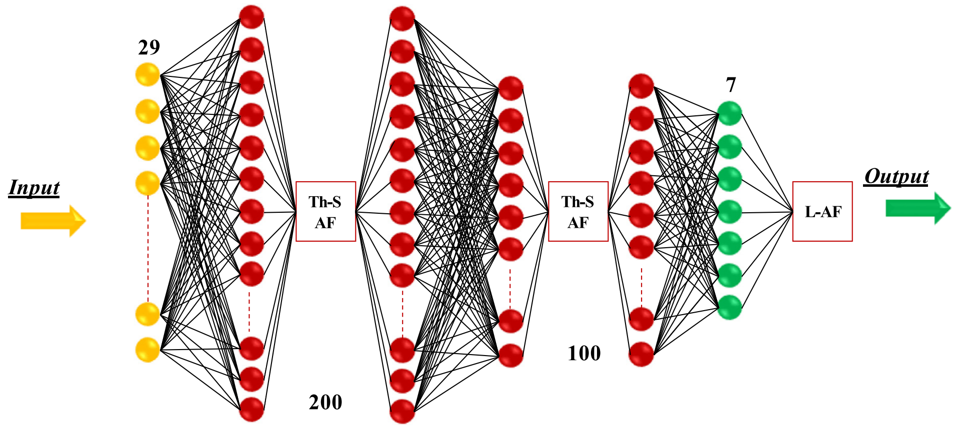


Fig. 10. Design of the ANN 1.

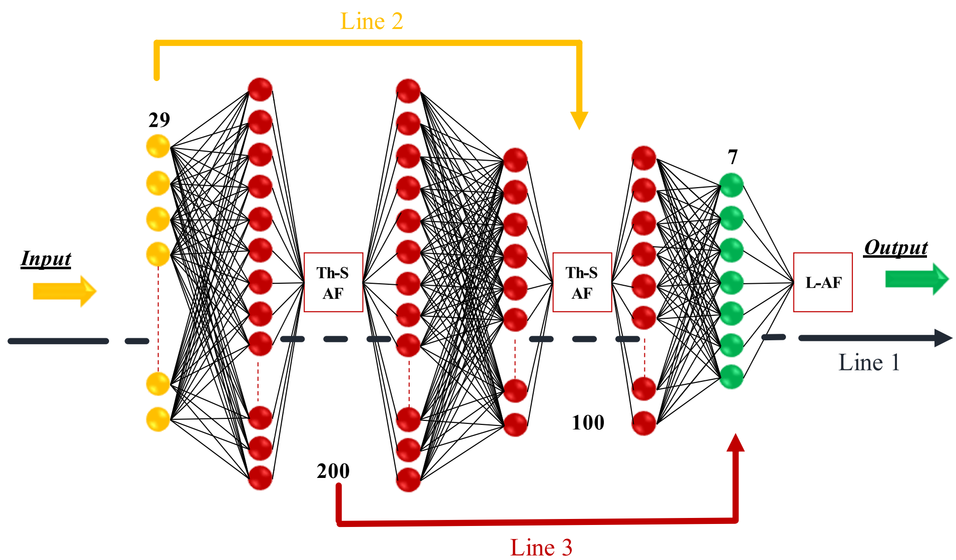


Fig. 11. Design of the ANN 2.

neurons. This ANN presents a higher complexity than the previously evaluated ones. The input signal follows 5 different paths; the first 3 lines replicate the same path of Lines 1, 2, and 3 of ANN 2. The others two paths are as follows:

- Line 4. The input signal starts from the input layer and directly reaches the output neurons (shortest path);
- Line 5. The input layer is connected to the third hidden layer (6 neurons) passes through the fourth hidden layer (8 neurons) and is connected to the output layer. The input signal follows an alternative path compared to the previous one.

5. Results and discussions

Based on the comparison of the results from the three ANNs the optimal solution and the best network conditions that solve the complex energy and environmental building performance problem were identified.

5.1. ANN results

The post-processing phase is characterised by the results associated with the training phase (Table 12) and the validation phase (Table 13). In each phase and for each ANN, the data for Mean, Median, Standard Deviation (StD) and confidence range of each output were collected.

5.2. Comparison and performance of the ANN

As previously mentioned, some of the most commonly used criteria were chosen to evaluate the performance of a model (Elhami et al., 2017; Taki et al., 2018): RMSE, MAPE, and R^2. These statistical parameters are defined by the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - x_i)^2}{N}} \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{|y_i - x_i|}{x_i} \tag{6}$$

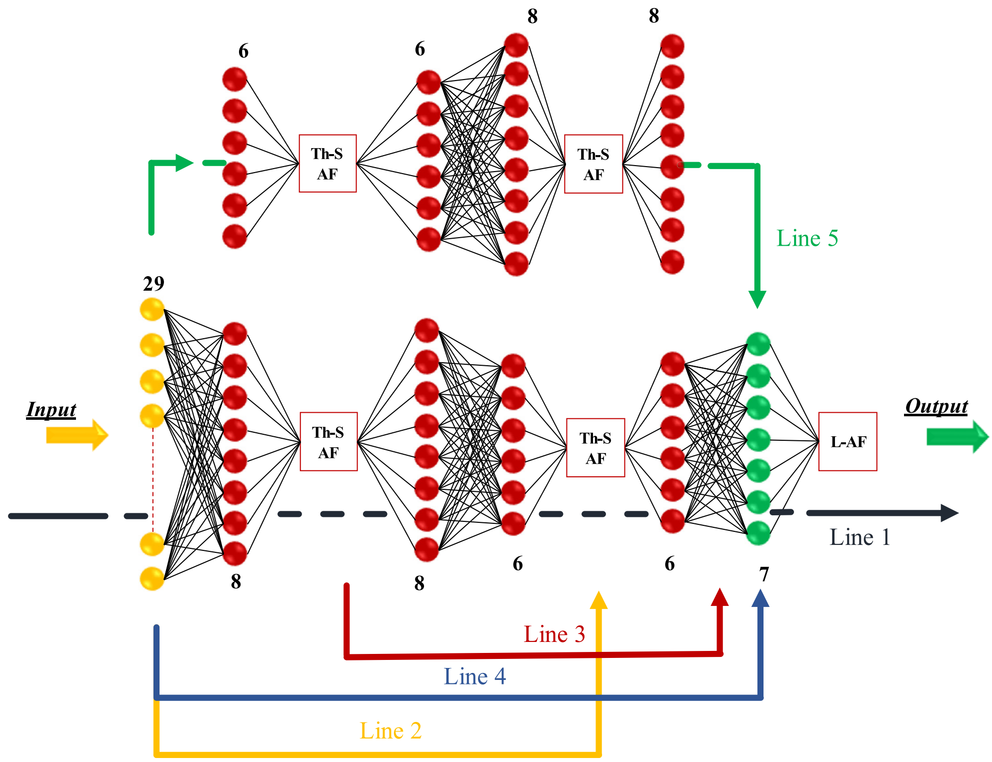


Fig. 12. Design of the ANN 3.

Table 12
Post processing data of ANNs for the training dataset.

Training Set								
ANN Models	Results	H_d	GWP	ODP	AP	Ep	POCP	ADP_{Fossil}
		$kWh/(m^2 \cdot year)$	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
ANN 1	***Mean***	−0.0097	1793.63	0.0002	5.96	1.22	0.3520	22570.42
	Median	−0.0090	−0.0090	−0.0090	−0.0090	−0.0090	−0.0090	−0.0090
	StD	0.0061	3397.67	0.0004	17.32	6.98	0.5401	45858.94
	Confidence Range (95%)	±0.0224	±7525.82	±0.0009	±35.87	±13.87	±1.26	±100117.40
ANN 2	***Mean***	0.0629	4557.28	0.0002	8.39	0.2608	0.7276	39024.21
	Median	0.0594	0.0594	0.0594	0.0594	0.0594	0.0594	0.0594
	StD	0.0782	15626.09	0.0019	78.24	31.11	2.77	196384.15
	Confidence Range (95%)	±0.1967	±31880.33	±0.0038	±154.12	±60.93	±5.62	±392146.9
ANN 3	***Mean***	−0.0217	11920.66	0.0005	−27.74	−21.06	0.9974	−54311.08
	Median	−0.0237	−0.0237	−0.0237	−0.0237	−0.0237	−0.0237	−0.0237
	StD	0.0752	32867.02	0.0043	175.61	72.42	5.0350	52341.09
	Confidence Range (95%)	±0.1533	±68478.63	±0.0085	±348.20	±147.71	±10.05	±1030621

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{7}$$

Where

x_i is the i-th component of the desired output for the i-th pattern;
y_i is the i-th component of the predicted output produced by the network for the i-th pattern; and
$\overline{x}$ and $\overline{y}$ are the average of the whole desired and predicted output, respectively, and N is the number of samples.

The RMSE (Eq. (5)) represents the square root of the quadratic mean of the difference between predicted and expected values. The MAPE (Eq. (6)) evaluates the relative percentage deviation between the predicted and expected values;if it is smaller than 10% it is considered acceptable.

R^2 evaluates the accuracy of the model compared to the actual data points. The higher is R^2, the more efficient is the model (Elhami et al., 2017). The best ANN is characterised by small MAPE and RMSE and high R^2. Table 14 summarizes the RMSE data of the three ANNs; in general, the lowest values are related to ANN 2, expect for the H_d value.

The following figures compare the MAPE (Fig. 13) and R^2 (Fig. 14) obtained from the three ANNs for each output.

In this case, except for the H_d value, the smallest MAPE values for all outputs are related to ANN 2. The smallest MAPE for H_d was obtained from ANN 1. Regarding R^2, the highest values are always

Table 13
Post processing data of ANNs for the validation dataset.

Validation Set								
ANN Models	Results	H_d	GWP	ODP	AP	Ep	POCP	ADP_{Fossil}
		$kWh/(m^2 \cdot year)$	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
ANN 1	***Mean***	−0.0110	2389.01	0.0008	3.54	−2.63	0.4387	868.81
	Median	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150
	StD	0.1164	35432.40	0.0036	204.27	74.62	6.62	619265.44
	Confidence Range (95%)	±0.2280	±69307.16	±0.0072	±398.70	±145.73	±12.94	±1208541
ANN 2	***Mean***	0.0625	2734.19	0.0006	−10.60	−8.73	0.3938	9817.31
	Median	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557
	StD	0.1320	26795.77	0.0030	161.12	64.31	4.64	395709.99
	Confidence Range (95%)	±0.2820	±52567.69	±0.0060	±315.12	±126.68	±9.09	±772495.4
ANN 3	***Mean***	−0.0208	13507.18	−0.0002	−17.31	−16.10	0.7230	−154543.78
	Median	−0.0097	−0.0097	−0.0097	−0.0097	−0.0097	−0.0097	−0.0097
	StD	0.0953	39022.90	0.0057	242.13	101.79	5.85	799055.47
	Confidence Range (95%)	±0.1905	±80626.15	±0.0110	±473.75	±201.12	±11.51	±1588558

Table 14
Root Mean Square Error of the validation dataset.

ANN Configurations	H_d	GWP	ODP	AP	Ep	POCP	ADP_{Fossil}
	$kWh/(m^2 \cdot year)$	kg CO_2 eq	kg CFC11 eq	kg SO_2 eq	kg PO_4^{3-} eq	kg C_2H_4 eq	MJ
ANN 1	0.12	35361.44	0.0037	203.42	74.35	6.60	616613.94
ANN 2	0.14	26820.74	0.0031	160.78	64.63	4.64	394137.58
ANN 3	0.10	41136.54	0.0056	241.71	102.62	5.87	810503.70

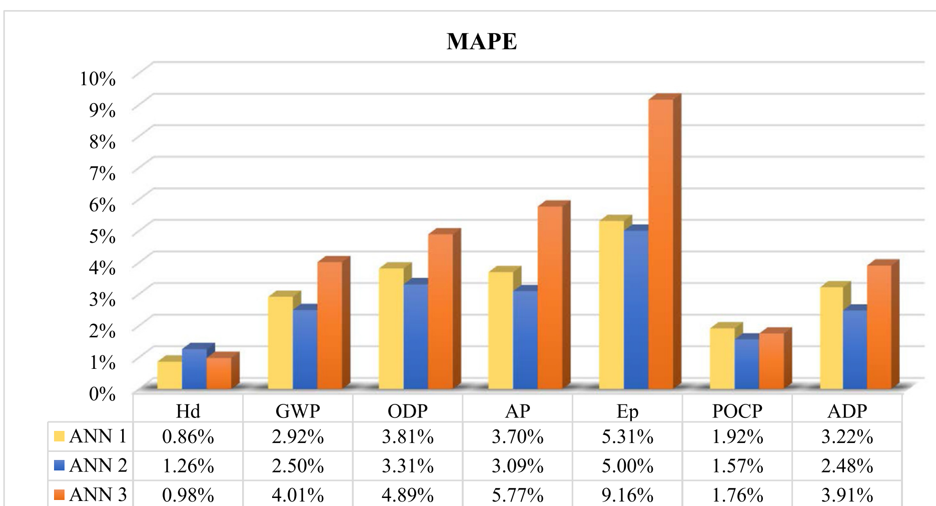


Fig. 13. Mean Absolute Percentage Error of the validation dataset.

related to ANN 2. Therefore, ANN 2 was selected as the optimal energy and environmental solution. It was considered the best compromise, since the high MAPE and RMSE related to H_d were irrelevant compared to the other values.

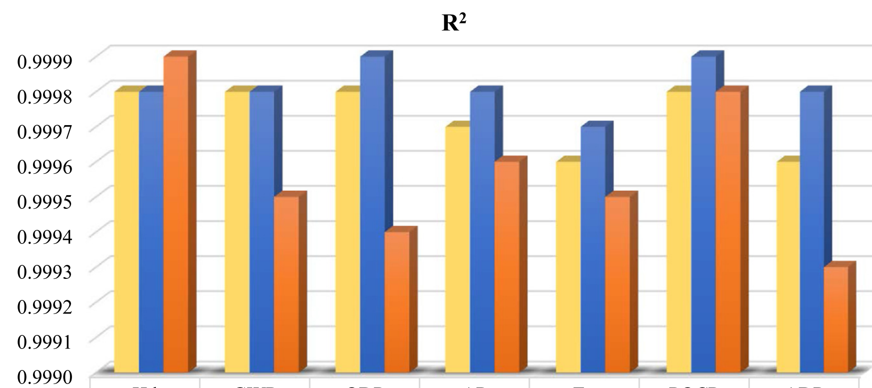
5.3. Best ANN

Considering the optimal solution (ANN 2), the frequency distribution trends of MSE for the training set between the expected and calculated output data are illustrated in the following figures. Fig. 15 illustrates the error frequency distribution between the predicted and expected H_d, and Fig. 16 the error frequency distribution of the predicted and expected GWP.

Fig. 17 illustrates the H_d trend with a margin error of approximately ±0.282 kWh/m^2 year for the validation dataset with a confidence range of 95%.

Similarly, Fig. 18 illustrates a confidence range of 95% for the GWP indicator, with a margin of error of approximately ±52567.69 $kgCO_2$ eq.

A common and simple approach to evaluate and compare the performance of prediction models is the linear regression between expected and predicted values, and the comparison of intercept and slope parameters against the 1:1 line (Piñeiro et al., 2008). For this reason, from Figs. 19–22,presents one graph for each output of the best ANN. R^2 and the comparison between the regression line (continued black line) and the 1:1 line (dashed red line) for the validation dataset are also displayed. The goodness of the ANN is emphasized not only by the scatter plots and high R^2 values, but



	Hd	GWP	ODP	AP	Ep	POCP	ADP
ANN 1	0.9998	0.9998	0.9998	0.9997	0.9996	0.9998	0.9996
ANN 2	0.9998	0.9998	0.9999	0.9998	0.9997	0.9999	0.9998
ANN 3	0.9999	0.9995	0.9994	0.9996	0.9995	0.9998	0.9993

Fig. 14. Determination coefficient of the validation dataset.

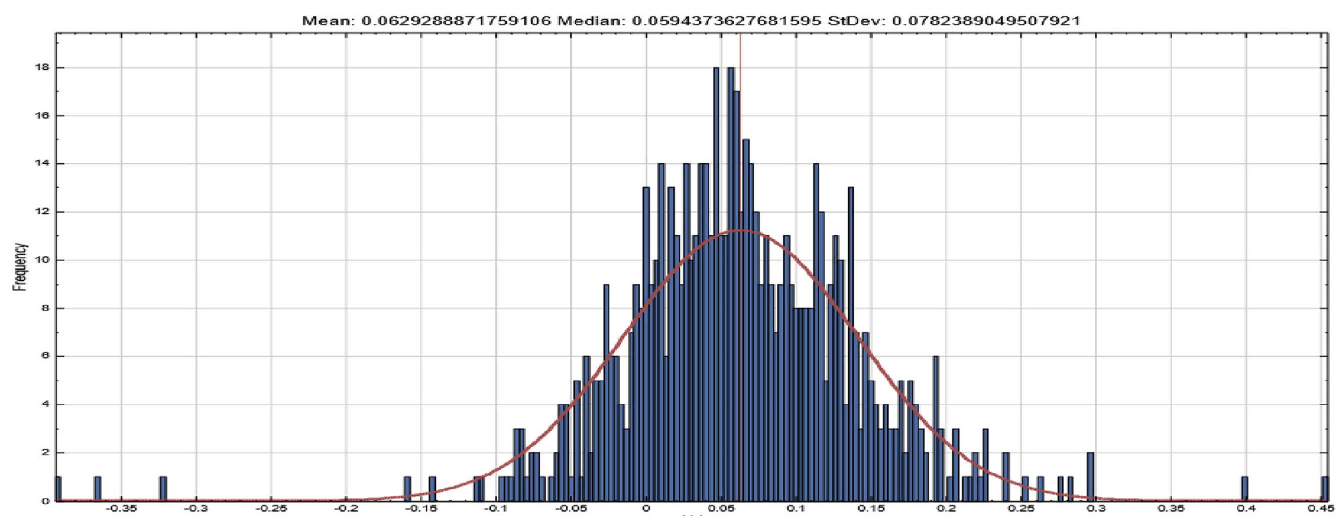


Fig. 15. Error frequency distribution for the training set of the H_d.

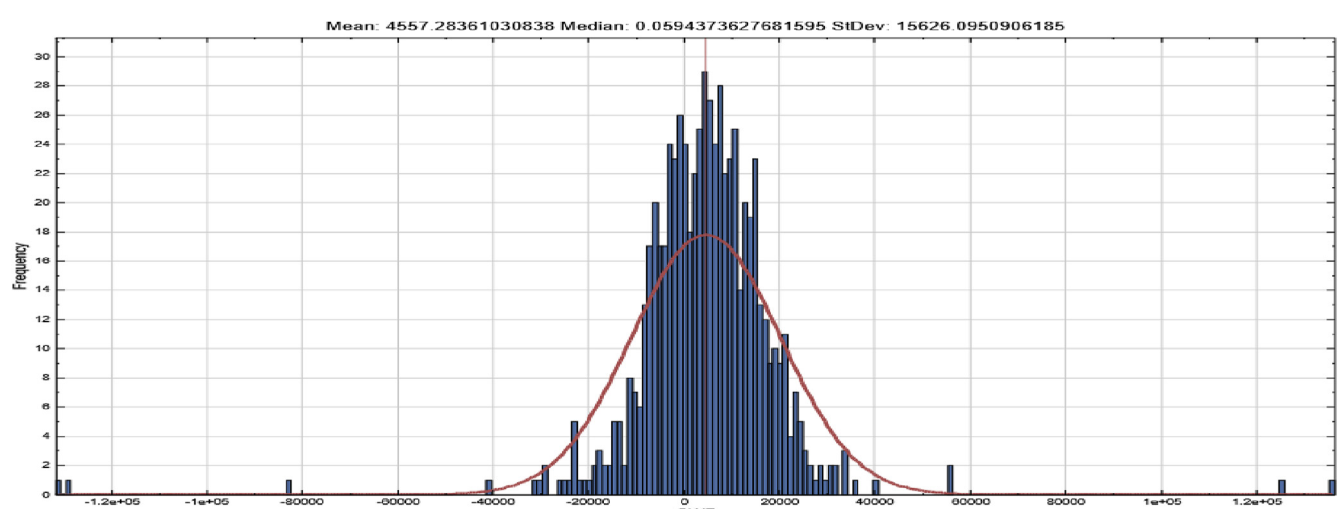


Fig. 16. Error frequency distribution for the training set of the GWP.

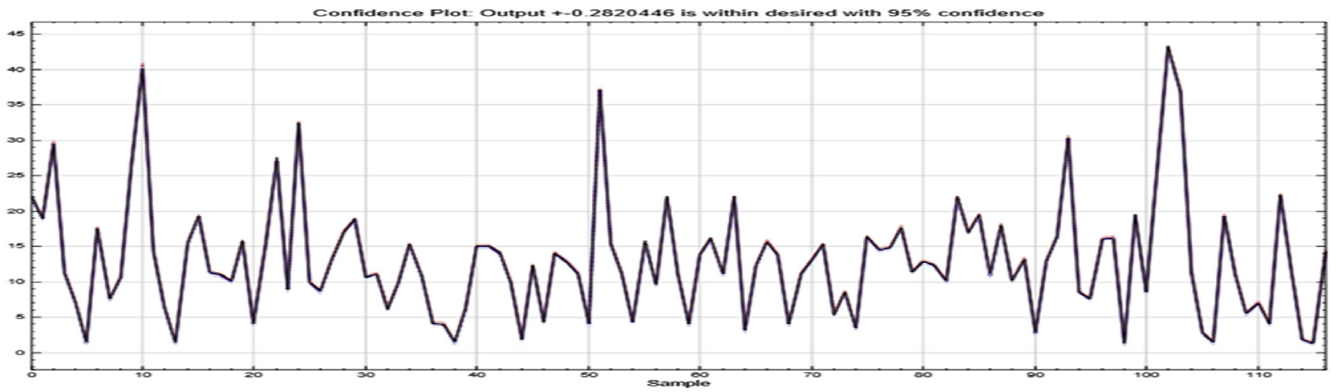


Fig. 17. Confidence range (95%) of the validation set of the H_d.

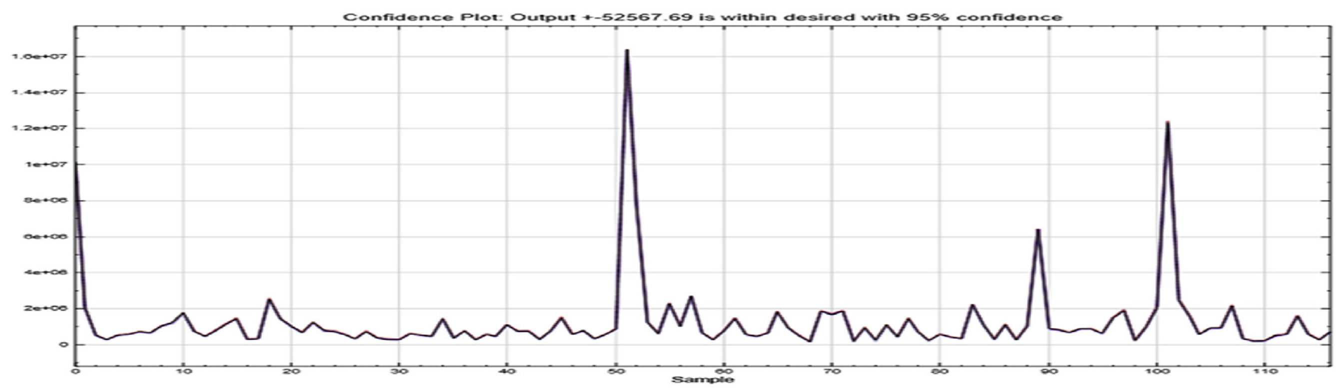


Fig. 18. Confidence range (95%) of the validation set of the GWP.

also by the excellent intercept and slope values of the regression line calculated for all outputs.

The results for RMSE, MAPE, R^2, and the intercept and slope of regression lines emphasise the potential of the proposed ANN model to predict the energy demand and environmental impacts of a building. Hence, the authors demonstrated that, ANN is a reliable alternative to reach the goal of the work. ANN are advantageous due to their capability to overcome several typical limitations of traditional software, such as the collection of energy and environmental data, knowledge on the physical problem and the software language, long computational time, and necessity to calibrate the model. Furthermore, traditional tools issue a single solution for a specific condition, and cannot provide results generalization. In contrast, an ANN application, trained on a wide range of cases, can provide a reliable solution for any building under any condition. Another advantage is the possibility to have several outputs from the same ANN, so different problems of the same case study can be solved which would normally require multiple software tools and expert users. However, the validity of the neural network solution is strongly linked to the reliability of the database, which is generally difficult to implement, but reached acceptable levels in this work.

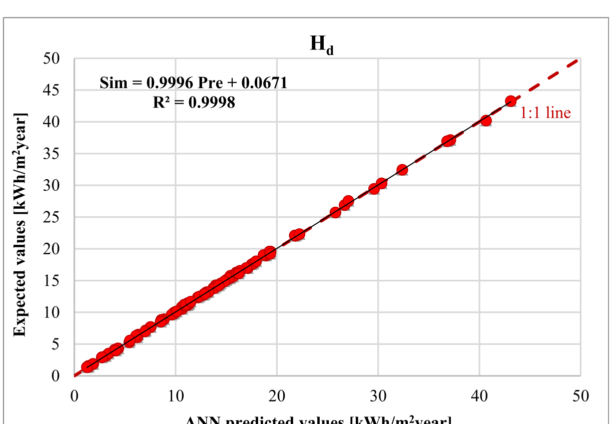


Fig. 19. Regression between expected versus predicted H_d value.

6. Conclusion

To correctly propose measures to save energy and reduce environmental impacts of a building such as the contribution to the greenhouse effect, a comprehensive energy and environmental assessment of the building's performance is necessary. Currently, the solution of this complex problem normally requires an interdisciplinary team, knowledge on specific software or algorithm, an expert user, collection of a large amount of data, and long computational time. The lack of a common language often complicates the interpretation of the results between these two areas that are significantly different but highly connected. Based on these observations, the authors developed a decision support tool that quickly and reliably, determines the performance of buildings with minimum effort Hence the application of the Artificial Neural Networks to simultaneously determine the energy demand and environmental impacts was investigated. The neuro-computing approach establishes the relationships between input and output

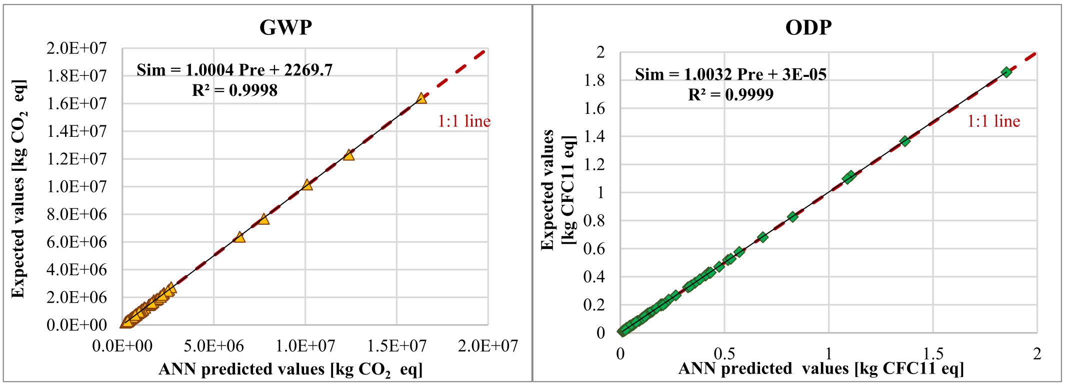


Fig. 20. Regression between expected versus predicted GWP and ODP values.

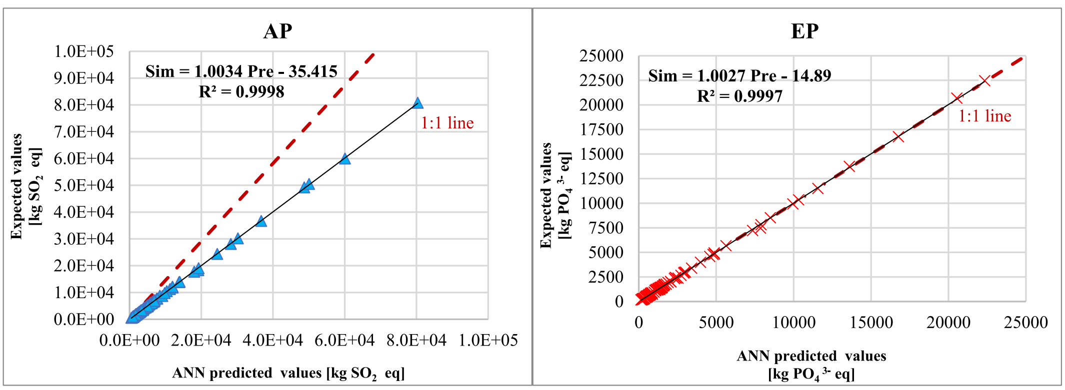


Fig. 21. Regression between expected versus predicted AP and EP values.

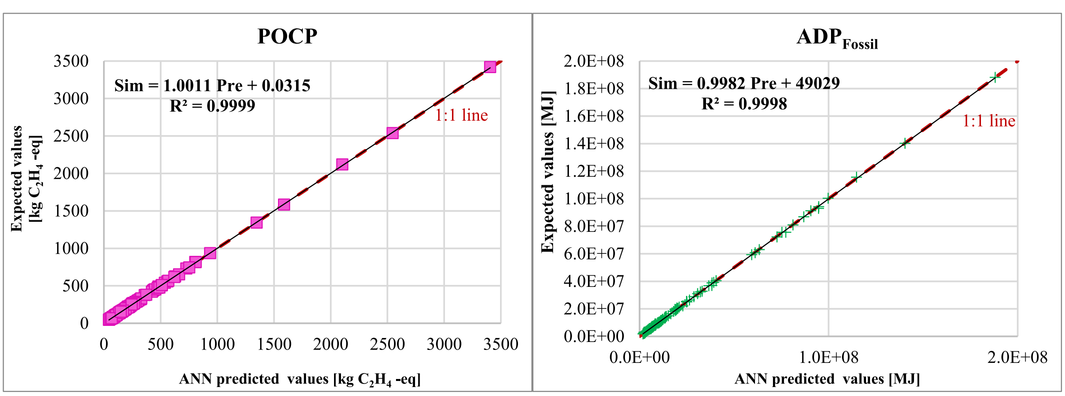


Fig. 22. Regression between expected versus predicted POCP and ADP_{Fossil} values.

variables even when a problem is complex. In this paper the Artificial Neural Networks capacity was exploited to retrieve the energy and environmental performance of non-residential buildings designed with high-performance, according to Italian energy standards. To apply this methodology, it was necessary to create a reliable database of training and validation data. For this reason, the authors used the energy database created in a previous work, representatives of the Italian building stock. Based on Environmental Product Declarations and Simapro©, 6 environmental indicators were calculated for each envelope surface (opaque and glazed) to measure their environmental impact. These indicators were: Global Worming Potential, Ozone Depletion Potential, Acidification Potential, Eutrophication Potential, Photochemical Ozone Creation Potential and Abiotic Depletion Potential-Fossil. Furthermore, to evaluate the impacts related to the thermal needs of the building and how these impacts change according to the energy carrier used 4 scenarios of heating energy source, were investigated: electricity, natural gas, liquid propane gas and biogas.

This large database, composed by 36 columns and 780 rows with a total of 28,080 records, was used to train the Artificial Neural Networks. Several topologies of Artificial Neural Networks were analysed and the best results were described in the section 4. Following a deep statistical analysis and results comparison (sections 5.1 and 5.2), the optimal solution was represented by ANN 2 (section 5.3). The good results and high degree of reliability emphasise the use of the Artificial Neural Network as an excellent alternative method to solve the complex problem of assessing building energy and environmental performances.

This work represents only the initial step in the research for an instrument that solves complex and different problems with a single informatics tool and a single language. The specific Italian case study enabled the understanding of a methodology that can be extended in any context and to any condition (other countries and building stocks). Future research should include the integration and implementation of a database with energy (cooling and electricity demand), environmental (considering all phases of an LCA), economic (costs and return time) and social aspects. It should provide a comprehensive building sustainability assessment.

Furthermore, the implementation of the Artificial Neural Network algorithm in a software will enable the development of a suitable decision support tool. This tool should be, simple, reliable, and accessible for immediate use. The high reliability of the results should be assured even in a case of partial knowledge of the input data. The possibility to use an extremely consistent instrument to predict a building's performance before it is built, empowers decision-maker towards more sustainable choices upon analysing of reliable energy and environmental evaluations.

The presented results represent only the first step, in which the authors propose an alternative procedure for determining the energy and environmental performance of a building. Obviously, given the complexity of the problem, at this moment the answer provided by the ANN is linked to the building typology, materials and energy vectors explored and implemented in the database. In the future, for a greater capacity for generalization it will be necessary to implement the database and its features by the authors or other researchers.

References

Anand, C.K., Ben Amor, M., 2017. Recent developments, future challenges and new research directions in LCA of buildings: a critical review. Renew. Sustain. Energy Rev. 67, 408–416. https://doi.org/10.1016/j.rser.2016.09.058.

Asdrubali, F., Baldassarri, C., Fthenakis, V., 2013. Life cycle analysis in the construction sector: guiding the optimization of conventional Italian buildings. Energy Build. 64, 73–89. https://doi.org/10.1016/j.enbuild.2013.04.018.

ASHRAE, 1980. Energy Conservation in New Building Design - ASHRAE Standard 90A-1980.

Attia, S., Beltrán, L., De Herde, A., Hensen, J., 2009. “Architect friendly”: a comparison of ten different building performance simulation tools. In: IBPSA 2009 - International Building Performance Simulation Association 2009, pp. 204–211.

Azadeh, A., Ghaderi, S.F., Sohrabkhani, S., 2008. Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors. Energy Convers. Manag. 49, 2272–2278. https://doi.org/10.1016/j.enconman.2008.01.035.

Azari, R., Abbasabadi, N., 2018. Embodied energy of buildings: a review of data, methods, challenges, and research trends. Energy Build. 168, 225–235. https://doi.org/10.1016/J.ENBUILD.2018.03.003.

Beccali, M., Ciulla, G., Lo Brano, V., Galatioto, A., Bonomolo, M., 2017. Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy. Energy 137, 1201–1218. https://doi.org/10.1016/J.ENERGY.2017.05.200.

Bovea, M.D., Ibáñez-Forés, V., Agustí-Juan, I., 2014. Environmental product declaration (EPD) labelling of construction and building materials. Eco-efficient Constr. Build. Mater. 125–150. https://doi.org/10.1533/9780857097729.1.125.

Bozorg Chenani, S., Lehvävirta, S., Häkkinen, T., 2015. Life cycle assessment of layers of green roofs. J. Clean. Prod. 90, 153–162. https://doi.org/10.1016/j.jclepro.2014.11.070.

Buyle, M., Braet, J., Audenaert, A., 2013. Life cycle assessment in the construction sector: a review. Renew. Sustain. Energy Rev. 26, 379–388. https://doi.org/10.1016/j.rser.2013.05.001.

Ciulla, G., Lo Brano, V., D'Amico, A., 2016. Modelling relationship among energy demand, climate and office building features: a cluster analysis at European level. Appl. Energy 183, 1021–1034. https://doi.org/10.1016/j.apenergy.2016.09.046.

Ciulla, G., D'Amico, A., Lo Brano, V., 2017. Evaluation of building heating loads with dimensional analysis: application of the Buckingham π theorem. Energy Build. 154, 479–490. https://doi.org/10.1016/J.ENBUILD.2017.08.043.

Ciulla, G., D'Amico, A., Di Dio, V., Lo Brano, V., 2019a. Modelling and analysis of real-world wind turbine power curves: assessing deviations from nominal curve by neural networks. Renew. Energy 140, 477–492. https://doi.org/10.1016/J.RENENE.2019.03.075.

Ciulla, G., D'Amico, A., Lo Brano, V., Traverso, M., 2019b. Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level. Energy 176, 380–391. https://doi.org/10.1016/J.ENERGY.2019.03.168.

Czarnowski, I., Je,drzejowicz, P., 2006. An agent-based approach to ANN training. Knowl. Based Syst. 19, 304–308. https://doi.org/10.1016/J.KNOSYS.2005.11.012.

De Lassio, J., França, J., Espirito Santo, K., Haddad, A., 2016. Case study: LCA methodology applied to materials management in a Brazilian residential construction site. J. Eng. 2016 https://doi.org/10.1155/2016/8513293.

De Rosa, M., Bianco, V., Scarpa, F., Tagliafico, L.A., 2014. Heating and cooling building energy demand evaluation; A simplified model and a modified degree days approach. Appl. Energy 128, 217–229. https://doi.org/10.1016/j.apenergy.2014.04.067.

Decreto 26 giugno, 2015. Applicazione delle metodologie di calcolo delle prestazioni energetiche e definizione delle prescrizioni e dei requisiti minimi degli edifici; Adeguamento del decreto del Ministro dello sviluppo economico, 26 giugno 2009 - Linee guida nazionali per la cer.

Díaz, J., Antön, L.Á., 2014. Sustainable construction approach through integration of LCA and BIM tools. In: Computing in Civil and Building Engineering - Proceedings of the 2014 International Conference on Computing in Civil and Building Engineering, pp. 283–290. https://doi.org/10.1061/9780784413616.036.

Dixit, M.K., 2019. Life cycle recurrent embodied energy calculation of buildings: a review. J. Clean. Prod. 209, 731–754. https://doi.org/10.1016/J.JCLEPRO.2018.10.230.

Dlg n° 192, 2005. Dlg. N° 192. Attuazione Della Direttiva 2002/91/CE Relativa Al Rendimento Energetico Nell'edilizia.

DPR 412/93, 1993. Regolamento recante norme per la progettazione, l'installazione, l'esercizio e la manutenzione degli impianti termici degli edifici ai fini del contenimento dei consumi di energia. In: Attuazione Dell'art. 4, Comma 4, Della Legge 9 Gennaio 1991, N. 10. Gazz. Uff. della Repubb. Ital. SO.

D'Amico, B., Pomponi, F., 2018. Accuracy and Reliability: A Computational Tool to Minimise Steel Mass and Carbon Emissions at Early-Stage Structural Design. Energy Build. https://doi.org/10.1016/j.enbuild.2018.03.031.

D'Amico, A., Ciulla, G., Panno, D., Ferrari, S., 2019a. Building energy demand assessment through heating degree days: the importance of a climatic dataset. Appl. Energy 242, 1285–1306. https://doi.org/10.1016/J.APENERGY.2019.03.167.

D'Amico, B., Myers, R.J., Sykes, J., Voss, E., Cousins-Jenvey, B., Fawcett, W., Richardson, S., Kermani, A., Pomponi, F., 2019b. Machine learning for sustainable structures: a call for data. Structures. https://doi.org/10.1016/j.istruc.2018.11.013.

Elhami, B., Khanali, M., Akram, A., 2017. Combined application of Artificial Neural Networks and life cycle assessment in lentil farming in Iran. Inf. Process. Agric. 4, 18–32. https://doi.org/10.1016/j.inpa.2016.10.004.

EN 15804, 2014. EN 15804:2012 - standards Publication Sustainability of construction works — environmental product declarations — core rules for the product category of construction products. Int. Stand.

EN ISO 13790, 2008. ISO 13790: 2008 Energy performance of buildings-Calculation of energy use for space heating and cooling. Order A J. Theory Ordered Sets Its Appl. https://doi.org/10.3168/jds.2007-0930.

EN ISO 14040, 2006. EN ISO 14040, Environmental Management — Life Cycle Assessment — Principles and Framework.

EN ISO 14044, 2006. EN ISO 14044: 2006 Environmental Management - Life Cycle Assessment - Requirements and Guidelines. ISO, Geneva (Switzerland).

Eurostat, n.d. Eurostat, the Statistical Office of the European Union — 2920 Luxembourg

Ferrari, S., Zagarella, F., Caputo, P., D'Amico, A., 2019. Results of a literature review on methods for estimating buildings energy demand at district level. Energy 175, 1130–1137. https://doi.org/10.1016/j.energy.2019.03.172.

Floreano, D., Mattiussi, C., 2002. Manuale Sulle Reti Neurali.

Gervasio, H., Dimova, S., Pinto, A., 2018. Benchmarking the life-cycle environmental performance of buildings. Sustain. Times 10. https://doi.org/10.3390/su10051454.

ISO 14025, 2006. ISO 14025 Environmental Labels and Declarations — Type III Environmental Declarations — Principles and Procedures. International Organization. https://doi.org/10.1021/es0620181.

ISO 15686, 2011. ISO 15686-1: 2011 - Buildings and constructed assets — service life planning Part 1: general principles and framework. Int. Stand. 34.

Jha, S.K., Bilalovic, J., Jha, A., Patel, N., Zhang, H., 2017. Renewable energy: present research and future scope of Artificial Intelligence. Renew. Sustain. Energy Rev. 77, 297–317. https://doi.org/10.1016/j.rser.2017.04.018.

Jrade, A., Abdulla, R., 2012. Integrating building information modeling and life cycle assessment tools to design sustainable buildings. In: CIB W78 2012 29th Int. Conf.

Kayfeci, M., Yabanova, İ., Keçebaş, A., 2014. The use of artificial neural network to evaluate insulation thickness and life cycle costs: pipe insulation application. Appl. Therm. Eng. 63, 370–378. https://doi.org/10.1016/j.applthermaleng.2013.11.017.

Khanali, M., Mobli, H., Hosseinzadeh-Bandbafha, H., 2017. Modeling of yield and environmental impact categories in tea processing units based on artificial neural networks. Environ. Sci. Pollut. Res. 24, 26324–26340. https://doi.org/10.1007/s11356-017-0234-5.

Klein, S.A., others, 1996. TRNSYS-A transient system simulation tool, ver 14.2. Sol. Energy Lab. Univ. Wis. (MadLson, WI).

Krygiel, E., Nies, B., McDowell, S., 2008. Green BIM : Successful Sustainable Design

with Building Information Modeling. John Wiley & Sons.
Lazzerini, G., Lucchetti, S., Nicese, F.P., 2016. Green House Gases(GHG) emissions from the ornamental plant nursery industry: a Life Cycle Assessment(LCA) approach in a nursery district in central Italy. J. Clean. Prod. 112, 4022–4030. https://doi.org/10.1016/J.JCLEPRO.2015.08.065.
Li, J., Wu, Z., Zhang, H.C., 2015. Application of neural network on environmental impact assessment tools. Int. J. Sustain. Manuf. https://doi.org/10.1504/ijsm.2008.019229.
Maren, A.J., Harston, C.T., Pap, R.M., 1990. Handbook of Neural Computing Applications. Academic Press.
McDougall, F., White, P., Franke, M., Hindle, P., 2001. Life Cycle Assessment in Integrated Solid Waste Management: a Life Cycle Inventory. Malden USA Blackwell Sci. Publ, pp. 103–128.
Moncaster, A.M., Pomponi, F., Symons, K.E., Guthrie, P.M., 2018. Why method matters: temporal, spatial and physical variations in LCA and their impact on choice of structural system. Energy Build. https://doi.org/10.1016/j.enbuild.2018.05.039.
Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S.S., Hosseinzadeh-Bandbafha, H., Chau, K., 2018. Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Sci. Total Environ. 631–632, 1279–1294. https://doi.org/10.1016/j.scitotenv.2018.03.088.
Najjar, M., Figueiredo, K., Palumbo, M., Haddad, A., 2017. Integration of BIM and LCA: evaluating the environmental impacts of building materials at an early stage of designing a typical office building. J. Build. Eng. 14, 115–126. https://doi.org/10.1016/j.jobe.2017.10.005.
Oduyemi, O., Okoroh, M., Dean, A., 2015. Developing an artificial neural network model for life cycle costing in buildings. In: Proc. 31st Annu. Assoc. Res. Constr. Manag. Conf. ARCOM, 2015.
ÖKOBAUDAT, 2019 [WWW Document]. https://www.oekobaudat.de/en.html. (Accessed 3 May 2019).
Omid, M., Baharlooei, A., Ahmadi, H., 2009. Modeling drying kinetics of pistachio nuts with multilayer feed-forward neural network. Dry. Technol. 27, 1069–1077. https://doi.org/10.1080/07373930903218602.
Ozbilen, A., Aydin, M., Dincer, I., Rosen, M.A., 2013. Life cycle assessment of nuclear-based hydrogen production via a copper–chlorine cycle: a neural network approach. Int. J. Hydrogen Energy 38, 6314–6322. https://doi.org/10.1016/J.IJHYDENE.2013.03.071.
Pacheco, R., Ordóñez, J., Martínez, G., 2012. Energy efficient design of building: a review. Renew. Sustain. Energy Rev. 16, 3559–3573. https://doi.org/10.1016/J.RSER.2012.03.045.
Pahlavan, R., Omid, M., Akram, A., 2012. Energy input–output analysis and application of artificial neural networks for predicting greenhouse basil production. Energy 37, 171–176. https://doi.org/10.1016/J.ENERGY.2011.11.055.
Peltarion, 2019 [WWW Document]. https://peltarion.com/. (Accessed 5 May 2019).
Peltokorpi, A., Talmar, M., Castrén, K., Holmström, J., 2019. Designing an organizational system for economically sustainable demand-side management in district heating and cooling. J. Clean. Prod. 219, 433–442. https://doi.org/10.1016/J.JCLEPRO.2019.02.106.
Peng, C., 2016. Calculation of a building's life cycle carbon emissions based on Ecotect and building information modeling. J. Clean. Prod. 112, 453–465. https://doi.org/10.1016/j.jclepro.2015.08.078.
Pikoń, K., 2012. Abiotic depletion in energy and waste management systems. Polityka Energetyczna 15, 87–101.
Piñeiro, G., Perelman, S., Guerschman, J.P., Paruelo, J.M., 2008. How to evaluate models: observed vs. predicted or predicted vs. observed? Ecol. Model. 216, 316–322. https://doi.org/10.1016/j.ecolmodel.2008.05.006.
Proietti, S., Sdringola, P., Desideri, U., Zepparelli, F., Masciarelli, F., Castellani, F., 2013. Life Cycle Assessment of a passive house in a seismic temperate zone. Energy Build. 64, 463–472. https://doi.org/10.1016/j.enbuild.2013.05.013.
Qin, S., Yang, X., Xue, X., Song, J., 2017. A one-layer recurrent neural network for pseudoconvex optimization problems with equality and inequality constraints. IEEE Trans. Cybern. 47, 3063–3074. https://doi.org/10.1109/TCYB.2016.2567449.
Roh, S., Tae, S., Suk, S.J., Ford, G., Shin, S., 2016. Development of a building life cycle carbon emissions assessment program (BEGAS 2.0) for Korea's green building index certification system. Renew. Sustain. Energy Rev. 53, 954–965. https://doi.org/10.1016/J.RSER.2015.09.048.
Ruiz, L.G.B., Rueda, R., Cuéllar, M.P., Pegalajar, M.C., 2018. Energy consumption forecasting based on Elman neural networks with evolutive optimization. Expert Syst. Appl. 92, 380–389. https://doi.org/10.1016/J.ESWA.2017.09.059.
Safa, M., Samarasinghe, S., 2011. Determination and modelling of energy consumption in wheat production using neural networks: "A case study in Canterbury province, New Zealand. Energy 36, 5140–5147. https://doi.org/10.1016/J.ENERGY.2011.06.016.
SDG, 2012. About the sustainable development goals - United Nations sustainable development [WWW Document]. https://www.un.org/sustainabledevelopment/sustainable-development-goals/. (Accessed 30 January 2019).
Senjyu, T., Takara, H., Uezato, K., Funabashi, T., 2002. One-hour-ahead load forecasting using neural network. IEEE Trans. Power Syst. 17, 113–118. https://doi.org/10.1109/59.982201.
Shafiq, N., Nurrudin, M.F., Gardezi, S.S.S., Kamaruzzaman, A. Bin, 2015. Carbon footprint assessment of a typical low rise office building in Malaysia using building information modelling (BIM). Int. J. Sustain. Build. Technol. Urban Dev. 6, 157–172. https://doi.org/10.1080/2093761X.2015.1057876.
Stephan, A., Athanassiadis, A., 2017. Quantifying and mapping embodied environmental requirements of urban building stocks. Build. Environ. 114, 187–202. https://doi.org/10.1016/j.buildenv.2016.11.043.
Stephan, A., Crawford, R.H., De Myttenaere, K., 2012. Towards a comprehensive life cycle energy analysis framework for residential buildings. Energy Build. https://doi.org/10.1016/j.enbuild.2012.09.008.
Taki, M., Ajabshirchi, Y., Ranjbar, S.F., Rohani, A., Matloobi, M., 2016. Heat transfer and MLP neural network models to predict inside environment variables and energy lost in a semi-solar greenhouse. Energy Build. 110, 314–329. https://doi.org/10.1016/j.enbuild.2015.11.010.
Taki, M., Rohani, A., Soheili-Fard, F., Abdeshahi, A., 2018. Assessment of energy consumption and modeling of output energy for wheat production by neural network (MLP and RBF) and Gaussian process regression (GPR) models. J. Clean. Prod. 172, 3028–3041. https://doi.org/10.1016/J.JCLEPRO.2017.11.107.
Thibodeau, C., Bataille, A., Sié, M., 2019. Building rehabilitation life cycle assessment methodology–state of the art. Renew. Sustain. Energy Rev. 103, 408–422. https://doi.org/10.1016/j.rser.2018.12.037.
Tohidi, M., Sadeghi, M., Mousavi, S.R., Mireei, S.A., 2012. Artificial neural network modeling of process and product indices in deep bed drying of rough rice. Turk. J. Agric. For. 36, 738–748. https://doi.org/10.3906/tar-1106-44.
Volk, R., Stengel, J., Schultmann, F., 2014. Building Information Modeling (BIM) for existing buildings — literature review and future needs. Autom. ConStruct. 38, 109–127. https://doi.org/10.1016/J.AUTCON.2013.10.023.
Wijnants, L., Allacker, K., De Troyer, F., 2019. Life-cycle assessment of timber frame constructions – the case of rooftop extensions. J. Clean. Prod. 216, 333–345. https://doi.org/10.1016/J.JCLEPRO.2018.12.278.
Wong, J.K.W., Zhou, J., 2015. Enhancing environmental sustainability over building life cycles through green BIM: a review. Autom. ConStruct. 57, 156–165. https://doi.org/10.1016/j.autcon.2015.06.003.
Wu, W., Issa, R., 2013. Integrated process mapping for BIM implementation in green building project delivery. In: Proc. 13th Int. Conf. Constr. Appl. Virtual Real.
Zangeneh, M., Omid, M., Akram, A., 2011. A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran. Span. J. Agric. Res. 9, 661. https://doi.org/10.5424/sjar/20110903-371-10.
Zhang, X.-Y., Yin, F., Zhang, Y.-M., Liu, C.-L., Bengio, Y., 2018. Drawing and recognizing Chinese characters with recurrent neural network. IEEE Trans. Pattern Anal. Mach. Intell. 40, 849–862. https://doi.org/10.1109/TPAMI.2017.2695539.