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Research paper

Predictive modelling of cooling consumption in nursing homes using artificial neural networks: Implications for energy efficiency and thermal comfort

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ABSTRACT

The growing need for cooling within the built environment, propelled by climate change and the expansion of nursing homes due to the increase in life expectancy, highlights the urgency of implementing energy-efficient strategies in buildings occupied by older populations. As of today, there remains a need for comprehensive research into the influence of indoor and outdoor conditions, building, operational, and occupant characteristics, on energy consumption specifically for nursing homes. This study develops a systemic artificial neural network-based model with a multi-layer perceptron architecture to assess HVAC energy implications during the cooling season for older populations. Using monitored data from eight nursing homes, the model includes cooling area, construction age, outdoor and indoor temperatures, and outdoor relative humidity as inputs, and cooling consumption as the output. Results show excellent predictive capability (R^2=0.95), with mean error of −0.5 kWh, root mean squared error of 13.7 kWh, mean absolute error of 10.2 kWh, and relative error of 0.051. These outcomes are better compared to linear models (R^2≈0.65) under the same data set. Adjusting operative temperatures adaptively can significantly enhance resident comfort and achieve up to 23.4 % energy savings, particularly in hotter, drier climates. These findings are of paramount importance for effective energy management in buildings.

1. Introduction

Climate change stands as a global challenge (Hallegatte et al., 2016) that permeates various facets of contemporary society, from energy consumption patterns (Akhmat et al., 2014) to architectural design principles (Andrić et al., 2021). The urgency for climate-responsive solutions is underscored by the increasing occurrence of heatwaves and the progressive rise in global temperatures (Arnell et al., 2019). These climatic shifts necessitate a recalibration of the way indoor environments are controlled while emphasising the imperative of sustainable energy practices (Potera, 2011; Šujanová et al., 2019).

The construction and operation of buildings significantly contribute to greenhouse gas emissions and other pollutants (IPCC, 2023). According to the European Commission (2023) and the United Nations (2022), buildings account for roughly 36 % of CO_2 emissions and approximately 40 % of the European Union's energy consumption, with nursing homes representing an increasing share of these emissions year after year, due to the progressive ageing of the population and the rising life expectancy trend (Izekenova et al., 2015). Besides the inherent environmental repercussions of energy consumption, it is noteworthy that an estimated 75 % of European buildings are categorised as energy inefficient (European Commission, 2020). This diminished efficiency can be attributed to various factors, including suboptimal building design and material selection, inferior construction quality, and inadequate testing, operation, and maintenance practices, among others (Yik and Lee, 2002). Many of these factors are closely linked to the age of the buildings, with a significant portion of them having been constructed between the 1950s and the 1970s (Butala and Novak, 1999; Fouseki and Cassar, 2014; Galvin, 2022). The significance of these lies in the fact that more inefficiency corresponds to higher energy consumption (Sheng and Guo, 2018), resulting in a notable increase in the aforementioned environmental consequences.

Moreover, HVAC systems represent the foremost contributors to energy consumption. They are responsible for nearly 40 % of energy usage in commercial buildings and 36 % in residential structures (IEA, 2022; Jamil et al., 2021). As a result, optimising HVAC consumption is

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vital to achieve higher operational efficiency regarding energy usage in buildings.

Several studies appointed that active control of HVAC systems, which entails the utilisation of automated mechanisms to regulate and fine-tune environmental parameters such as temperature, humidity, and air quality within various spaces (Montgomery and McDowall, 2008), is an almost necessary methodology to guarantee a feasible and efficient acclimatisation process (Gholamzadehmir et al., 2020; Guo and Zhou, 2009; Teke and Timur, 2014; L. Wang et al., 2013). Specifically, and according to Gholamzadehmir et al. (2020) literature review, the implementation of active control systems in the residential sector has been shown to potentially achieve cost savings ranging from 5 % to 45 %.

In fact, predictive modelling techniques that anticipate HVAC consumption can help these HVAC active control systems (Afram and Janabi-Sharifi, 2014; Afroz et al., 2022). This facilitates adaptive system adjustments based on environmental parameters, leading to improved energy efficiency and overall performance (Asad et al., 2019). Although some researchers have developed consumption prediction models based on the indoor and outdoor conditions of buildings using linear regressions, their coefficients of determination were typically below 0.8 (Aranda et al., 2012; Fumo and Rafe Biswas, 2015; Vergés et al., 2023), highlighting the opportunity for further enhancement in predictive potential.

Linear modelling techniques generally provide reasonably accurate approximations, but as seen above, certain limitations may arise, rendering the applicability of these models insufficient in some situations. Alternative approaches can yield improved results compared to linear modelling techniques, such as the use of neuro-fuzzy, neural, and Bayesian networks (Samhouri et al., 2009; Pino-Mejías et al., 2017; Ilbeigi et al., 2020). Benedetti et al. (2016) emphasised that the utilisation of neural networks can result in highly precise energy consumption control with straightforward implementation. Likewise, Tso and Yau (2007) suggested that neural network models represent feasible alternatives to stepwise regression models for comprehending energy consumption patterns and forecasting energy usage.

The selection of the most suitable machine learning modelling tool can be a challenging task. Amasyali and El-Gohary (2021) tackled this issue by examining various machine learning models for predicting occupant-behaviour-sensitive cooling consumption in office buildings. Their study involved regression trees, ensemble bagging trees, artificial neural networks, and deep neural networks. The findings revealed that for data sets with more than 10,000 values, deep neural networks were the most effective model for predicting cooling consumption ($R^2 = 0.998$). Nonetheless, in scenarios with a more restricted data set, the artificial neural network presented superior performance, achieving an R^2 value of 0.989 for a data set consisting of 1000 values. Furthermore, it was observed that the training time for deep neural networks significantly exceeded that of artificial neural networks, taking nearly ten times longer for the aforementioned case. As a result, these studies demonstrated the importance of opting for deep neural networks primarily when dealing with exceptionally large data sets and using artificial neural networks otherwise. Other approaches, such as quantum computing methods, also exist and offer promising advancements in optimising HVAC systems by efficiently solving large-scale non-linear discrete optimisation problems (Deng et al., 2023). However, the practical implementation of quantum computing in building applications remains challenging due to the complexity, specialised expertise required, and the need for advanced infrastructure (Deng et al., 2023). Moreover, the utilisation of quantum computing techniques for limited data sets is not yet sufficiently justified, as the computational effort is not a constraining factor in such instances.

The application of artificial neural networks in HVAC consumption analysis has been extensively investigated. A study by Kim et al. (2020) compared the predictive abilities of artificial neural networks and linear regression models for electricity consumption in a campus building using occupant rates and weather-related factors, accompanied by sensitivity analysis. The findings indicated that artificial neural networks outperformed the linear models, demonstrating mean bias errors of 10.9 and 17.6, respectively. Furthermore, Xu et al. (2022) investigated the impact of eight key building parameters (surface area, wall area, roof area, relative compactness, overall height, orientation, glazing area, and glazing area distribution) on heating and cooling loads using an artificial neural network-based model which demonstrated remarkable predictive accuracy and effectiveness with a coefficient of determination as high as 0.92.

Considering the life expectancy increases and the specific characteristics of nursing homes (they maintain consistent occupancy year-round with minimal day-to-day and seasonal variations; they involve large communal spaces where residents engage in various activities, including occupational therapy, feeding and mobility exercises (Sanford et al., 2015); they are generally old buildings) it is worthy studying and predicting the energy consumption of these type of facilities.

Some researchers developed neural network models for different building types. Fouladfar et al. (2023) proposed an adaptive thermal load prediction in residential buildings using outdoor temperature, global horizontal irradiation, zone temperature (living room), time, and measured internal gain as inputs, resulting in root mean squared errors of 12 W/m^2 (winter) 10 W/m^2 (summer), highlighting the possibility of performing precise predictions of thermal loads using artificial neural networks. Similarly, Wang et al. (2023) developed a model capable of predicting energy consumption in office buildings, achieving a coefficient of determination of 0.91. However, as can be seen, none of them focused on nursing homes, which are spaces with unique requirements. In that sense, no existing studies have investigated in a comprehensive manner the influence of indoor and outdoor conditions and the building and operative characteristics on energy consumption in nursing homes in a holistic manner. Therefore, the prediction of building energy consumption considering occupant's comfort is currently inaccurate. Additionally, another research gap is the absence of a systemic single model applicable to any nursing home, regardless of dimensions, location, or climate situation. Vergés et al. (2023) developed linear models applicable to individual nursing homes, thus this being a constraint both in terms of accuracy (R^2 of 0.65 in average) and extensibility to other nursing homes beyond their data set. As a response, this study intends to fill this void by developing a holistic neural network model applicable to any nursing home irrespective to its characteristics as well as providing insights of implementing existing adaptive thermal comfort models to extract conclusions whether this implementation could potentially serve as an energy-saving procedure without compromising seniors' well-being.

The main contributions of this paper are fourfold: i) Addressing the gap in inaccurate energy modelling by developing a model capable of predicting cooling consumption in nursing homes more accurately than existing studies, ii) Creating a holistic model applicable to any nursing home, whether included in the data set or not, thereby resolving the issue that previous studies did not address (using one linear model for each nursing home), iii) Study the influence of indoor & outdoor conditions, and nursing home characteristics on cooling consumption, including their non-linear behaviour (which was not possible to address in previous studies) and iv) Implementing existing adaptive thermal comfort models into the developed model to evaluate whether this approach could potentially serve as an energy-saving procedure without compromising the well-being of seniors.

The manuscript is structured as follows. It begins with an explanation of the methodology (Section 2), followed by the identification of key parameters, preliminary neural network architecture (Section 3), and data set definition (Section 4). The development of the neural network is then discussed (Section 5), followed by an analysis of the neural network's response to input variations and an analysis of energy implications adopting adaptive thermal comfort models (Section 6). Finally, the paper concludes with key findings and insights (Section 7).

2. Methodology

The study consisted of the following phases:

- Phase 1. Identification of key parameters and network architecture. Determination of parameter candidates affecting cooling consumption, according to academic literature review.
- Phase 2. Data set definition, specifying its size, the selected parameter candidates, identifying the equipment and data sources used, and preliminary neural network architectural element candidates, addressing neural network size to mitigate overfitting issues, and including the definition of control cases and the partition of the data set into training and testing subsets.
- Phase 3. Development of neural network-based energy consumption models for the cooling season.

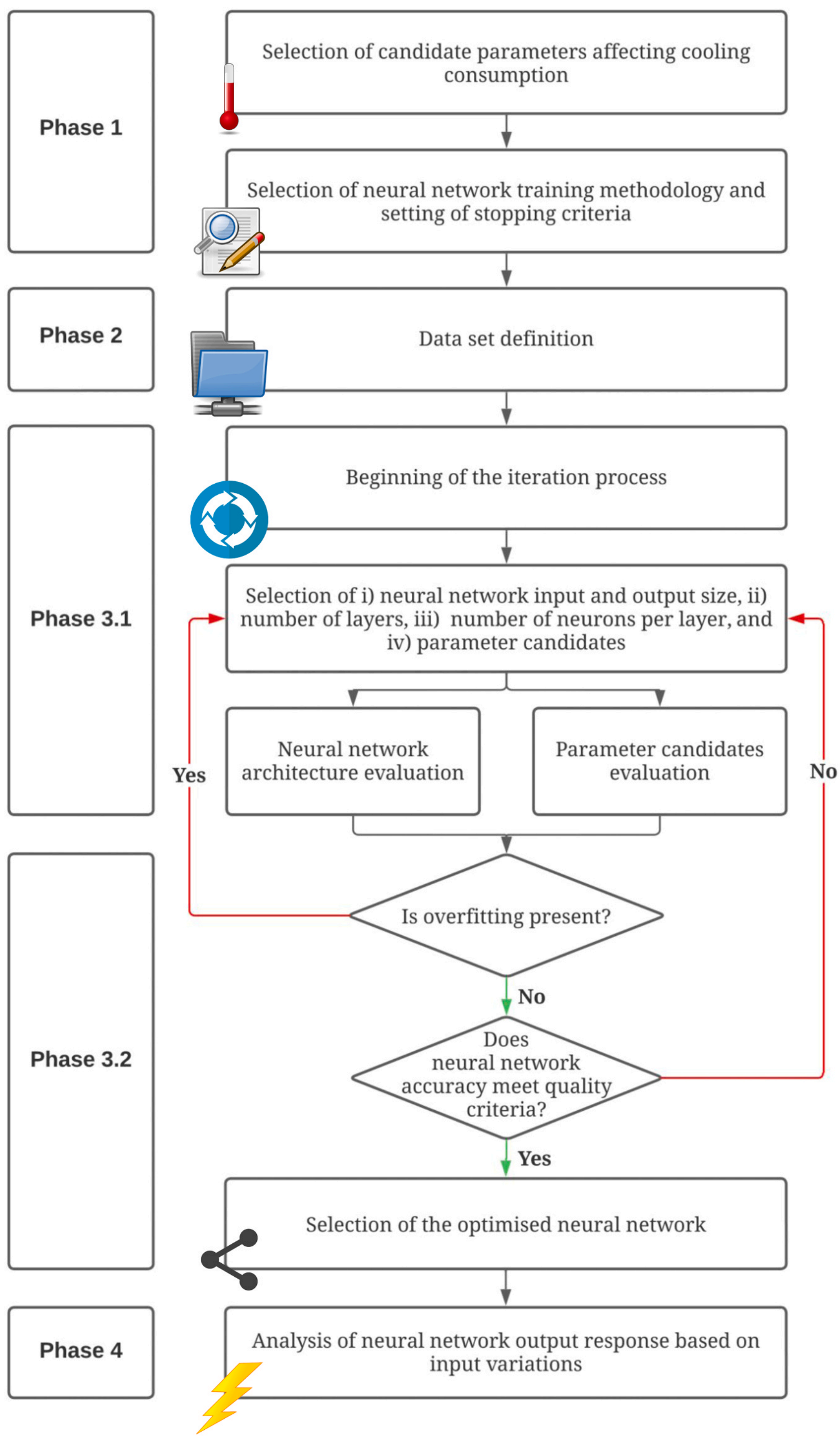

Fig. 1. Methodology scheme flowchart.

o Phase 3.1. Evaluation of parameters and architectural elements appropriateness and neural network optimisation through an iterative process, evaluating both overfitting and predictable capabilities of the model.
o Phase 3.2. Neural network testing and validation.

- Phase 4. Analysis of neural network output response based on input variations and analysis of energy implications adopting adaptive thermal comfort models.

For a more structured overview of the process, Fig. 1 illustrates the key tasks associated with the construction of a neural network-based model designed to predict cooling consumption for any nursing home, and the subsequent pertinent analysis.

2.1. Identification of key parameters and network architecture

Through a review of relevant academic literature on predictive modelling for HVAC cooling consumption, key influencing parameters – i.e., variables and factors - were identified. Variables encompass continuous values, including temperature or relative humidity, among others, while factors pertain to segmented cases, such as the age of construction or the HVAC typology. Both can be incorporated into the neural network-based model as inputs, and despite their conceptual differences, they can be processed in a uniform manner.

This initial exploration, accompanied by the cooling consumption data, led to the establishment of the final data set and the preliminary design of the neural network architecture.

2.2. Data set definition

Real monitored data of HVAC energy consumption, indoor and outdoor climatic conditions and building characteristics based on the defined key influencing parameters, were used as the data set. The HVAC energy consumption was standardised employing the same method used by Vergés et al. (2023).

To ensure the reliability of the data for training the neural network, dummy data points were introduced as control inputs, and thus added to the data set. These dummy data points capture unrealistic or absurd results that may arise due to data inconsistencies (Draper and Smith, 1998), such as energy consumption associated with a cooling area of zero square metres, and to prevent the model from misinterpreting the input parameters and generating unreliable or nonsensical predictions under extreme or unexpected scenarios. The method for introducing dummy data points involves the following steps: i) Identifying key scenarios, based on literature review, where the data might be inconsistent or extreme, such as areas with no cooling, low outdoor temperatures, or excessively high running mean temperatures, ii) Defining control cases based on these scenarios to represent realistic outcomes, and iii) Integrating these cases into the dataset for training purposes. For detailed information on the implementation of this method, refer to **Section 4** .

Then, the data set was divided into two distinct partitions: the training sample and the testing sample. This partitioning process was executed randomly to ensure a higher degree of result consistency. However, the control cases were willingly incorporated into the training batch, thus enabling the neural network to learn from these specific cases. A minimum allocation of 70 % of the total data set was dedicated to the training sample, ensuring an adequate amount of data for the network to acquire comprehensive knowledge and refine its predictive capabilities (Basheer and Hajmeer, 2000).

2.3. Development of neural network-based energy consumption models for the cooling season

Prior to commencing the iterative process, the training methodology and stopping criteria was established. This was done to ensure the generation of consistent neural networks throughout the iterations, thereby enabling a comparative analysis of their development in terms of predictive capabilities and the mitigation of overfitting.

Regarding the training methodology, backpropagation through a gradient descent algorithm is a training technique in neural networks that involves the iterative refinement of internal parameters, including weights and biases. This refinement is achieved through the calculation in the reverse direction (from output layer back to the input layer) of gradients representing the cost function's sensitivity to these parameters (Chauvin and Rumelhart, 1994; Galushkin, 2007). Also, as noted by Hecht-Nielsen (1992) and Kumar et al. (2013), backpropagation is a potent learning algorithm extensively employed in the training of neural networks. Therefore, it has been adopted as the chosen approach in this study.

The learning speed in the backpropagation methodology, using gradient descent, is determined by two parameters: the initial learning rate and the momentum. Higher learning speeds can lead to more computationally efficient outcomes, but they also carry the risk of inducing instability and generating suboptimal results (Zhang et al., 2019). To achieve the optimal balance for the data set, values for the initial learning rate and momentum were fine-tuned through a process of trial and error.

Concerning the stopping criteria, the rules are employed to determine when the model training phase should conclude. The considered stopping rules include: i) maximum steps without a decrease in error (Max_e) (set to 1000 steps), ii) maximum training time (Max_t) (set to fifteen minutes), iii) maximum number of epochs (Max_{ep}) (computed automatically), iv) minimum relative change in training error (Min_e) (set to 0.0001), and v) minimum relative change in training error ratio (Min_{er}) (set to 0.001).

The weights and biases of a neural network are connected through an activation function. While weights and biases in neural networks can assume any numerical value, it is common to assign activations within a range of 0–1 (Hecht-Nielsen, 1992). To ensure the activations fall within this desired range, various functions are employed to transform the input values (Sharma et al., 2020). For this study, the sigmoid activation function was chosen as the most suitable option. It is described below:

$$\sigma = 1/(1 + \exp(-x)) \quad (1)$$

To enhance efficiency of the neural network activation functions, input and output parameters were normalised (Ioffe and Szegedy, 2015). Normalisation ensures that all variables have a similar range and distribution, aiding in the convergence and stability of the neural network during training, as stated by Sola and Sevilla (1997). The formulation is shown in Eq. 2:

$$X_{norm} = (X - \min)/(\max - \min) \quad (2)$$

Where X_{norm} represents the normalised variable, X denotes the input variable to normalise, and min and max represent the minimum and maximum values of the variable within the data set, respectively.

Afterwards, and through an iterative process, the parameter candidates were subjected to evaluation to assess the appropriateness of such variables and factors to the developed preliminary neural network. This evaluation sought to determine the resulting coefficient of determination between the real cooling consumption data and the neural network response, both encompassing training and testing subsets. With that, it was also possible to detect the impossibility to generalise the neural network response with unseen data due to overfitting issues (Mutasa et al., 2020), and assess overall predictive capabilities.

In parallel to the previous step, the neural network architecture was also adjusted throughout the iterative process to evaluate the best response according to neural network input and output size. The neural architecture concerns the number of inputs, number of outputs, number of layers, number of neurons per layer, and type of activation function between layers. Here, overfitting concerns were prioritised, due to an excessive neural network size being the direct responsible of overfitting within the neural response (Decuyper et al., 2019). Some studies, such as Tetko et al. (1995), found that overfitting can be mitigated if the neural network is not overtrained, which can be assessed by cross-validation analysis. This analysis can be conducted through the stratification of the data set into training and testing subsets, enabling the assessment of the predictive capabilities of both sub-cases. In this evaluation, the coefficient of determination and standard deviation were considered, as suggested by Hawkins et al. (2003). If these metrics show consistent patterns, it suggests that the neural network is not suffering from overtraining, thus mitigating the risk of overfitting. The range of acceptability for both subsets is contingent upon specific exigency levels, but as suggested in studies such as Lauret et al. (2016), deviations in the standard deviation of up to 10 % between the training and testing sets, as well as differences in R^2 of 0.1 between these subsets, could be deemed appropriate.

The choice of hidden layers in a neural network depends on the characteristics of the data set, as stated by Bebis and Georgiopoulos (1994). For data sets with linear separability, no hidden layers may be necessary. For data sets with lower complexity and fewer dimensions or features, 1–2 hidden layers typically provide satisfactory results. As the complexity of the data increases, opting for 3–5 hidden layers can lead to improved performance. However, excessive hidden layers can result in overfitting, where the model becomes too specialised to the training data and performs poorly on new, unseen data.

After determining the appropriate number of hidden layers, the number of neurons per layer and the total number of neurons must be selected. Following the guidelines presented by Heaton (2015), approximately two-thirds of the input layer neurons, plus the output neuron, were allocated to each hidden layer. Also, as for the total number of neurons in the neural network (excluding inputs and outputs), approximately double the number of neurons compared to the input layer was set as an appropriate preliminary estimate.

Validation of the neural network-based model not only encompassed overfitting assessment but also predictable capabilities, which was set at a R^2 value of 0.9 with the aim of improving the previous developed linear models (0.65) under the same data set (Vergés et al., 2023).

Moreover, in recognition of the fact that every model inherently possesses associated errors, an additional approach to assessing its predictive capabilities is to establish a confidence interval, following the assumption of normality, as discussed by Schmidt and Finan (2018). This assumption can be established based on the residuals of the model, which represent the disparities between the neural network's output and the actual values (see Eq. 3). Therefore, if the histogram of residuals presents a distribution resembling normality, it becomes feasible to define a confidence interval, defined in Eq. 4.

$$r = \overline{X} - X \tag{3}$$

With r denoting the residual, $\overline{X}$ representing the predicted estimate from the model, and X representing the actual observed value.

$$CI = \overline{x} \pm z \cdot \sigma_d / \sqrt{n} \tag{4}$$

Here, $\overline{x}$ refers to the sample mean, σ_d represents the standard deviation, n denotes the sample size, and z signifies the point on the standard normal density curve where the probability of observing a value greater than z is equivalent to the probability p. In a 95 % confidence interval, z is set to 1.96 (Patel and Read, 1996).

The model will be evaluated using several metrics to assess its performance. These metrics include Mean Error (ME), Standard deviation (σ_d), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), coefficient of determination (R^2), and Relative Error (RE).

Having encountered a balance between number of inputs, number of outputs, number of layers, number of neurons, overall predictive capabilities, and overfitting, the optimised final neural network, once validated, was selected to perform the subsequent cooling consumption analysis, both studying the neural network response to input variations and incorporating an adaptive-based thermal comfort approach to the model.

2.4. Neural network output response subjected to input variations and implementation of adaptive thermal comfort models

The study proceeded by analysing the insights from the neural network-based energy consumption model. To evaluate the response of the neural network, the parameters constituting the input layer of the neural network were subjected to variations. The analysis mainly centred around identifying discrepancies in tendencies, patterns, and modifications, with a specific focus on discerning any variations attributable to climate, age of the buildings, or other relevant information concerning the nursing homes.

Subsequently, validated adaptive thermal comfort models by Baquero and Forcada (2022) and Forcada et al. (2020) were employed to compute the comfort temperature for the nursing homes using outdoor temperature data. The use of adaptive thermal models was primarily driven by two main considerations. First, these models were explicitly tailored to suit ageing populations, making them highly applicable in the context of nursing homes. Second, the decision to adopt these models was influenced by prior research conducted by Vergés et al. (2023), where the same comfort models were employed. This alignment in model selection allowed for a direct and meaningful comparison between the linear models and the neural network-based model developed in this study, given the shared use of the same data set in both studies.

This information was then utilised as inputs for the neural network to investigate their impact on cooling energy consumption. The research framework is summarised in Fig. 2.

3. Identification of key parameters and network architecture

From the literature review, twelve candidate parameters were selected, as summarised in Table 1. The selection was based on prior research studies, exemplified by Ibarra et al. (2023) and Kassas (2015), have provided insights into potential parameters that influence cooling consumption. Building upon the knowledge derived from these investigations and leveraging the available data set for the field study, the following preliminary environmental outdoor variables were considered:

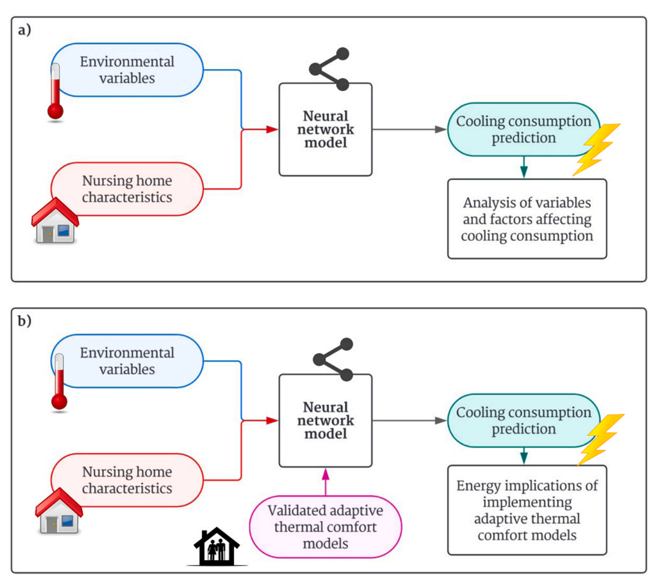

Fig. 2. Research framework, including (a) neural network output response subjected to input variations, and (b) implementation of adaptive thermal comfort models.

- Running mean temperature (T_{rm}): This variable represents the overall outdoor temperature trend over a specific period. While the running mean temperature offers comparable insights into the required cooling loads as the outdoor temperature, it also provides valuable information about the thermal inertia of the environment, which significantly influences occupants' thermal comfort. The utilisation of outdoor temperature as a pivotal factor in scientific literature for HVAC consumption estimation is well-established, as demonstrated in the recent study by Chen et al. (2023). In their work, they crafted a predictive model employing neural networks, resulting in a mean bias error within the range of ±10 %. The calculation of T_{rm} is done as follows (ISO, 7726, 1998):

$$T_{rm} = (T_{ed-1} + 0.8T_{ed-2} + 0.6T_{ed-3} + 0.5T_{ed-4} + 0.4T_{ed-5} + 0.3T_{ed-6} + 0.2T_{ed-7})/3.8 \quad (5)$$

where T_{ed-1} represents the daily mean outdoor temperature for the previous day, T_{ed-2} is the daily mean outdoor temperature for the day before that, and so forth.
- Outdoor relative humidity (RH_{out}): Relative humidity refers to the proportion of water vapour present in the air, expressed as a percentage of the amount required for saturation at the given temperature. This parameter significantly influences human perception of heat and, consequently, plays a crucial role in evaluating both thermal comfort and HVAC consumption within a building. This parameter has been previously employed in various studies and analyses, as exemplified by Lei and Yin (2022), wherein they developed a predictive energy consumption model for tall buildings utilising the LMBP neural network with an average Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of 2.96 and 4.59, respectively.

As regards the indoor variables, they are summarised below:

- Operative temperature (T_{op}): It is the weighted average of air temperature and radiant temperature, representing the hypothetical uniform temperature of an imaginary black enclosure. This value corresponds to the heat exchange, considering both radiation and convection, that an occupant would experience in the real, nonuniform environment. Its relevance in cooling consumption was assessed by different research studies (Pereira et al., 2014; Memon et al., 2008). It is calculated as follows:

$$T_{op} = (T_a + T_r)/2 \quad (6)$$

with T_a and T_r representing the air temperature and the radiant temperature, respectively.
- Indoor relative humidity (RH): Indoor relative humidity is akin to outdoor relative humidity, but it specifically pertains to the moisture levels within a building's enclosed environment.
- Cooling area (S): The cooling area refers to the area in which the HVAC system operates to provide acclimatisation. It offers valuable insights into the amount of cooling required, and its significance becomes more pronounced with larger cooling areas (Liusheng, 2014).
- Air speed (v_a): Indoor air velocity is a control variable that determines when the HVAC system is deactivated or activated, with non-null air speed indicating the latter (Kavgic et al., 2008).

The preliminary considered factors include:

- Climate: It was hypothesised that climate variations could lead to differences in HVAC behaviour, following Vergés et al. (2023) findings. Moreover, various prior research has studied the development of neural network-based models for assessing HVAC consumption across a spectrum of climate zones, including hot-humid (Seo et al., 2019), arid (Al-Shargabi et al., 2021), and even climates like arctic, subarctic, and continental conditions (Swan et al., 2011). This body of research underscored the significance of accounting for climate-related factors in predictive models, further reinforcing the inclusion of climate as a parameter in the analysis.
- HVAC system typology: the HVAC system influences the energy consumption of the building (Gustafsson et al., 2014; Khatri and Joshi, 2017; Wang et al., 2011; Zhao et al., 2021). Two main HVAC systems were used in the nursing homes under study (Vergés et al., 2023): All-Water HVAC systems and Variable Refrigerant Volume (VRV) systems. They were both used for heating and cooling in buildings, but they operated on different principles. All-Water systems use water as the heat transfer medium for both heating and cooling. In general, they incorporate a boiler to heat the water and a chiller to cool it. Then, the most common energy source for heating is gas and for cooling is electricity. On the other hand, VRV systems use refrigerant as the heat transfer medium. A single outdoor condensing unit is connected to multiple indoor units. Electricity source is used both for heating and cooling and thus, have energy fluctuations along the different seasons.
- Construction Age: The age of construction was recognized as a suitable parameter candidate for generating robust and resilient predictions for cooling consumption, as it serves as an indicator of the thermal performance of the buildings, reflecting the impact of evolving efficiency-related regulations, directives, and policies over the years (Idae, 2021). To account for this, the construction age factor was divided into two categories: nursing homes constructed prior to and after the year 2000. This segmentation, apart from segmenting the data set equally, aligns with the evolving energy efficiency regulations in the European building sector. The introduction of key directives and regulations, including LOE 1999 (Gobierno de España, 1999) (later modified by RD 47/2007 (Gobierno de España, 2007)), Directive 2002/91/EC (European Commission, 2002), Directive 2010/31/EU (European Commission, 2010), and Directive 2018/844/EU (European Commission, 2018), has significantly impacted building energy performance standards since their implementation.
- HVAC operation time: The timing of HVAC system usage plays a crucial role in energy consumption patterns, as different activities were typically performed at different hours of the day. For instance, den Ouden et al. (2015) analysed the activities performed by senior residents in different nursing homes throughout the day. Their study revealed that residents frequently exhibited inactivity, with most of their activity patterns scheduled at specific times, such as during meals or mobility-related activities, which were monitored by the caregivers. Regarding this study, the neural network considered three distinct time segments: before 12:00 am, between 12:00 am and 4:00 pm, and after 4:00 pm.
- Nursing home: This classification encompasses factors like maximum occupancy, number of floors, building enclosure, HVAC efficiency, and more. Studies like Tsanas and Xifara (2012) employed different building characteristics to estimate energy performance of residential buildings. Although the inclusion of this factor might limit the generalisability of results to the specific nursing homes within the data set, it has the potential to accurately capture energy usage behaviour. Alternatively, if satisfactory results can be achieved with other considered elements, this factor can be omitted.

4. Data set definition

The selected parameter candidates affecting cooling consumption, which conformed the foundation of the data set, together with the data size are summarised in Table 1.

This data set was extracted from eight Spanish nursing homes with different characteristics and locations. Of the eight Spanish nursing homes in this study, four were situated in a Mediterranean climate (Csa-m), located in the Community of Valencia and Catalonia, while the other four were in a Continental-Mediterranean climate (Csa-c), located in the Community of Madrid. The residents in these nursing homes had an

Table 1
Selected candidate parameters affecting cooling consumption.

Parameter	Type of parameter	Unit	Data type	Data size
HVAC cooling consumption (CED_c)	Variable	kWh	Nursing home information	280,320
Running mean temperature (T_rm)	Variable	°C	Outdoor environmental	2920
Outdoor relative humidity (RH_{out})	Variable	%	Outdoor environmental	2920
Indoor relative humidity (RH)	Variable	%	Indoor environmental	196
Operative temperature (T_op)	Variable	°C	Indoor environmental	196
Air speed (v_a)	Variable	m/s	Indoor environmental	196
Cooling area (S)	Variable	m^2	Nursing home information	196
Nursing home	Factor	-	Nursing home information	8
HVAC operation time	Factor	-	Nursing home information	3
Construction age	Factor	-	Nursing home information	2
HVAC system typology	Factor	-	Nursing home information	2
Climate (nursing home location)	Factor	-	Nursing home information	2

average age of 84 years, with approximately 70 % being female and 30 % male. The primary HVAC system employed in these nursing homes was an all-water system with fan-coils, except for two of them which utilise Variable Refrigerant Volume (VRV) systems for cooling.

The consumption data acquisition spanned one year for nursing homes in the Mediterranean region, from December 1, 2018, to November 30, 2019. For nursing homes in the Continental-Mediterranean region, data collection occurred from February 1, 2021, to February 28, 2022. Each nursing home yielded 35,040 quarter-hour consumption measurements, resulting in a total of 280,320 data points prior to processing. Consumption data was monitored and acquired through *Supervisory Control And Data Acquisition* (SCADA) systems, featuring three levels of operation.

The outdoor environmental data, including running mean temperature and outdoor relative humidity, was sourced from AEMET (2011), with 365 measurements per nursing home, totalling 2920 outdoor environmental data points.

During indoor environmental data collection, measurements were taken for globe temperature, dry air temperature, relative indoor humidity, and air speed. This data was gathered on-site, with three random days selected for each nursing home during each season. The data collection window extended from 10 a.m. to 6 p.m., corresponding to peak room occupancy. After a 10-minute equipment stabilisation period, measurements were recorded every 15 seconds for durations ranging from 15 to 60 minutes. In total, 156 unique averaged indoor environmental data points were specifically acquired during the cooling season.

For a more comprehensive definition of the data set obtaining, especially concerning the utilised equipment specifications, refer to Vergés et al. (2023).

Also, control data points must be established and included in the data set. These control data points were selected based on the parameters identified through literature review and include:

- Characterisation of null consumption for a null cooling area: To account for cases where there is no cooling area (e.g., unoccupied, or unutilised spaces), a control case characterising null consumption was introduced ($CED_c = 0$ when $S = 0$ independently to other indoor & outdoor conditions).
- Definition of null HVAC cooling consumption for low outdoor temperatures: In situations where the outdoor temperature could be exceptionally low, a control case was defined to represent null cooling consumption under such conditions ($CED_c = 0$ when $T_{rm} \leq 18^oC$ independently to other indoor & outdoor conditions). This control input guided the neural network to understand that minimal cooling is required or that the HVAC system may not be operational at all under extremely low outdoor temperatures, representing non-cooling periods.
- Maximum energy consumption for extreme running mean temperatures: To account for power limitations or constraints associated with HVAC systems, a control case was introduced to stabilise energy usage when the running mean temperature could be excessively high, causing the system to work at full capacity. This value significantly exceeded the maximum value in the data set ($CED_c \approx 150\% CED_{c,\max}$en $T_{rm} \geq 40^oC$ independently to other conditions), ensuring realistic results while helping the model comprehend the impact of extreme temperature conditions on energy consumption and avoid producing unrealistically large consumption over-predictions.

Hence, a total of 40 supplementary control cases were introduced for the neural network training process, resulting in a total of 196 data points related to indoor characteristics.

The data set was then partitioned into training and testing subsets based on its size. As suggested by Hawkins et al. (2003), a random allocation approach may be employed when the data set comprises approximately 150 or more instances, which was precisely the case of this study. So, a random data partitioning was used to maintain consistency and ensure the representativeness of all data. However, control data points were incorporated into the training sample, enabling the neural network to learn from these specific cases consistently.

Due to the size of the data set, containing 196 data points, partitioning it into different mini batches for training purposes was not feasible in this case. This decision was made in consideration of the requirement for mini batches to maintain representativeness of the entire data set, as recommended by Shallue et al. (2019). So, instead, a batch was preferred, involving the processing of the entire data set at once. Although this approach may be less computationally efficient compared to mini-batch training, as appointed by Radiuk (2018), it ensured that the neural network utilised the available data as comprehensively as possible during the training process. In fact, the study found that the optimal batch size for representativeness is around 200 items, which was approximately the size of the data set in this study.

Given the size of the data set, the most suitable architectural characteristics for the neural network were selected as 1–2 layers.

5. Development of neural network-based energy consumption models for the cooling season

5.1. Iterative process

The iterative process commenced with the evaluation of all potential inputs for the neural network. As a result, a refinement process was undertaken, which required up to nine iterations to achieve a robust and dependable neural network.

An initial learning rate of 10 and a momentum of 0.9 were identified as offering the most favourable performance and stability for the given data set and were consequently adopted as the final values for the whole iterative process. Nonetheless, note that slight variations in hyper-parameters also consistently resulted in stable performance across all iterations.

The process is summarised in Table 2. IBM SPSS Statistics software (version 29.0.0.0) (Ibm, 2023) served as the platform for executing the essential steps involved in developing and fine-tuning the neural network model. Also, note that all activation functions used in the neural

Table 2
Results of neural network training and testing for each iteration.

Iteration	Inputs	Layers	Neurons per layer	R^2 (Training)	R^2 (Testing)	σ_d(Training)	σ_d(Testing)	Drawbacks, dependencies, and comments
1	T_{op}, T_{rm}, RH_{out}, RH, v_a, S, Age, Time, Typ, Climate	2	11	0.99	0.47	1.4	47.7	Severe overfitting. Dependency on large amounts of training data. High variance between training and testing sets. Inconsistent performance.
2	T_{op}, T_{rm}, RH_{out}, RH, v_a, S, Age, Time, Typ, Climate	1	13	0.98	0.56	1.6	32.2	Severe overfitting. Dependency on large amounts of training data. High variance between training and testing sets. Inconsistent performance.
3	T_{op}, T_{rm}, RH_{out}, RH, S, Age, Time, Typ	2	7	0.99	0.64	1.9	18.3	Severe overfitting. High variance between training and testing sets. Inconsistent performance.
4	T_{op}, T_{rm}, RH_{out}, RH, S, Age, Typ	2	7	0.98	0.74	2.3	15.6	High overfitting. Dependency on large amounts of training data. Significant variance between training and testing sets. Inconsistent performance.
5	T_{op}, T_{rm}, RH_{out}, RH, Nur	2	7	0.97	0.94	11.0	8.4	Possible overfitting. Relevant variance between training and testing sets. Generalisation issues.
6	T_{op}, T_{rm}, RH_{out}, RH, Nur	1	8	0.96	0.94	11.1	11.3	No overfitting. Consistent performance. Generalisation issues.
7	T_{op}, T_{rm}, RH_{out}, S, Age, Typ	2	10	0.99	0.97	2.8	6.8	Possible overfitting. Relevant variance between training and testing sets.
8	T_{op}, T_{rm}, RH_{out}, S, Age, Typ	2	6	0.99	0.96	4.5	7.2	Possible overfitting. Relevant variance between training and testing sets.
9	$\boldsymbol{T_{op}}$, $\boldsymbol{T_{rm}}$, $\boldsymbol{RH_{out}}$, $\boldsymbol{S}$, **Age**	**2**	**5**	**0.95**	**0.94**	**9.3**	**8.9**	No overfitting. Consistent performance.

*S: cooling area, T_{op}: operative temperature, T_{rm}: running mean temperature, RH_{out}: outdoor relative humidity, **Age**: construction age, **Typ**: HVAC system typology, **Nur**: nursing home.

network iterations were sigmoid (see Eq. 1). All neurons in the last layer had cooling consumption as the primary output, and no other outputs were considered. Total training time averaged between 30 and 50 seconds for all model iterations. The models were trained on hardware featuring an Intel Core i5–7400 CPU running at 3.0 GHz, 8.0 GB of memory, and Intel® HD Graphics 630.

As observed, in the initial iteration, a comprehensive assessment of all parameter candidates was carried out. Several key observations and findings emerged from this first iteration:

i) The neural network exhibited substantial overfitting, indicated by the considerably higher training R^2 compared to the testing one (0.99 vs. 0.47). Moreover, the standard deviations between subsets were deemed unacceptable.
ii) The neural network was determined to be overly complex, attributed to either the excessive number of parameters or the architectural design.

In the second iteration, the objective was to examine the performance of the neural network under a less complex architecture. This involved the removal of an entire hidden layer and adjusting the remaining one in accordance with the recommended guidelines. While the testing results demonstrated a modest improvement compared to the first iteration (R^2 increased from 0.47 to 0.56), the overall assessment did not meet the criteria, as overfitting persisted. Consequently, it was deduced that the primary issue laid with the size of the input layer, as an excessive number of parameters were being considered relative to the data set size.

To address this issue, during the third and fourth iterations, several parameters were excluded. The climate factor was omitted because its influence was considered to be implicitly captured by the outdoor temperature and relative humidity variables (Bolle, 1985), allowing for the assessment of different climates even without an explicit climate factor.

Moreover, considering that the air speed reflects the operation of the HVAC system (Zaatari et al., 2014), and given that the period of the study is when the cooling system is on, the air velocity was excluded from further consideration. The outcomes indicated that the performance of the neural network was not compromised and, in fact, presented slightly less overfitting than in previous iterations. Another factor that was excluded from consideration was the HVAC operation time. This decision was based on the following reasons: i) The trinary segmentation of HVAC operation time unnecessarily expanded the input layer, and ii) Results obtained without including this parameter demonstrated reduced overfitting without a significant loss in overall predictive capabilities.

However, as the challenge of eliminating overfitting persisted, an alternative approach was implemented. During the fifth iteration, all parameters related to the building characteristics of individual nursing homes were removed, and the nursing home parameter was introduced. This change yielded significant improvements, with both the training and testing subsets demonstrating similar predictions (R^2 of approximately 0.97 and 0.94, respectively). Nevertheless, disparities arose when examining the standard deviations of both subsets (differences of 23.6 % between subsets), indicating that overfitting still existed. Subsequently, a more streamlined neural network was devised in the sixth iteration, and the results indicated the development of a robust neural network without overfitting, characterised by excellent predictive capabilities (R^2 approximately 0.95) without remarkable differences between subsets. However, it became apparent that the neural network was not sufficiently generalisable for application beyond the specific case study. As a result, additional efforts were dedicated to creating a neural network that could be applied to a broader range of nursing homes.

Several studies confirmed that indoor relative humidity depends on outdoor relative humidity conditions (Nguyen et al., 2014). Consistently, the Pearson test results in this study indicated a strong correlation between indoor relative humidity and outdoor relative humidity ($r = 0.765, p < 0.001$). So, in the seventh iteration, the indoor relative humidity parameter was also excluded from consideration. The results demonstrated that the removal of this variable continued to yield exceptional performance (R^2 of approximately 0.98) with less overfitting than previous iterations.

To address the remaining overfitting issue, the last parameter considered for removal was the HVAC system typology. While the preliminary results from previous iterations initially suggested the HVAC typology as a potentially significant factor, it presented challenges due to the limited availability of Variable Refrigerant Volume (VRV) system data within the data set. Attempting to train and test the neural network exclusively for this factor yielded results that were impractical and infeasible, as demonstrated in Table 2. Upon closer examination of the processed data, consumption disparities between VRV and direct expansion systems were especially noticeable in heating (due to the use of electricity and gas, respectively), although these differences were not present in cooling. To enhance the overall reliability of the network by expanding the data set, and based on this consideration, the differentiation between the two typologies was no longer pursued. While these systems are technically distinct, given the data set's limitations and the similarity in HVAC consumption behaviour during the summer, it was deemed preferable to treat the two typologies as indistinct for the purpose of this study.

Ultimately, the iterative process bore fruit in the ninth iteration, yielding a viable neural network ($R^2 \approx 0.95$), with a small standard deviation difference of just 4.3 % between subsets, thus devoid of overfitting.

The final neural network presented the following characteristics:

- Regarding the input variables, five parameters were considered: i) Cooling area (m^2), ii) Operative temperature ($^\circ C$), iii) Running mean temperature ($^\circ C$), iv) Outdoor relative humidity (%), and v) Construction age.
- Within this specific case, the neural network architecture comprised five inputs (excluding biases) and a single output. Additionally, the multi-layer perceptron model consisted of two hidden layers, with each layer containing five neurons. For a visual representation of the final neural network model, see Fig. 3.

Both the hidden layers and the output layer employed the sigmoid function as the primary activation function. Concerning the weights and biases related to each neuron within the model, they are elucidated in Table 3.

5.2. Neural network testing and validation

The developed neural network was subjected to validation strategies to see its degree of reliability and predictability. Error budget analysis is summarised in Table 4.

The model stopping rule that halted the training phase was the minimum relative change in training error ratio (0.001), according to IBM SPSS Statistics results.

The close correspondence in mean error, standard deviation, root mean squared error, mean absolute error, coefficient of determination, and relative error between the training and testing phases reinforced the consistency and reliability of the outcomes of the model. This agreement between the two phases indicated the capacity of the neural network to generalise effectively and make precise predictions beyond the training data (Hawkins et al., 2003; Mutasa et al., 2020).

The regression studies are summarised in Fig. 4.

The combined training and testing subsets yielded a mean coefficient of determination of 0.95, indicating a strong predictive capability of the neural network for HVAC cooling consumption. Moreover, the similarity in outcomes between the testing ($R^2 = 0.94$) and training ($R^2 = 0.95$) phases confirmed the accurate predictions of the model in unseen scenarios without overfitting issues. Along with results presented in Table 4, it was concluded that the neural network was consistent, and had no overfitting. The similar performance across various evaluation metrics further reinforced the reliability and effectiveness of the neural network in estimating HVAC consumption during the cooling period.

The error of the model can also be estimated through a confidence interval analysis. Thus, the residuals are plotted in Fig. 5.

Upon examination, the plot indicated a specific pattern in the residuals, suggesting a distribution that bears semblance to the normal curve. Moreover, the occurrences of extremes were less frequent when compared to the central values, thus leading to the assumption of normality. With this insight in mind, and through Eq. 4, the confidence interval reads as follows:

$$CI = [-2.39, 1.48] kWh$$

The results showed that the neural network predictions tended to slightly overestimate cooling consumption. However, the average of residuals was nearly negligible, −0.46 kWh, and 10.2 kWh in absolute value.

5.3. Comparison with existing models

A useful way to evaluate the reliability of the developed neural network is to compare it with existing models (Adya and Collopy, 1998). A direct comparison can be made with the work outlined by Vergés et al. (2023), because the developed linear models present the same data set as the one used to train and test the neural network. However, it must be noted that, in the aforementioned paper, there were eight different models that each one corresponding to a different nursing home set, which is different from the neural network, that is a single model for all nursing homes. So, for the metrics assessment, the averaged results of all

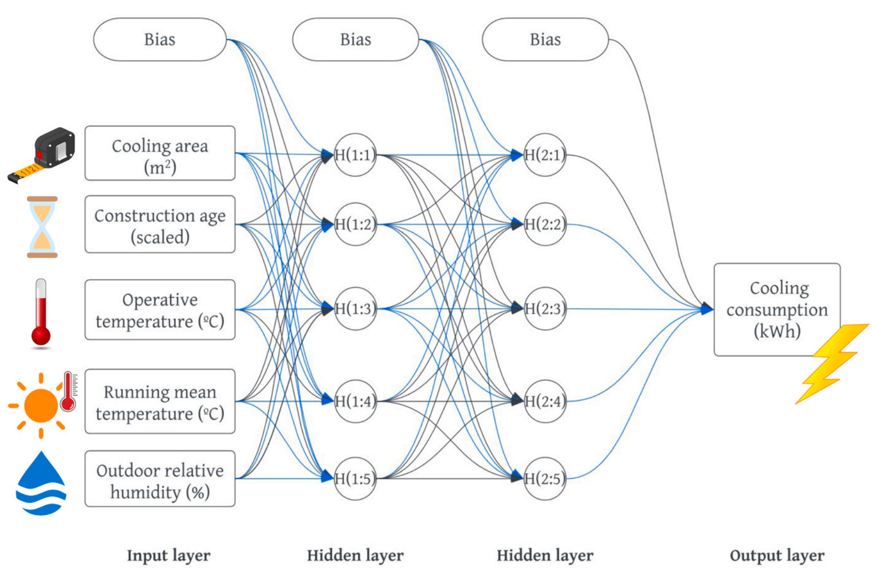

Fig. 3. Final neural network architecture. Black: positive synaptic weights; Blue: negative synaptic weights.

Table 3
Weights and biases associated with each neuron in the developed neural network.

Predictor		Predicted										
		Hidden layer 1					Hidden layer 2					Output layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(2:1)	H(2:2)	H(2:3)	H(2:4)	H(2:5)	*CEDc*
Input layer	**Bias**	−1.342	0.739	0.516	−0.243	−1.406						
	S	−2.522	−0.134	−0.750	−0.304	−0.701						
	Age	0.332	0.034	−0.745	−0.790	1.285						
	T_{op}	−0.497	−0.448	−1.967	0.115	−1.741						
	T_{rm}	0.312	1.693	0.496	−0.804	−2.112						
	RH_{out}	0.087	−0.355	0.407	0.285	−0.506						
Hidden layer 1	**Bias**						−0.013	−0.271	0.249	0.577	−0.508	
	H(1:1)						−0.975	0.683	1.214	1.961	0.812	
	H(1:2)						0.906	−0.717	−0.477	0.144	−0.188	
	H(1:3)						1.159	−0.398	−1.367	−2.120	−0.952	
	H(1:4)						−0.886	0.913	0.933	1.965	0.685	
	H(1:5)						−1.684	0.740	1.027	1.288	1.231	
Hidden layer 2	**Bias**											0.904
	H(2:1)											3.670
	H(2:2)											−1.129
	H(2:3)											−1.910
	H(2:4)											−3.806
	H(2:5)											−1.360

Table 4
Error budget analysis.

Metric	Formula	Training	Testing	Overall
Sample size (n)		156 (79.59 %)	40 (20.41 %)	196 (100 %)
ME (kWh)	$ME = 1/n \sum_{i=1}^{n}(Actual_i - Predicted_i)$	−0.2	−1.6	−0.5
σ_d **(kWh)**	$\sigma_d = \sqrt{1/n \sum_{i=1}^{n}(Residuals_i - \overline{Residuals})^2}$	9.3	8.9	9.2
RMSE (kWh)	$RMSE = \sqrt{1/n \sum_{i=1}^{n}(Actual_i - Predicted_i)^2}$	13.9	13.2	13.7
MAE (kWh)	$MAE = 1/n \sum_{i=1}^{n}\lvert Actual_i - Predicted_i\rvert$	10.3	9.8	10.2
$\mathbf{R^2}$	$R^2 = 1 - \sum_{i=1}^{n}(Actual_i - Predicted_i)^2 / \sum_{i=1}^{n}(Actual_i - \overline{Actual})^2$	0.95	0.94	0.95
RE	$RE = 1/n \sum_{i=1}^{n}\lvert(Actual_i - Predicted_i)/Actual_i\rvert$	0.048	0.061	0.051

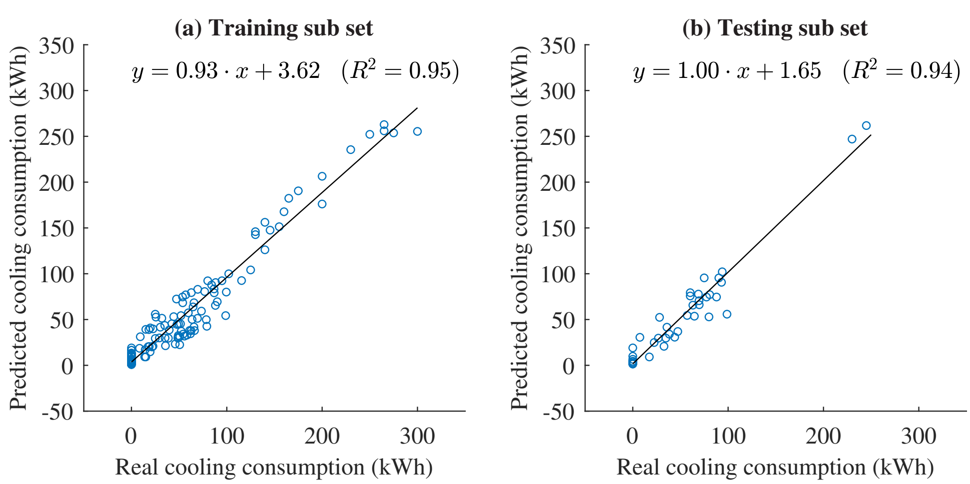

Fig. 4. Regression model for the predicted consumption against the real consumption.

eight linear models combined were used.

The linear models used the same data for both training and testing (since training was not required). In the linear budget error analysis, averaging it by combining all models, the results indicated the following metrics: ME of 22.4 kWh, σ_d of 24.0 kWh, RMSE of 32.8, MAE of 26.6, R^2 of 0.65, and RE of 0.24. Each of these demonstrated significantly poorer performance compared to those obtained from the neural network, as shown in Table 4. Interestingly, the linear models tended more to overestimate cooling consumption, produced less consistent results, and were unable to generalise to unseen nursing homes. Fig. 6 shows the residuals depending on the model used. Note that control points were excluded from the linear set because linear models could not adapt to

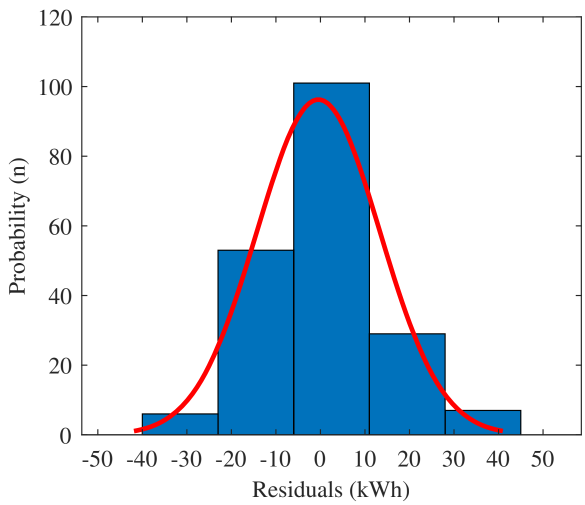

Fig. 5. Residuals of the model encompassing training and testing subsets.

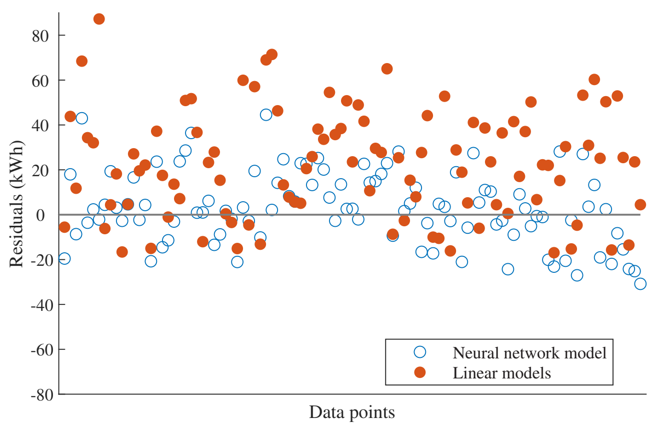

Fig. 6. Residual analysis of cooling consumption predictions depending on the model.

such cases, as they are specific to individual nursing homes.

The neural network demonstrated consistent performance, with residuals mostly falling within the −20–20 kWh range. In contrast, linear models had significant outliers beyond 50 kWh, indicating high variance in their predictions. Based on this analysis, the neural network outperformed the linear models in terms of performance, consistency, adaptability to unseen nursing homes, and capability to analyse the parameters influencing cooling consumption.

6. Analysis and discussion

6.1. Neural network output response subjected to input variations

The variables and factors considered in this study include: i) operative temperature (T_{op}), ii) running mean temperature (T_{rm}), iii) outdoor relative humidity (RH_{out}), iv) cooling area (S), and v) age of construction. They are illustrated in Fig. 7. Note that to understand the response of these inputs, the other parameters should remain constant. The value range was determined based on the average values of these parameters in the data set during the cooling season, which were as follows: T_{op} from 22 °C to 24 °C, T_{rm} from 26 °C to 27 °C, RH_{out} was set at 60 %, and S from 5000 m^2 to 6000 m^2. The two building typologies were also analysed.

To evaluate the influence of the running mean temperature, cooling area, and construction age on the response (energy consumption) of the neural network, Fig. 7(a) illustrates the cooling energy consumption under the influence of the T_{rm}. The analysis revealed a clear positive correlation between the running mean temperature and cooling consumption. This finding is coherent with fundamental HVAC principles, as higher outdoor temperatures require more effort from the system to maintain comfortable indoor conditions (Delfani et al., 2010). Also, as expected, the bigger the cooling area of the nursing home, higher the cooling energy consumption, as illustrated in Figs. 7(a) and 7(c). The study also unveiled a distinct trend when examining the percentage of energy savings for both building types. The consumption curves for the two construction age categories remained consistent as the area increased. This implied that the energy efficiency advantage offered by newer buildings over older ones remained relatively stable regardless of the area size. Consequently, smaller buildings benefitted more significantly from this circumstance, leading to higher savings in terms of percentage. The influence of the cooling area is higher compared to the insulation efficiency of the buildings (represented by the construction age factor) due to the exponential trend observed as T_{rm} increases.

Two different findings were observed in Fig. 7(b). On the one hand, newer nursing homes had HVAC systems that were designed to be more responsive to changes in environmental conditions, including relative humidity. These systems were equipped with advanced sensors and control algorithms that optimise energy efficiency based on real-time data. When outdoor relative humidity increased, these HVAC systems automatically adjusted their operation to maintain desired indoor conditions, leading to increased energy consumption. On the other hand, older nursing homes had HVAC systems with simpler control mechanisms that were not as sensitive to changes in humidity. These systems had relatively constant levels regardless of outdoor relative humidity, leading to a more consistent consumption pattern across different humidity values.

Regarding the neural network response on the operative temperature variation, Fig. 7(d) shows that given fixed outdoor conditions and building area, the consumption decreases with the T_{op} with a higher influence on those nursing homes with lower energy performance. When T_{op} are close to T_{rm}, the influence on the building performance is lower because the thermal loads are also lower.

Throughout all analyses a prominent disparity was present in the cooling consumption levels between nursing homes constructed before the year 2000 and those built afterward. Repeatedly, the data showed that nursing homes constructed before 2000 presented notably higher cooling consumption, while their newer counterparts demonstrate more restrained energy usage. These findings aligned with the prevailing understanding that newer systems boast superior efficiency and are less susceptible to degradation, ultimately leading to a reduced overall consumption footprint (Reyna and Chester, 2017), which was a consistent pattern also seen in previous analysis.

To further investigate these dynamics, multiple variables were simultaneously varied, and the corresponding results were extracted and analysed to study the cross-influence of the parameters. One such investigation focused on the crossed influence of the running mean temperature and operative temperature, as depicted in Fig. 8(a). The impact of outdoor relative humidity in conjunction with the running mean temperature was also examined, which is illustrated in Fig. 8(b).

Results uncovered a relationship between high indoor operative temperatures and low running mean temperatures, resulting in negligible cooling energy consumption. Remarkably, when the running mean temperature was low enough (approximately 20–22°C), the specific value of the operative temperature became inconsequential, as the cooling consumption remained nearly zero. This phenomenon can be readily explained by considering that low running mean temperatures correspond to non-summer periods, thus indicating times when cooling the building is unnecessary. In such situations, the cooling demand diminishes significantly, leading to minimal energy consumption by the HVAC system. The energy residuals can be explained by the fact that even when cooling was not necessary, ventilation might still be turned on, causing some energy consumption to occur.

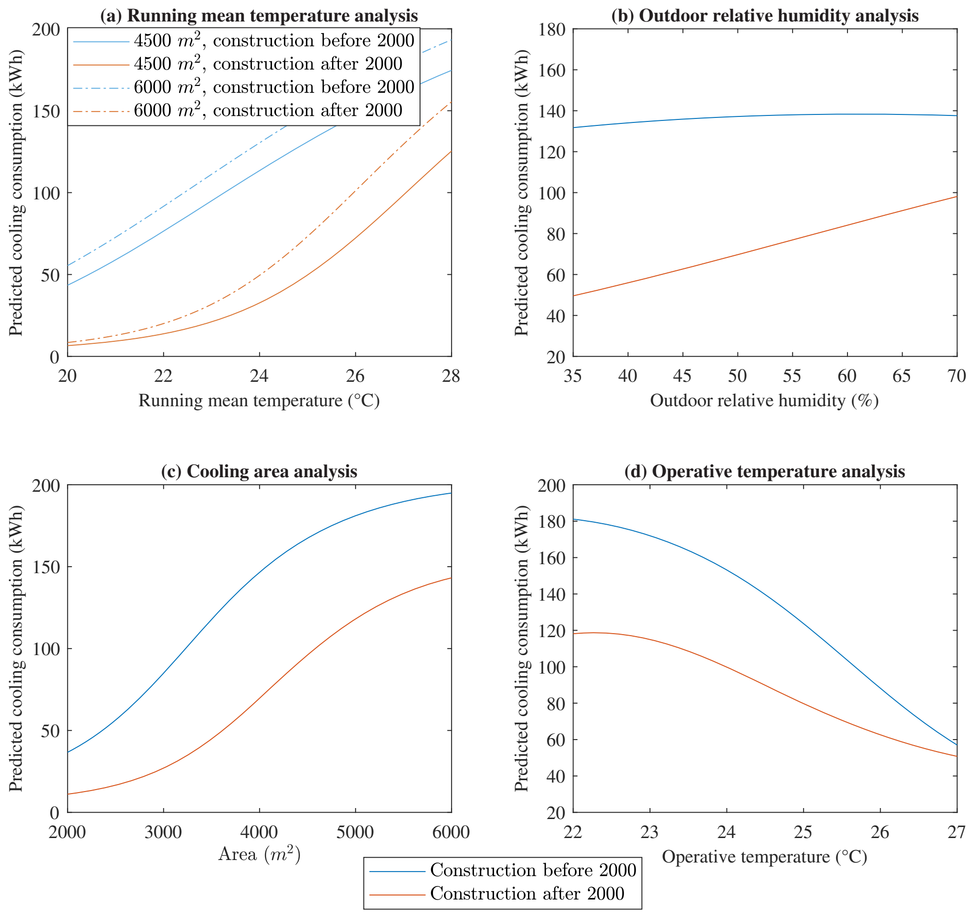

Fig. 7. Predicted cooling consumption input analysis depending on (a) running mean temperature, cooling area, and construction age, (b) operative temperature and construction age, (c) cooling area and construction age, and (d) outdoor relative humidity and construction age.

The analysis identified a pattern where, even at high indoor temperatures, cooling consumption increased as the running mean temperature reached a certain level. The relationship between indoor temperature and cooling usage was influenced by outdoor weather conditions. In general, as indoor temperatures decreased, cooling consumption tended to rise for the same outdoor conditions, highlighting the interplay between indoor and outdoor temperatures in determining cooling energy needs. This underscored the accuracy and consistency of the neural network's output.

Higher relative humidity values were associated with slightly higher overall consumption under the same temperature conditions. Building on the field study of this analysis, this finding was particularly significant in Continental-Mediterranean environments, where summers tend to be drier compared to Mediterranean zones. The heightened cooling consumption in regions with higher outdoor relative humidity could be attributed to its effect on human comfort and cooling system performance. In more humid conditions, the air contains more moisture, requiring additional energy to effectively dehumidify and cool the indoor environment. This extra energy demand contributes to a slight increase in cooling consumption. This conclusion was consistent with previous analyses, as seen in Fig. 7(b).

6.2. Implementation of adaptive thermal comfort models

The next step involved examining the energy consequences of implementing this energy consumption model into the nursing homes in the data set, with a particular focus on thermal comfort.

Thermal comfort is significantly influenced by climate conditions, indoor environment, and the unique characteristics of occupants (Baquero et al., 2023; Baquero and Forcada, 2022; Forcada et al., 2020). Older adults, for instance, perceive and respond to temperature differently than younger adults or children. As such, it was crucial to tailor thermal comfort models to the specific demographic, rather than relying on generic models that may lack precision and relevance.

The adaptive thermal comfort models for the cooling season used in this study were derived from the research conducted by Baquero and Forcada (2022) and Forcada et al. (2020). This choice was made because these models specifically consider the older population segment, which aligned with the type of residents in the nursing homes being studied. Both models determine the optimal comfort temperature based on outdoor conditions, which were identified as the primary driver of thermal comfort ($R^2 \approx 0.9$). In the context of the neural network-based consumption model, the energy implications were evaluated by dynamically adjusting the operative temperature during the cooling season based on the comfort temperature, which, in turn, was influenced by the prevailing climatic conditions. They are summarised in Table 5.

The nursing homes from the data set pertained to two different climates, Mediterranean, and Continental-Mediterranean. Fig. 9 illustrates the comfort temperature derived from the application of the adaptive comfort models throughout the evaluation period for both climates. As anticipated, the comfort temperature increased as the outdoor temperature rose.

Fig. 10 offers a glimpse into the real energy consumption of the nursing homes, juxtaposed with the predicted cooling consumption values generated by the neural network when implementing the adaptive thermal comfort models, along with their respective 95 % confidence intervals. Note that the real cooling consumption monitored data did not consider the thermal comfort of the residents and typically

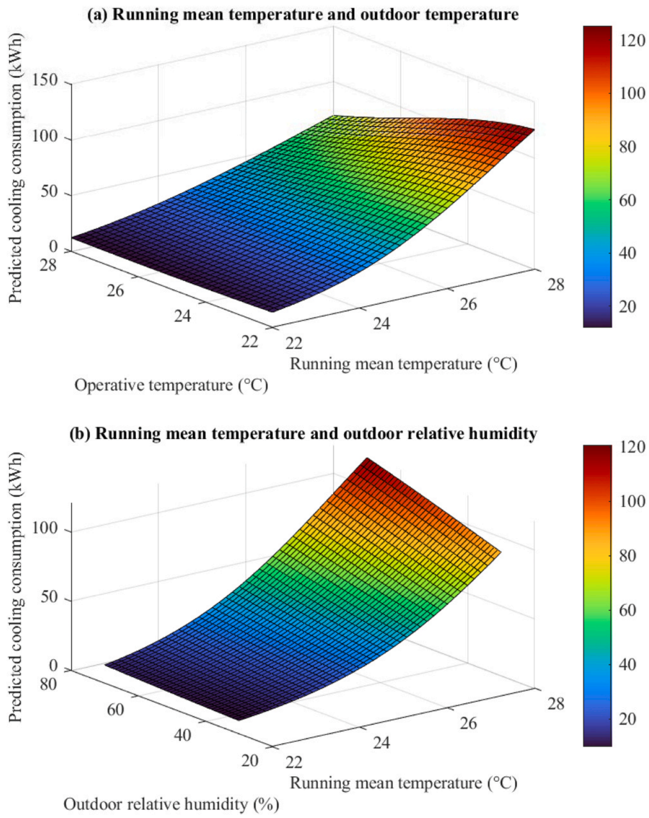

Fig. 8. Predicted cooling consumption crossed analysis, depending on (a) running mean temperature and operative temperature, and (b) running mean temperature and outdoor relative humidity.

Table 5
Adaptive thermal comfort models under study.

Adaptive thermal comfort model	Application	Formula
Baquero and Forcada (2022)	Continental-Mediterranean climates	$T_c = 0.16 \cdot T_{rm} + 20.4$
Forcada et al. (2020)	Mediterranean climates	$T_c = 0.16 \cdot T_{rm} + 20.8$

adhered to a fixed set-point operative temperature throughout the summer. As a result, while the results from the neural network might not precisely replicate real-world data, they were expected to exhibit general trends that aligned with the impact of fluctuating outdoor temperatures.

Upon examination, despite the inherent disparities between the evaluation approaches (fixed set-point temperatures for the monitored nursing homes vs. implementation of adaptive thermal comfort models through a neural network-based consumption model), the broader trends were consistent when comparing real-world data to the predictions of the neural network.

Nevertheless, results indicated that, on average, the neural network predicted slightly lower HVAC system consumption throughout the summer, and this difference became more pronounced as outdoor temperatures soared, especially in July and August. This outcome suggested that nursing homes, in general, may be over-cooling during the summer months. While the current indoor temperature set point fell within the range of 22–24°C, the neural network, particularly through the implementation of adaptive thermal comfort models (refer to Fig. 9), indicated the potential to increase this set point to a range of 24–26°C without compromising thermal comfort. This adjustment of 2–3°C can yield significant energy savings. These outcomes aligned with those of other research endeavours, exemplified by Bienvenido-Huertas et al. (2021), who similarly ascertained that the implementation of adaptive setpoint temperatures represented a viable strategy for ameliorating building energy consumption while concurrently safeguarding occupants' thermal comfort.

When evaluating the cumulative savings (calculated by comparing the real monitored energy consumption values with the predicted energy consumption values generated by the neural network), implementing adaptive models resulted in a remarkable 23.4 % reduction in energy consumption. Given that seniors often have distinct thermal comfort preferences and tend to favour higher operative temperatures than the general population, these savings carried substantial and meaningful implications.

There is no comparable literature that allows for a suitable comparison with the findings of this study. Nevertheless, note that Vergés et al. (2023) used the same data set as this study, enabling a direct comparison to be drawn. This includes not only the modelling techniques employed but also the results obtained in terms of energy savings. The results of this study and their analysis are summarised in Table 6.

The study from Vergés et al. (2023) had several limitations, including models' accuracy, the inability to analyse VRV nursing homes, and the tendency to overestimate cooling consumption. The development of a neural network-based model addressed these issues

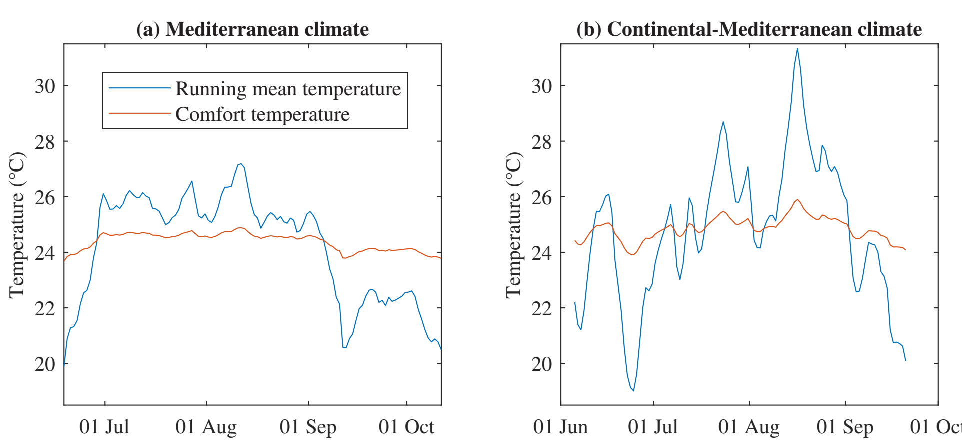

Fig. 9. Comfort temperature variation based on adaptive thermal comfort models.

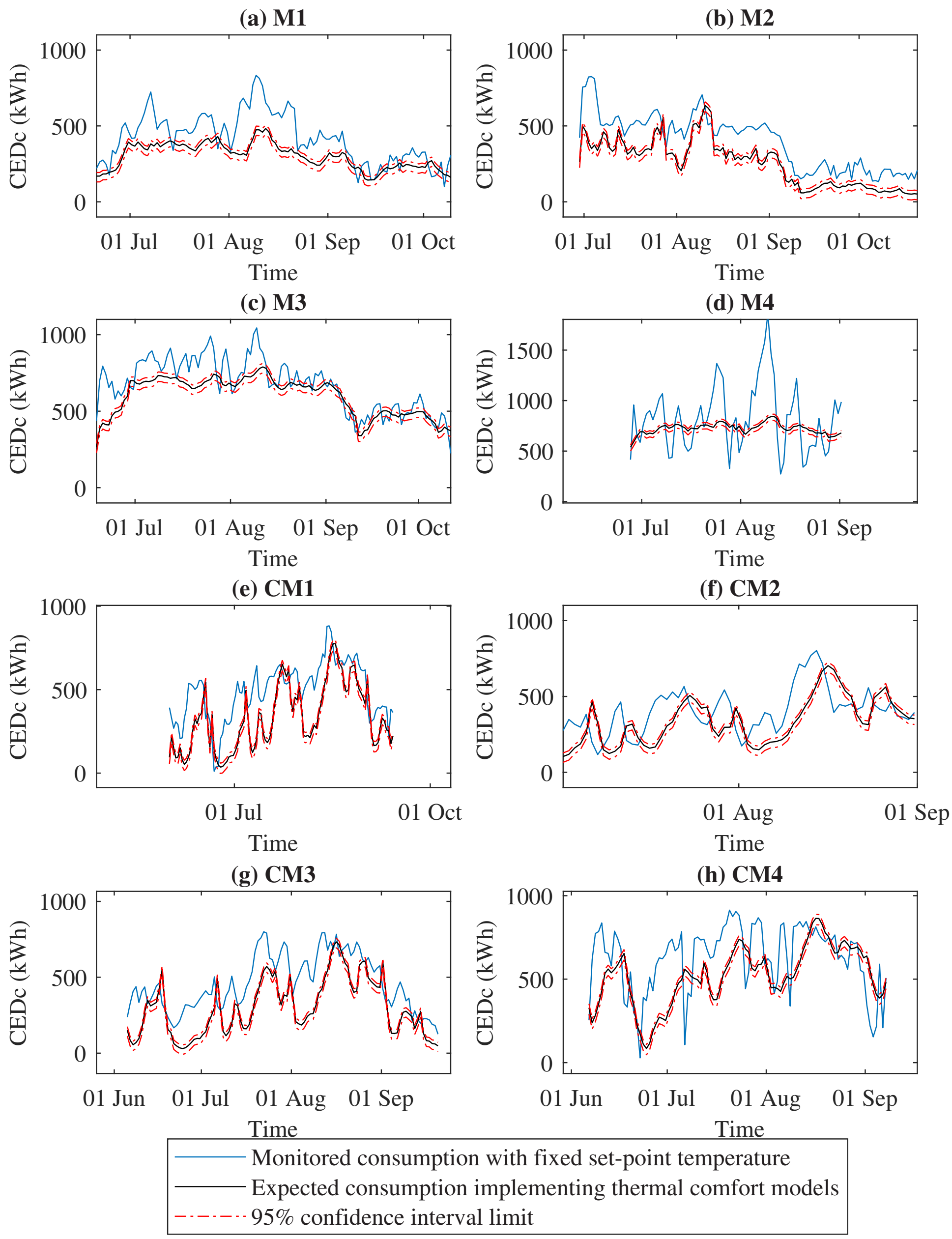

Fig. 10. Comparison of the neural network-based consumption model's response implementing adaptive thermal comfort models with monitored cooling energy consumption.

Table 6
Savings potential when implementing adaptive thermal comfort models using the neural network, and comparison with the linear modelling technique approach.

Consumption model	R^2	Savings (%)							
		M1	M2	M3	M4	CM1	CM2	CM3	CM4
Present study	0.95	28.9	35.6	11.3	12.2	31.7	16.2	34.8	16.7
Vergés et al. (2023)	≈ 0.65	10.2	7.2	6.9	-	16.7	-	8.9	9.4

effectively. Firstly, it significantly improved the accuracy from 0.65 to 0.95. Additionally, the neural network could consider all nursing homes with a single model, achieving a level of generality that the linear models could not have. When analysing the energy savings provided by both models, linear models were more conservative due to their limited predictability, with savings of 9.9 %. In contrast, the neural network yielded substantial savings, up to 21.9 % in Mediterranean nursing homes and 24.9 % in Continental-Mediterranean nursing homes.

7. Conclusions and future research

An artificial neural network to predict HVAC energy consumption in buildings inhabited by elderly people was developed using monitored data from eight nursing homes. This model was then used to assess

HVAC system energy implications during the cooling season implementing validated adaptive thermal comfort models.

7.1. Conclusions

The most relevant conclusions extracted from the study are elucidated below:

- The developed neural network-based consumption model demonstrated precise predictions of cooling consumption, without overfitting, using relatively straightforward parameters, including i) Cooling area, ii) Operative temperature, iii) Running mean temperature, iv) Outdoor relative humidity, and v) Construction age. This indicated the capacity of the developed neural network to characterise cooling consumption without the need for complex input parameters and relying on data from nearby meteorological stations, integrated indoor sensors, and building drawings.
- The neural network's capacity to provide accurate cooling consumption predictions under diverse conditions underscored its superiority over previously used linear modelling techniques, as indicated by a substantially enhanced coefficient of determination ($R^2 = 0.95$ compared to $R^2 \approx 0.65$). Furthermore, the versatility of the neural network allowed for a single, all-encompassing model for multiple buildings, in contrast to earlier models that were specific to individual nursing homes. Therefore, this model can be applied to unseen cases and has the potential for systematic implementation. In addition, should more data be available, the model could be further refined, potentially achieving even greater accuracy.
- Nursing homes constructed before 2000 had higher cooling consumption compared to newer buildings, suggesting the need for improved insulation and updated cooling systems in older structures. Newer nursing homes consistently demonstrated lower cooling consumption than older buildings, proving the benefits of advancements in construction practices and energy-efficient technologies. Smaller nursing homes benefited the most from these improvements.
- Operative temperature inversely influenced cooling consumption, with higher indoor temperatures leading to reduced energy usage.
- The cooling consumption in nursing homes was influenced by outdoor relative humidity, where higher humidity levels led to a slight increase in energy consumption due to the necessity for dehumidification. The presence of dehumidifiers in newer buildings could explain the consistent consumption levels observed in older nursing homes, as outdated systems may lack sufficient humidity control capabilities. Hence, drier climates generally offer more potential for energy savings compared to humid ones.
- The adoption of thermal comfort models designed for older populations revealed that nursing homes were typically over-cooling by about 2–3℃ during the summer. Adjusting the operative temperature to a more comfortable range for the residents led to energy savings of 23.4 %. These results highlight that the linear approaches tended to be conservative, with initial evaluations showing savings of only 9.9 %.

7.2. Limitations and future research

Further research is needed to explore the impacts of variables and factors associated with climate variability. The data set used in this study encompasses only Mediterranean and Continental-Mediterranean climates, thereby accounting for the climates with validated results. While the parameters studied are potentially relevant in other environments, such as alpine or desert regions, results with training data specific to those climatic conditions should be necessary for validation purposes. Therefore, future investigations should encompass a broader range of climatic scenarios to ensure the robustness and applicability of the findings across diverse environmental contexts, currently unseen by the neural network.

Another research direction involves extending the current model by introducing additional parameters to the neural network, aimed at further improving prediction accuracy. Furthermore, investigating the impact of other potentially significant variables such as rainfall precipitation, solar irradiance, or building geometry could provide additional insights currently not studied. Should these parameters be implemented, the inclusion of supplementary data points in the dataset is encouraged to avoid overfitting. As a response to the expanded dataset, a feasible research direction is to explore the applicability of alternative ways of predicting HVAC consumption, such as quantum computing, as a means to optimise computational efficiency.

CRediT authorship contribution statement

Roger Vergés: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kàtia Gaspar:** Writing – review & editing, Validation, Supervision, Methodology, Investigation. **Núria Forcada:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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