Chapter

Sustainable Energy Management of Institutional Buildings through Load Prediction Models: Review and Case Study

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Abstract

Institutional buildings need smart techniques to predict the energy consumption in a smart grids' framework. Here, the importance of dynamic load forecasting as a tool to support the decision in smart grids is addressed. In addition, it is reviewed the energy consumption patterns of institutional buildings and the state-of-the-art of load forecast modeling using artificial neural networks. The discussion is supported by historical data from energy consumption in a university building. These data are used to develop a reliable model for the prediction of the electric load in a campus. A neural network model was developed, which can forecast the load with an average error of 6.5%, and this model can also be used as a decision tool to assess the convenience of supplying this load with a set of renewable energy sources. Statistical data that measure the availability of the local renewable sources can be compared with a load model in order to assess how well these energy sources match the energy needs of buildings. This novel application of load models was applied to the campus where a good correlation (Pearson coefficient of 0.803) was found between energy demand and the availability of the solar resource in the campus.

Keywords: sustainable energy management, renewable energy, load prediction, artificial intelligence, smart systems, smart grid

1. Introduction

Institutional buildings present similar patterns in their occupancy level and therefore in their energy consumption. Examples of this type of buildings are museums, hospitals, libraries, schools (secondary and University), non-profit foundations, governmental administrative offices, and prisons. Sometimes, as in the case of administrative and hospital complexes or University campuses, a set of buildings are grouped within a vast area reaching the energy consumption level of a small city. They all offer opportunities for energy improvement [1] which reflect in the saving of public money. Moreover, due to their similar characteristics, these buildings can share a similar energy-efficiency approach [2, 3].

There is a growing interest in technologies to perform effective management of these buildings, leading them to the transition into energy efficient smart buildings.

Among the research trends, two are assessed in this paper. The first one refers to smart techniques to predict the energy consumption in a smart grids' framework. In particular, it will be discussed the importance of dynamic load forecasting as a decision support system for a smart grid. The smart grid concept can be defined as an electrical grid that utilizes advanced control and telecommunication in order to optimize the energy generation, distribution, and consumption. This concept will be discussed and applied to the small electric network of a University Campus. After a review of load forecast models using artificial neural networks, a case-study using real data from a University building is presented. The main objectives of this work are:

- Offer an insight about the importance of load forecasting in smart grids;
- Apply the smart grid concept to a complex of institutional buildings;
- Review the state-of-the-art of load forecast modeling using artificial neural networks;
- To detail and develop an accurate model for the prediction of the load demand in a University campus.

In addition, a second research trend will be assessed in this paper. Future institutional buildings and smart campuses will also have an increasing level of self-supply through renewable energy sources. Therefore, it is presented a new approach that, to our knowledge, has not been done previously: To use the load forecast model for studying the correlation between the energy demand and the availability of renewable energy sources in the campus (solar and wind power).

We hope readers will appreciate this novelty. Overall, this work aims to contribute to the interesting topic that is the development of smart grids in institutional buildings.

2. The smart grid concept and the importance of load forecasting

The graphical representation of the demand of energy in a power system is called a load curve or load profile. Therefore, a load curve is a graph that illustrates the variation in demand/electrical load over a specific time, typically cycles of 24 h (daily load curve), 7 days, and 12 months (yearly load curve).

Load curves are determined based on the historical records of energy consumption of the system. Available data can be obtained from direct metering or other means: transformers' readings, utility meter load profilers and smart-grid automatic meters, or even customer billing [4]. Other influential parameters can be added to these energy consumption data in order to develop an energy demand model capable of forecasting the variation of the electric load. These models consider the weight of each type of consumer (residential, commercial, and industrial) in the system, their behavior and variables such as temperature variation or seasonal holydays.

Reliable and dynamic energy demand models are crucial elements of any smart grid [5–7]. They allow a better management of an electric system, so power supply can match demand in a more efficient way. The energy demand of a region is constituted by the sum of the effect of residential, commercial, and industrial loads and can vary greatly within a short period of time (hours). Power generation must fit this demand in an effective way or otherwise imports/exports of energy should be needed, if available. Nuclear or coal thermal plants lack the flexibility of varying their output and thus constitute the baseline of power generation. Based on load forecasts, the power output of the most flexible generation units (such as gas thermal plants) can be scheduled according to daily and seasonal cycles. Typically, gas power plants work at their maximum to supply daily peaks of load and have their output reduced during low demand hours. Hydroelectric power plants have also some capacity of power regulation and, in the case of pumped-storage hydroelectricity, can absorb the excess of power generated during night time and return it during peak times. Renewable energy, in particular wind power, arises as a destabilizing source of the system due to its intermittent and unpredictable characteristics. Its effective integration in the electric system is one of the main technical challenges for smart grids. Also, in demand-side management (demand response), daily load curves are used to set up electric tariffs in order to influence demand. Better prices of energy during low-demand hours encourage some consumers to move their activity to those hours and thus reduce the intensity of load peaks.

When talking about a much smaller system, such as a University campus or a small village, the situation is quite different, but knowing the local load profile can also lead to optimum operation as well as important energy savings.

In such a small system, the generation capacity would be represented by local distributed generation systems, such as roof-top solar systems or small wind turbines. Biomass boilers could also make use of neighboring agricultural residues, woods, or pruning waste. The latter resource should not be neglected as several institutional buildings such as University campuses, administrative and hospital complexes or prisons count with vast green areas in their surroundings. Diesel-fueled generators are present in many on-grid electric systems. In the case of commercial buildings, depending on the energy tariffs, it could be economic to switch off the building from the grid during peak hours and supply its own power demand burning diesel or other fuel. In the case of some institutional buildings such as hospitals and prisons, or some administrative buildings with data-centers, emergency generators are generally mandatory. Besides the use of diesel generators to supply power during peak times, some big commercial buildings resort to co-generation. In those buildings where HVAC systems are responsible for most of the power demand, it may be profitable the use of gas engines for the combined generation of electric power and heat. The latter can be transformed into refrigeration through thermal-chemical or other absorption system.

In addition, diesel generators can be coupled with energy systems that make use of local renewable resources conforming hybrid systems (mixture of PV solar, wind turbines, and biomass). Hybrid systems are a convenient option to gain reliability and diminish the intermittency problem of renewable sources, especially when coupled with batteries and are widely used in small isolated off-grid systems [8]. For small-scale systems, batteries are practically the only available form of energy storage. They can be big battery packs made from sodium-sulfur, vanadium-redox flow batteries, or other materials, grouped in "battery farms," or the smaller lithium-ion batteries from electric cars plugged to the system. Gónzalez et al. assessed the infrastructure needed for enabling the transition to a smart grid in a University campus, and in particular peak shaving of load with battery storage, concluding that for such case it is only economically feasible with limited battery sizes, and only when there are renewable energy sources available on-site [9]. Besides batteries for electricity storage, a building complex could also have thermal storage for its HVAC needs. In such case, thermal storage would influence the load profile and should be included in the load forecasting models [10]. Whatever the case, energy storage is one of the main components to be considered in a smart grid, as shown in **Figure 1**.

As can be observed in the previous figure, distributed or embedded generation (either from intermittent renewable sources or from diesel/gas generators)

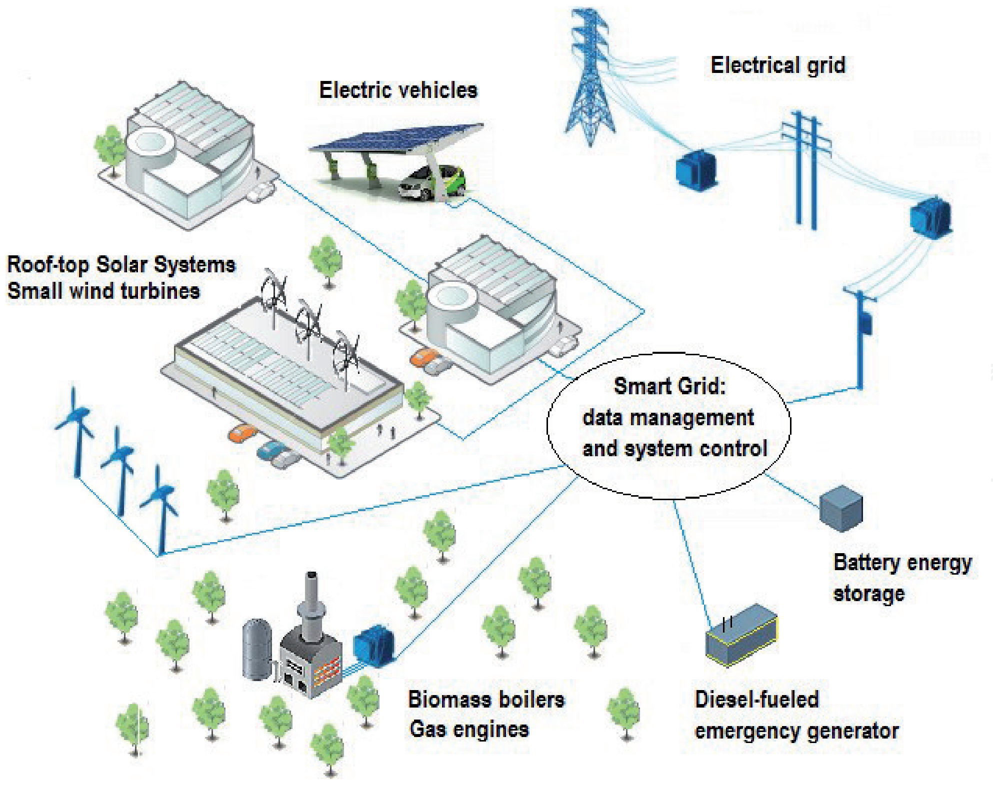

Figure 1.
Concept of a smart energy grid for a set of institutional buildings.

plays an important role in the design and operation of smart grids. The generation capacity could temporarily excess the local demand and then it would be necessary to either sell the excess power to the main grid or shut down the system if this option is not feasible (if local wind turbines are the ones to be turned off then it is called wind curtailment). When talking about the smart grid concept, a third option must be considered: to store that temporary surplus of energy. This can be done through the use of battery banks, as above-mentioned, or by increasing the energy consumption of a few selected utilities. Some examples: the HVAC system (cooling chillers, electric heaters, and heat pumps) could ramp its refrigeration/heat production and store the excess in a tank insulation system. Similarly, the local water/wastewater system could increase the consumption of pumps (switching them on or increasing their rotation through variable-frequency drives) to absorb a part of the excess of energy. The concept is similar to that of a load balancer in smart telecommunication grids, which distributes workloads across multiple computing resources [11, 12]. Another option usually considered in smart grids is the use of electric vehicles. In the case of institutional buildings with charging/discharging infrastructure for electric vehicles, those are more prone to act as a load to supply than as a source that can return the stored energy if needed. The reason is that in this type of buildings, the majority of the vehicles remain parked within the facilities only during workday while the charging time for electric vehicles currently requires periods of some hours. Therefore, the use of the vehicle's batteries by the local grid could leave them inoperative during some hours that could be coincident with the time that those vehicles are required.

There must be a system controller (an automated controller supervised by humans) that decides what to do, in each moment, to overcome a temporary surplus or deficit of energy forecasted for a close period of time. This controller has to deal with a number of input variables such as the state of the batteries (available storage capacity) or the number of electric vehicles plugged, as well as with short-term forecasts: predictions of weather (including solar and wind power), water and HVAC demand, and of course the forecasted electric load [13]. Therefore, the operation of a smart grid consists of an iterative process that considers the dynamic modeling of the load using a series of variables, with the aim of anticipating a situation through short-term predictions. Then, it uses this load forecast for the control process of the smart grid system and obtains feed-back through smart meters in the buildings facilities. Finally, it recalculates the load model and elaborates a new load prediction starting the control process again. **Figure 2** shows a diagram that schematizes the control process of a smart grid.

As shown in **Figure 2**, the advanced dynamic load model uses a historical database that is constantly refreshed with real-time measurements of energy demands [6]. Smart energy meters, deployed over the set of buildings and facilities, are thus a central part of the system. Those smart meters and sensors must transmit data to the control system through radio frequencies, Ethernet, Bluetooth, Wi-Fi, 6LoWPAN, Z-Wave or other technologies [14]. ZigBee wireless technology is the option chosen for the smart grid in the Illinois Institute of Technology main campus, which aims to reduce 20% of energy and 10% of gas consumption each year during a 5 years' period of time [15]. Other examples of smart grid design and concept applied in University campuses can be found in [9, 16].

Besides the smart grid concept, the use of data-driven analytical insights is widely used for a better energy management in buildings and in the power systems that supply them. Overall, the forecasting of energy demand in a building can lead to the following benefits:

1. To choose the most suitable tariff (contract power purchases);

2. Utilities and power system operators can respond quickly and confidently to forecasts and can improve performance for planning horizons that range from very short-term to very long-term. Forecasting peaks of energy demand is crucial to avoid black-outs, outages, and system failures;

3. Provides solid background to optimize the calculation of the power system components of the building. The most useful information is the maximum

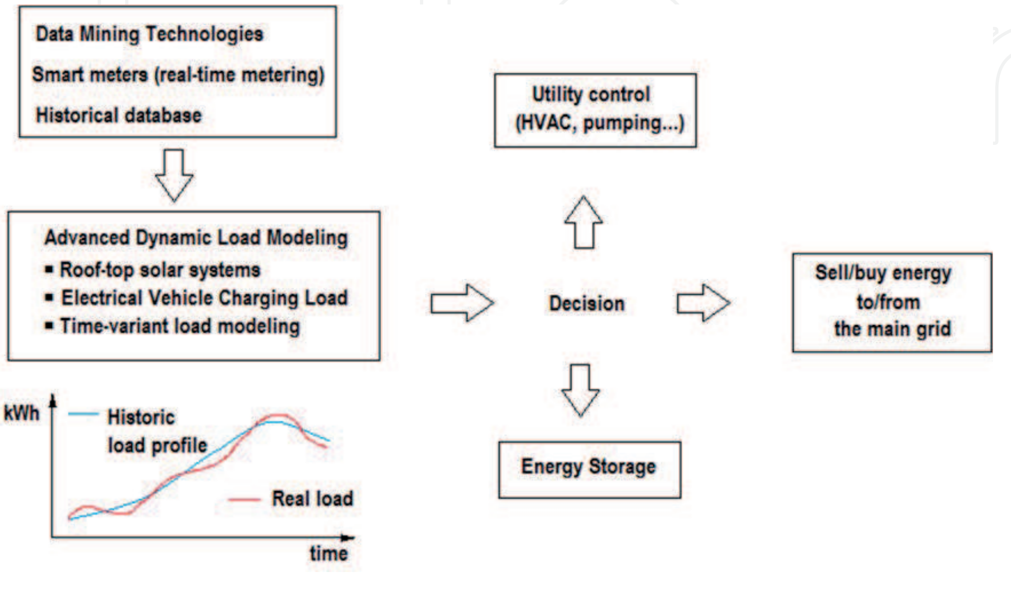

Figure 2.
Use of the dynamic load modeling for the control of a smart grid.

daily peak. Knowing the maximum expected current under normal conditions is crucial to calculate the transformers capacity and the size of conductors, as well as the power system protections. The hourly forecast of load is used in the calculation of either thermal or energy storage capacity;

4. Allows to define normal values of daily consumption and to compare different buildings of the same type that should present similar load profile. This is of particular interest for energy conservation programs in public, institutional buildings;

5. As highlighted by Dong et al. [17], the prediction of building energy consumption is increasingly important for building energy baseline model development and for performance Measurement and Verification Protocol (MVP). Having a computational model that models the energy consumption of a building along time is useful to verify savings after implementing energy conservation measures. Through calibrated simulation, any energy demand model can be tested and refined until it matches the actual energy performance measured in the facility with a high accuracy. Such a model may be valid for similar buildings of the same type and reliable in determining the savings of an energy efficiency project or calculating the energy consumption during the building life-time;

6. Energy consumption prediction for Building Energy Management systems (BEMS) allows building owners to optimize energy usage. In a similar way as the one described for smart grids, a smart building can vary its operation issues to respond to the demand signals from its sensors. Some authors agree that BEMS can be considered as one of the key factors in the success of energy saving measures in modern building operation [18].

3. State-of-the-art of load forecasting in buildings

Several computational models are used to forecast the demand of energy of different electric systems, ranging from small buildings and households [19] to big markets composed of several interconnected regions [20]. Multiple regression models are used, in which combinations of variables are tested sequentially for model improvement. Examples of these models are genetic algorithms [21], particle swarm optimization [22, 23], ant colony optimization [24], Fourier series [25], Support Vector Regression (SVR) [26–30], Support Vector Machine (SVM) [31], Autoregressive Integrated Moving Average (ARIMA) [20, 27, 28, 32–35], multiple linear regression [20, 26, 36, 37], Fuzzy logic [20, 38, 39], case-based reasoning [40], decision trees [41], and other data-driven forecasting algorithms [42–49], with special highlights to artificial neural networks [50]. For short-term load forecasting (daily demand profiles), exponential smoothing [51], least-square regression [52], and other methods may be more suitable while for a very short-term prediction, such as the prediction period of 1 hour, some authors have proposed a simple adaptive time-series model that considers the measurement history together with weather data [53]. Some complete reviews of buildings energy prediction techniques may be viewed at [54, 55].

This manuscript has the focus on load demand forecasting using artificial neural networks (ANN). Many readers are already familiar with these machine learning models that mimic a human neural system.

Among the Artificial Intelligence techniques, the ANN can be highlighted by its ability to track relationships between data groups. Their capacity to extract important information from data makes the ANNs an important tool in several fields. The overall structure of a ANN is composed by an input layer (where the data are presented to the model), hidden layers (where the extracted information is stored), and output layer where the response is given, as shown in **Figure 3**.

ANN can be used for forecasting water [56], gas [57–59], steam [60], and electricity demand in a set of buildings. They have also been proposed as a tool for evaluating energy performance of buildings and grant the correspondent energy performance certificates [61]. ANNs can model parameters that greatly influence the energy consumption of buildings such as HVAC performance [62, 63] or solar radiation [64, 65] and can also be used to accurately control and predict the performance of wind and solar energy systems [66–69].

Generally, the number of input variables would determine the complexity of the model. The three shown in **Figure 3** are the most common among the models found in the available literature. The "calendar" group of variables considers working days, holydays, and working hours. This type of variables has a great impact on office, administrative or University buildings as it determines the occupation level of the building, which is linked to its energy demand. The number of light hours per day, which affect the lighting needs of the building, can be modeled for each day of the year and therefore can be considered as a "calendar" variable. Sometimes there may be strikes or unexpected events, but their effect in the load prediction can be minimized with the use of the second group of variables: the load from the previous hours. The "weather conditions" type of variables directly influences the consumption of the HVAC systems. Some authors propose to develop an indicator of whether a building is likely to be weather sensitive (which measures the degree to which building loads are driven directly by local weather), for instance by using a Spearman Rank Order Correlation function [70]. Examples of this type of variables are dry bulb outdoor/indoor temperature and humidity. Ideally, these variables are measured in real time by wireless sensors and their variation trend is taken as an input for the model. If real-time

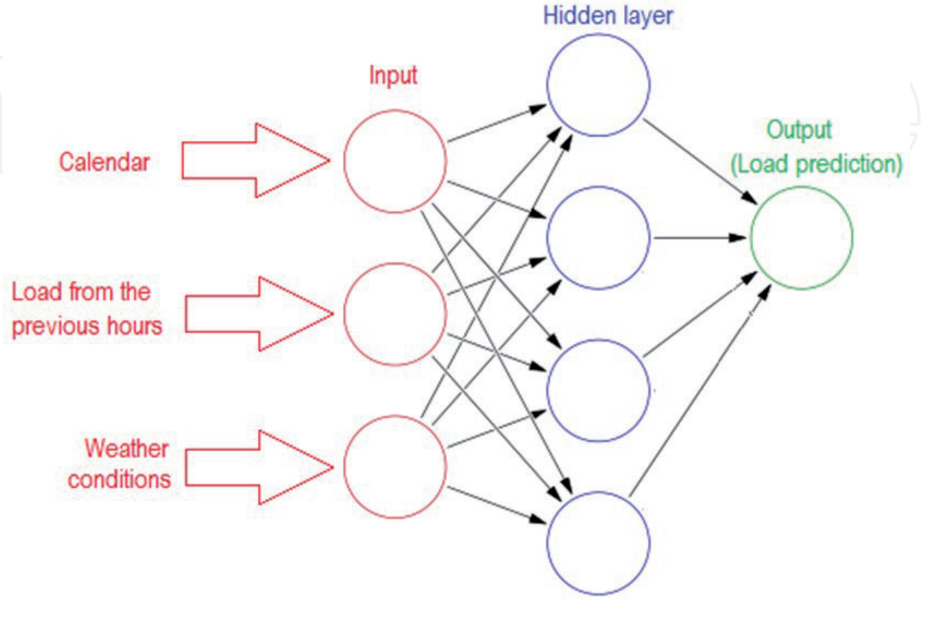

Figure 3.
Example of the architecture of an ANN that forecasts load in a building using three inputs.

measurement is not available, the input can be approximated with annual profiles from local historical data. Let us remember that, in addition to energy demand, "weather conditions" would have a great impact in solar and wind power production (the first one more predictable than the latter) so the monitoring of variables such as solar irradiation or wind speed/intensity would also be valuable for the forecast of the renewable energy generation of the building that aims to supply a part of the load.

The end-use approach aims to forecast separately the load demand of each of the main sub-systems that conform the building. In that approach, there is an ANN model for the HVAC system, another one for the water pumps, another one for the lighting needs, and so on. The final forecasted load will be the sum of the outputs of the set of models.

Other models may consider as inputs the state of the batteries or thermal tanks (available energy storage capacity) or the number of electric vehicles plugged.

The inputs presented to an ANN are weighted by parameters known as "weights." Moreover, each neuron will have a bias, which is another structure parameter. The product between the weights and inputs plus the bias will form the input argument of the so-called activation function. The output of the activation function will be the input of the subsequent layer and the final output of the model. In order to estimate the structure parameters, a train group is necessary, which will contain known inputs and outputs that is wanted to be tracked. Thus, the ANN prediction is compared to the known output for a given input. This "comparison" constitutes the objective function of the model training. Mean absolute percentage deviation (MAPE) and the coefficient of variation (CV) are usually used to evaluate the model performance during the training. In the present case, this error is function of consumption and the ANN prediction, given by:

$$MAPE = \frac{1}{n} \bullet \sum_{t=1}^{n} \left| \frac{C_t - F_t}{C_t} \right| \bullet 100\,(\%) \tag{1}$$

where C_t is the actual value (the measured consumption in the instant t) and F_t is the forecast value for that instant. The difference between C_t and F_t is divided by the actual value C_t again and the absolute value of the resulting division is summed for every forecasted point and divided by the number of fitted points n.

Meanwhile, the coefficient of variation (CV), also known as relative standard deviation (RSD), is a standardized measure of dispersion of a probability (frequency) distribution. As in the case of MAPE, it is often expressed as a percentage. It is defined as the ratio of the standard deviation to the mean or to the absolute value of the mean (Eq. (3)):

$$CV = \frac{\sigma}{\mu} \bullet 100\,(\%) \tag{2}$$

where σ is the standard deviation and μ is the mean.

A comprehensive review of applications of ANNs in the predictions of building's energy demand can be found in [71]. Following, in **Table 1**, a selected literature review is offered with the aim to offer a wide insight of the strategies and architectures used for load prediction using ANNs.

Type of system	Type of ANN (artificial neural network)	Accuracy (MAPE)	Accuracy (CV)	Year	Ref.
Main electric network	Cascaded neural network (CANN); short-term load forecasting	2.7%	—	1997	[72]
Main electric network	The annual growth rate is extracted from the data used for the ANN model	2.0%	—	2007	[73]
Main electric network	Nonlinear autoregressive with exogenous (NARX)	1.67%	3.60%	2015	[74]
Main electric network	Inputs: temperature and weather. Generalized regression neural network with decreasing step fruit fly optimization algorithm	0.024% (RMSE)	—	2017	[75]
Main electric network	Boosted neural network	1.42%	—	2017	[76]
Main electric network	Nonlinear autoregressive with exogenous (NARX)	1.0%	—	2017	[77]
Low-voltage smart electricity microgrid	Feed forward neural networks	4.0%	—	2016	[78]
Households (residential)	Elman ANN trained with the "back-propagation with momentum" algorithm. Multi-layer perception (MLP) with two inputs: weather data and electricity demand; short-term load forecasting	3.1%	0.36%	2008	[79]
Households (residential)	Feed-forward ANN and the Levenberg-Marquardt algorithm	10.0–23.5%	1.06%	2014	[80]
Households (residential) powered with wind and solar sources	Empirical mode decomposition, cascade-forward neural network (for solar and wind forecast) and a fuzzy logic-based controller (for load demand)	0.47% (wind) 19.2% (solar)	—	2014	[81]
Residential and commercial buildings with different wall types and insulation thickness	Backpropagation neural network	1.5%	3.43%	2009	[82]
Residential and commercial	Gated ensemble method (ordinary least squares and k-nearest neighbors)	55.8% (residential) and 7.5% (commercial)	—	2015	[83]
Residential and commercial	Nonlinear autoregressive with exogenous (NARX)	11.7%	55.89%	2017	[84]
Commercial building	Adaptive ANN models: accumulative training (AT) and sliding window training (SW)	13.3% (AT) and 12.9% (SW)	2.53% (AT) and 0.26% (SW)	2005	[6]
Commercial building	Adaptive ANN: accumulative training and sliding window training	—	2.50% and 0.36%	2005	[6]

Type of system	Type of ANN (artificial neural network)	Accuracy (MAPE)	Accuracy (CV)	Year	Ref.
Commercial building	Feed forward neural networks with hypothesis testing, information criteria and cross validation; 24 h forecast	1.5%	2.39%	2006	[85]
Commercial building	ANN model with Bayesian regularization algorithm; short-term load forecasting	5.0%	10.00%	2015	[86]
Commercial building	Three-layered perceptron with the logistic activation function and BFGS algorithm	1.3% (cooling energy consumption) and 2.4% (heating)	—	2017	[87]
Generic commercial building: ASHRAE contest	Input: relationship between load/temperature. Feedback ANN trained by hybrid algorithm	0.0033%	1.40%	2005	[88]
Commercial and industrial buildings	Seasonal ANN. Multi-layer perception (MLP) with two inputs: weather data and electricity demand	2.0–9.0%	—	2014	[89]
University campus	Input: temperature. ANN prediction method based on building end-uses	6.5%	—	2011	[90]
University campus (Library building)	Feed forward neural network with a single hidden layer of tansig neurons	—	0.03–0.10%	2011	[40]
University campus	Input: time temperature curve (TTC) forecast model. ANN prediction method based on building end-uses	6.3%	—	2013	[91]
University campus	Feed-forward with “Bayesian regularization” training algorithm	2.06%	—	2016	[92]
Institutional solar-powered building	17 inputs: weather data (indoor/outdoor sensors) and electricity demand; short-term load forecasting	11.5%	1.00–1.50%	2014	[93]
Institutional building	Feed forward neural network; short-term load forecasting	7.3–8.5%	—	2015	[41]
University campus	Feed-forward ANN trained with the Levenberg-Marquardt (LM) back-propagation algorithms	—	—	2018	[94]
Shopping mall	Optimized backpropagation and Levenberg-Marquardt back-propagation	4.267%	—	2018	[95]
Building energy consumption	Conditional restricted Boltzmann machine (CRBM) and factored conditional restricted Boltzmann machine (FCRBM)	—	—	2016	[96]

Table 1.
Literature review of load prediction using ANNs.

4. Energy profile and characteristics of the studied campus

This section presents an analysis of the characteristics that influence the load profile of the studied institutional building. The behavior of this building can be taken as representative for the set of buildings that compose the whole University campus in which it is inserted. Not surprisingly, all the buildings present the same occupation profile concentrated during working hours and workdays. In addition, almost all the buildings are of the same age and materials. The campus is located in the coast of Northeast Brazil, within a humid tropical region at 12° 58′ 16″ Latitude. In these conditions, the thermal comfort zone can be achieved through natural ventilation and several buildings were designed in that way, but as the University expanded the buildings ended up closing their indoor spaces in detriment of natural ventilation. Nowadays they are characterized by bad thermal insulation and by the massive use of small-size air-conditioning units instead of more efficient centralized units composed by chillers and cooling towers. This peculiarity, common in the majority of the Brazilian campuses and institutional buildings, is reflected in high energy consumption for cooling needs as well as a high dependence of the load curve with temperature. In other words, the building's load presents high weather sensitivity. Typically, the maximum load demand of the year occurs during the central hours of hot summer days.

The region is characterized by abundant renewable energy resources [97] but with water and energy supply problems [98]. Energy and water conservation are of crucial importance for both the region and the University institution. A great part of the budget of the campus is dedicated to water and energy. In this context, campus managers and researchers are considering options such as rainwater harvesting [99], water and energy conservation programs [100], and the transition into a smart grid [101, 102].

This campus has 15 university units within an area of almost 50 ha, providing services for approximately 15,000 students. Among these units, the Polytechnic School is composed of a main building and ancillary laboratories. Daily, almost 6,000 students as well as the correspondent University staff work and study at this particular facility.

The Polytechnic School presents mixed occupancies, which means that it may have multiple occupancies mainly educational, administrative, laboratory, and storage uses, as well as areas intended for food and drink consumption. The average energy consumption on a high-occupancy day is 462 kWh. The main end uses for energy are air conditioning (46.1%), lighting (30.9%), and electronic equipment (18.2%) as shown in **Figure 4**.

The rest of uses speak for almost 5% of the energy consumption of the building. Elevator and escalators typically represent from 3–8% of the energy used in most buildings [101]. However, during the period studied (years 2013 and 2014), the four elevators of the building were removed due to a reform. Besides the removal of the elevators, the reform did not have any other significant impact on the energy consumption.

The two following graphs illustrate very well the two main afore-mentioned variables that drive the load of the building. **Figure 5** shows the typical behavior of a daily load (period of 24 consecutive hours) for a working and a non-working day.

As can be observed in **Figure 5**, the daily profile of the load is directly dependent on the occupancy level of the building. Between 23 and 5 h, the energy demand remains at its minimum as the only load is outdoor lighting. On a working day (blue line), the load curve starts to ramp abruptly at 6 h and reaches a maximum at 9 h 30. There is a slight decrease in the load at lunch time, between 12 and 13 h, and then the load continues at its highest level until 18 h when it starts to decrease. Differently, on a non-working day (red line), the building remains unoccupied and the consumption continues at its lowest level, even with a slight decrease during the day as the outdoor lighting is automatically switched off.

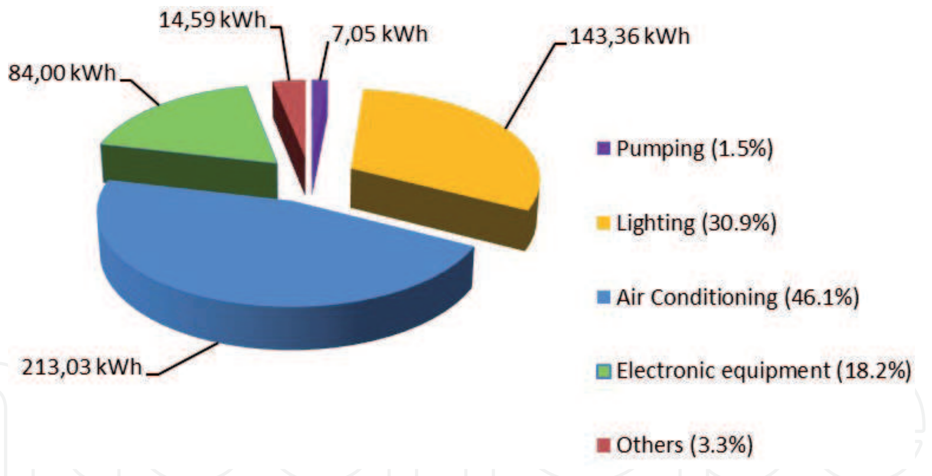

Figure 4.
Final uses of electric energy in the building (kWh/day).

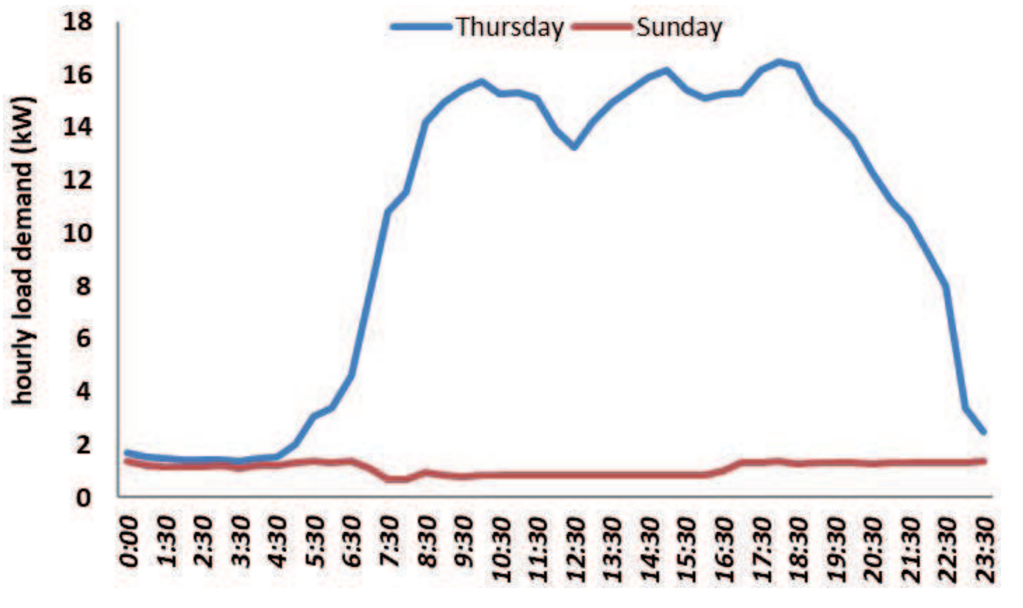

Figure 5.
Average daily load profiles of the building in both a working and a non-working day.

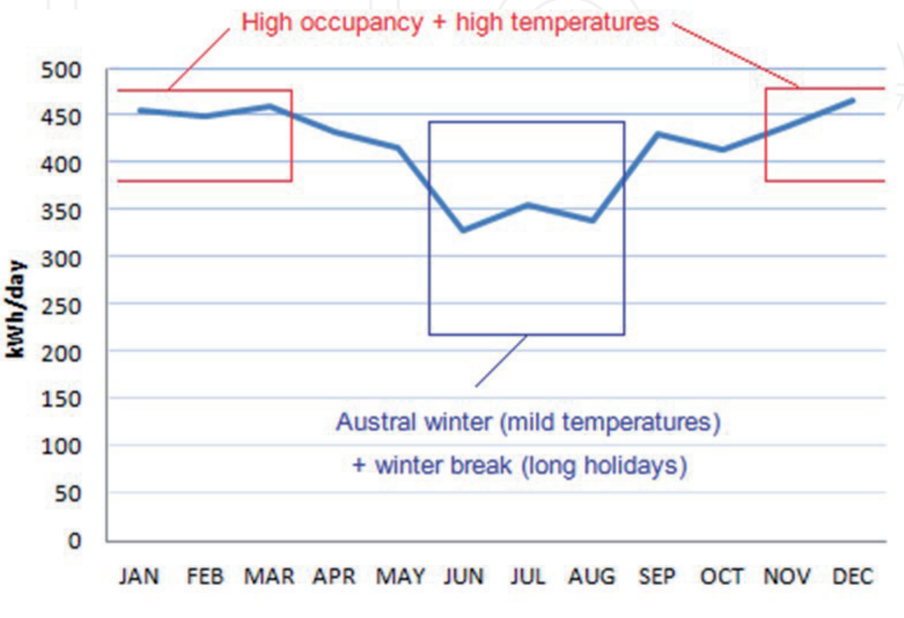

Figure 6.
Average curve of energy consumption in the building during years 2013/2014.

Figure 6 shows that the average daily consumption of energy in the building can vary ±30% because of the combined effects of temperature and calendar. The local temperature ranges from a minimum of 21.2°C in August to a maximum of 37.1°C in December.

5. Methodology

As historical data, it was used a database [102] containing energy consumption records from the building during more than 300 consecutive days. These data will serve as the foundation for a model that has to reflect as accurately as possible the effect of occupancy and temperature patterns in the load of any building in the campus, disregarding other effects in which the energy demand does not depend on.

When considering historical series of electric energy demand, especially in big electric networks, we must take into account that there is a rising tendency due to the influence of economic and population growth. This tendency must be extracted and modeled separately, typically as a constant rate related to the annual economic growth rate. It can also be modeled using ANN and regression models [103]. What remains is the fluctuation caused by the difference in demand from month to month, which depends among other factors on the seasonal variation of temperature. This fluctuation generates the annual load curve and must be modeled separately. After doing so, both effects can be summed up to obtain the series forecasting for upcoming months or years. The result is a more accurate model, achieving in some cases (with neural networks) values of the mean absolute percentage error (MAPE) of around 2% [73].

University buildings and campuses are within a much smaller scale. The only possible ways they can present the aforementioned growing trend in their energy consumption is due to:

- the use of new technologies and equipment, the implementation of new activities or the increase of existing ones, all of the above having a significant (and constant) impact on the energy consumption.

- an increase in the number of building occupants (alumni and workers).

Conversely, the energy consumption can present a constant decreasing trend, due to a decrease in the number of building occupants and – more frequently – due to the effects of energy conservation measures. In both cases, it is important to quantify and separate these rising/decreasing trends from the consumption pattern that it is intended to model.

However, this is not the case of the studied campus. During the one-year period of historical data, the energy consumption per capita has been constant. No major breakthroughs have occurred during that year, as was the case in some previous years thanks to, for example, the replacing of incandescent light bulbs with energy-efficient light bulbs, which produced a significant decrease in the load demand for the same occupation pattern. Moreover, the number of occupants in the building during that period (students and workers) also remained constant.

In addition, as pointed out by [90], the load in institutional buildings is also subjected to unpredictable factors: there are factors that may affect the consumption such as a failure of the HVAC system, strikes, etc. These events should be detected, and data must be filtered from the historical records in order to build a more reliable model. Those outliers were identified and removed prior to the development of the ANN model that is detailed from this point on.

The daily consumption is directly related to the period of the year and the day of the week. For this reason, the model structure may be a simple feed-forward as the one that was shown in **Figure 3**. However, the demand at any day may present some correlation with the one from the previous day. In order to take into consideration possible correlations between the daily demands, it is proposed a more evolved structure: a non-linear autoregressive exogenous model (NARX). Such structure consists basically in the feedback of the ANN using as part of its inputs the past outputs [104–107], as presented in Eq. (3):

$$y(t) = f\left(y(t-1),,,,,,y(t-2),,,,,,\ldots,,,,,,y\left(t-n_{ty}\right),,,,,,U(t-1),,,,,,U(t-2),,,,,,U\left(t-n_{tu}\right)\right) \quad (3)$$

where, y is the output values, u is the process input values, n_{ty}, n_{tu} the number of past values. The final structure of the ANN can thus be represented as shown in **Figure 7**.

After selecting the model structure, it is necessary for the overall architecture, which can be listed as: activation functions, number of hidden layers, and optimal number neurons. It is well known that one single layer is enough for a ANN model be able to approximate any function with relative precision [109]. The activation function is related to the dynamics of the systems being modeled, for example, pattern recognition case, where step functions are commonly used. To perform the training, usually the backpropagation method is employed [110–113]. The training is done until an acceptable MAPE is reached. The main point while identifying a ANN model is a careful selection of the optimal number of neurons, which is strictly correlated to the total number of parameters to be estimated. Thus, an excessive number of neurons might lead to a well-known problem, the overfitting. On the other hand, a small number might compromise the model prediction. In 1996, Schenker and Agarwal [114] proposed a method to identify the optimal number of neurons when few data are available, the dynamic cross-validation. The method consists in the usage of three data set, for example, set A, B, and C. The set A and B are employed in the training step, which will generate two different networks, for each neuron number. After the training, the network developed using

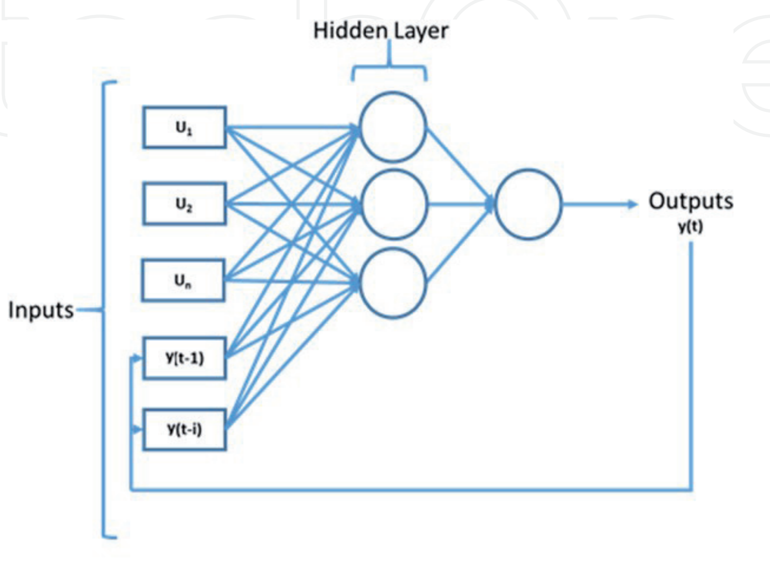

Figure 7.
Chosen structure for the neural network model: non-linear autoregressive exogenous model [108].

set A is validated using set B and the MAPE is calculated. The process continues up to a maximum number of neurons, which in the present work was 40 neurons. The optimal number of neurons is the one with lowest MAPE. The validation error is presented in **Figure 8** with its correspondent number of neurons. For the present case, the optimal number of neurons found was 5.

Finally, another network was trained using the optimal number of neurons. In order to avoid the overfitting, the early stopping criteria were employed [114–116]. This criterion consists in stop the training after a determined number of iteration where the validation error increased. The training of the final network was done with sets A and B, while the validation was done using set C. The general definitions of the final model are shown in **Table 2**.

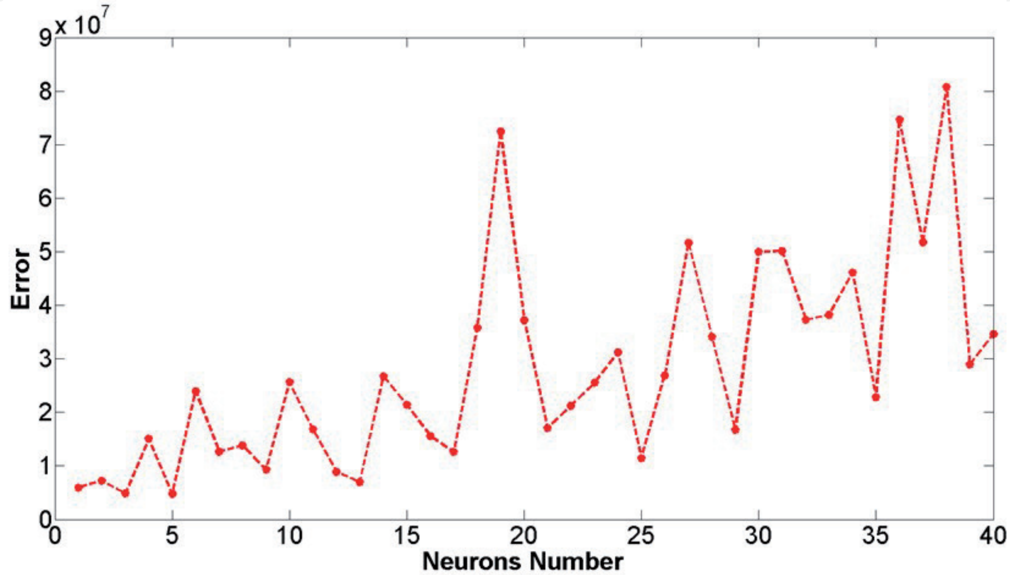

Figure 8.
Dynamic cross-validation for the selection of the optimal number of neurons of the hidden layer: validation errors for different number of neurons.

	ANN model parameters
Input	Database containing the energy consumption records of previous days
Output	Daily energy consumption
Total number of neurons evaluated	40
Total number of trainees done	40
Optimal number of neurons	5
Total iteration in training step	300
Minimum gradient	10^{-6}
Early stopping criteria	30
Transfer function in the first layer	Hyperbolic tangent sigmoid
Transfer function in the output layer	Linear function
Final model MAPE	6.54%

Table 2.
Characteristics of the proposed ANN model.

6. Results and discussion

6.1 Load demand model

In order to assess the generalization quality of the model, **Figure 9** shows the predicted data together with the validation data (real data).

As can be observed in the figure above, there are sudden variations in the daily consumption of energy, which repeat periodically in cycles of about 7 days. This refers to the load variation between workdays and weekends, with Saturdays presenting an intermediate value between a typical working day and the minimum consumption of Sundays. Overall, this type of curve can be taken as representative for an institutional building. Its variation depends directly on the occupation pattern of the University campus and, to a lesser extent, in the effect of temperature. The model developed using neural networks follows these consumption trends that were identified in **Figure 5** (working day versus non-working day) and **Figure 6** (seasonal variation of occupation and temperature).

The quality of the prediction was evaluated according to the MAPE, which was 6.54% for the final model. This means that through the proposed model, the campus managers can predict the electric consumption of any given day with an average error less than or equal to 6.54%. The average error is surprisingly similar to the ones achieved by different models for other university buildings (see the literature review in **Table 1**).

The error distribution, shown in **Figure 10**, revealed a slight trend of the model to underestimate the daily energy consumption.

The resulting set of errors showed a distribution with a high standard deviation. The standard deviation indicates how close the data points tend to be the mean of the set of errors. For the set of errors produced by this model, the standard deviation (sigma) is 20.75%. However, the model made some gross errors of up to −145% and + 85% at some points.

The CV depends on the standard deviation and on the mean of the forecast model data, as was shown in Eq. (2). Thus, the values calculated by the model showed a CV of 317%. This significant value of CV is due to the great variation between the load in working and in non-working days, typically between weekend and workweek. Together with the histogram of errors, **Figure 10** depicts the normal (or Gaussian) distribution of errors. This function is symmetric around the point

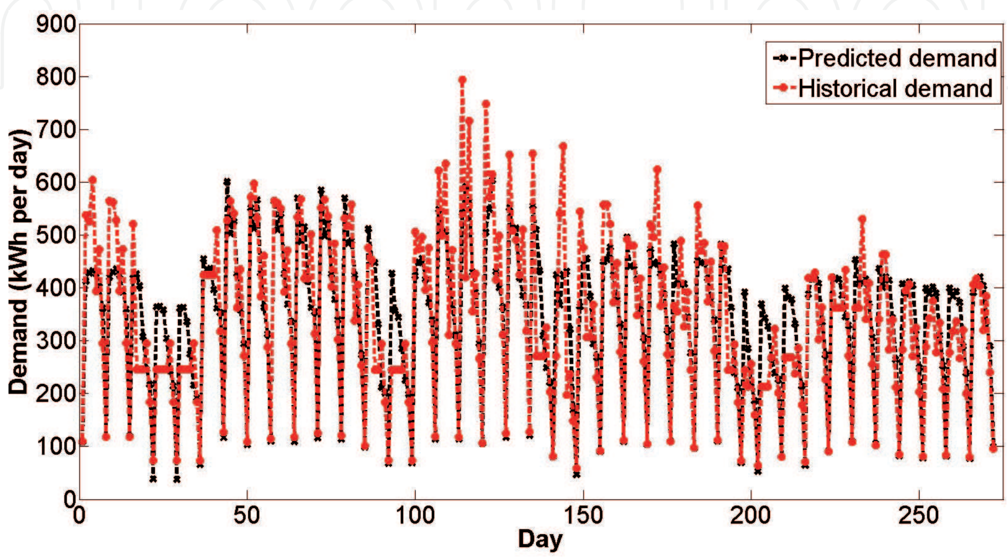

Figure 9.
Validation of the model with the demand data of the building from 300 consecutive days.

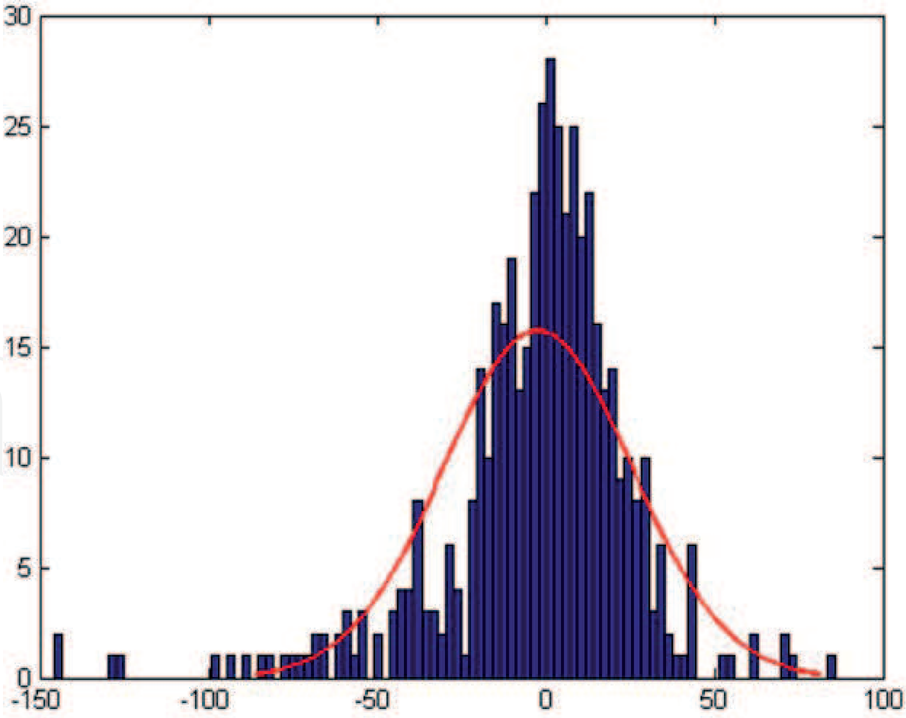

Figure 10.
Distribution of the errors made by the model.

−6.54 (mean value of the error). Within a normal distribution, the 3-sigma rule establishes that 68% of values are within one standard deviation away from the mean; about 95% of the values lie within two standard deviations; and about 99.7% are within three standard deviations. Therefore, it can be stated that by using the proposed ANN model, 68% of the forecasted values have an error of between −27.29 and +14.21% (MAPE ≤ 20.75%); 95% of the forecasted values have an error of between −48.04 and +34.96% (MAPE ≤ 41.50%); and about 99.7% of the forecasted values have an error of between −68.77 and +55.71% (MAPE ≤ 62.25%).

6.2 Correlation between the seasonal variation of load demand, solar, and wind energy availability

The proposed mathematical model can be taken as representative for the load profile of the campus where the building is inserted with an accuracy of 6.54%. This allows us to compare the load demand with the renewable energy availability in the campus. More precisely, allows the comparison of the seasonal variation of energy consumption versus the seasonal variation of the following meteorological parameters: wind speed and solar irradiation. There is a weather station in the campus that measures and records, among other parameters, global solar irradiation on a horizontal surface (MJ/m^2) and wind speed at 10 m height (m/s). The uncertainties of the measurements are ±5% for the solar pyranometer and ±1.5% for the wind anemometer [97]. Through this database, average values of wind speed and solar irradiation can be calculated for each day of the year, in order to build average curves that represent the seasonal variation of these two renewable sources. Then, these values can be compared with the load demand model, which yields the average value for energy consumption in the campus. To make this comparison, the Pearson product-moment correlation coefficient (hereafter Pearson correlation coefficient) will be used. This coefficient compares two sets of data and varies between −1 and 1. A value of 1 implies that a linear equation describes the relationship between the two compared variables perfectly, with all data points lying on a line for which

	Solar	Wind	Load demand
Solar	1	−0.008	0.803
Wind	−0.008	1	−0.505
Load demand	0.803	−0.505	1

Table 3.
Correlation (Pearson coefficient) between the seasonal variation of renewable energy resources and energy demand in the campus.

one increases as the other one increases. A value of −1 implies that all data points lie on a line for which one variable decreases as the other increases. A value of 0 for the coefficient implies that there is no linear correlation between the variables. The Pearson coefficient has proven to be useful in previous research in identifying which environmental variables (temperature and other weather conditions) correlate best (that is, have the greatest influence) in the energy consumption of buildings [117]. In our case, we are using the Pearson coefficient to assess the convenience of using some renewable energy sources by comparing its availability with the load of the campus. Three variables will be compared, namely "Solar," "Wind," and "Load demand." The Pearson correlation coefficient will indicate the strength of a linear relationship between them. As said, "Load demand" depends on the calendar but also on temperature, and thus may have some relationship with "Solar." "Solar" varies from a maximum in December to a minimum in August. "Wind" is the most intermittent and unpredictable, however tends to vary from a maximum in August to a minimum in March [97]. The Pearson correlation coefficient was calculated using the Statistical software Minitab® 16.2.1 and their resulting values are shown in **Table 3**.

Table 3 shows interesting results. "Solar" and "Wind" values show almost no relationship among them. When compared with the load demand of the campus, it was found that in the months were the load demand is higher the availability of wind resources tends to be lower and vice versa. The solar resource, meanwhile, showed a good correlation with the "Load demand." This is not surprising as the "Load demand" variable depends on temperature, which is related to solar irradiance. This correlation level means that in the months of high energy consumption, there is a higher availability of solar resource and vice versa. In other words, the variation of the solar resource matches very well the variation of the energy needs of the campus. When considering the daily variation of the load (as shown in **Figure 5**), the solar energy option gets reinforced, as most of the period with high load coincides with the peak of solar irradiation that occurs during the central hours of the day. Solar power is, therefore, the most convenient renewable energy source for this campus as is the one that best matches with the seasonal and daily variation of load demand.

7. Conclusion and future work

A reliable mathematical model was developed for the prediction of the electric load in a University campus. The neural network model was capable of forecasting the load with average error of 6.54%. The high standard deviation of the errors is the main weakness of this particular model. Load forecast models such as the one that is detailed in this article play an interesting role in the energy management of institutional buildings. First, as a powerful tool for the control of a smart grid that supplies either a single building or several of them grouped in a campus or a complex. Secondly, as a decision tool to assess the convenience of a set of renewable energy sources tend to vary seasonally. As was demonstrated in this study, statistical data that measure the availability of the local renewable sources can be compared with a load model in order to assess how well these energy sources match the variation of the energy needs of buildings. As future work the authors propose:

I. Applying calibration techniques to further reduce the error committed by the model;

II. Overcoming the high deviation of the errors by allowing the model to quickly recognize if a day is working-day or holiday;

III. Installing smart energy meters in the building with the aim to develop online building energy prediction using adaptive ANNs.

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