Universidad de Valladolid

DOCTORATE PROGRAM IN INDUSTRIAL ENGINEERING
AND
DOCTORAL PROGRAM IN ENERGY MANAGEMENT FOR SUSTAINABLE DEVELOPMENT

DOCTORAL THESIS IN INTERNATIONAL JOINT SUPERVISION:

DEMAND FORECASTING MODEL FOR LOAD SHIFTING STRATEGY IN BUILDING ENERGY MANAGEMENT SYSTEM

Presented by Deyslen Mariano Hernández
to qualify for the degree of
Doctor from the University of Valladolid
and the
Instituto Tecnológico de Santo Domingo

Directed by:

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Angel Zorita Lamadrid
Luis González Morales

PROGRAMA DE DOCTORADO EN INGENIERÍA INDUSTRIAL
Y
PROGRAMA DE DOCTORADO EN GESTIÓN ENERGÉTICA PARA EL DESARROLLO SOSTENIBLE

TESIS DOCTORAL EN RÉGIMEN DE COTUTELA INTERNACIONAL:

MODELO DE PRONÓSTICO DE DEMANDA PARA ESTRATEGIA DE DESPLAZAMIENTO DE CARGAS EN SISTEMA DE GESTIÓN ENERGÉTICA DE EDIFICIO

Presentada por Deyslen Mariano Hernández
para optar al grado de
Doctor por la Universidad de Valladolid
y
el Instituto Tecnológico de Santo Domingo

Dirigida por:

Luis Hernández Callejo
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Prologue

Under the current regulations for the presentation and defense of the doctoral thesis (RESOLUTION of June 8, 2016, of the Rectorate of the University of Valladolid, which orders the publication of the Agreement of the Governing Council of June 3, 2016, which approves the regulations for the presentation and defense of the doctoral thesis at the University of Valladolid), this Doctoral Thesis is presented as a compendium of publications.

Below are the published articles included in the compendium of publications that have given rise to the thesis, which are presented in Chapter II. The articles have been organized following a conceptual order that gives meaning to the doctoral thesis.

First Article - Published: 26 August 2021.

Article Type	Research Article
Title	A Data-Driven Forecasting Strategy to Predict Continuous Hourly Energy Demand in Smart Buildings.
Authors	Mariano-Hernández, D., Hernández-Callejo, L., Martín, S., Zorita-Lamadrid, A., Gonzalez-Morales, L., Duque-Pérez, O., & Santos García, F.
Journal	Applied Sciences 2021, 11(17), 7886.
Special Issue	Artificial Intelligence (AI) in Smart Buildings.
Category	Engineering, Multidisciplinary (39/92).
Quality Index	Journal Citation Report (JCR) 2021 - Impact Factor (IF): 2.838 (Q2) Scimago Journal Rank (SJR) 2021 - 0.51 (Q2)
DOI	https://doi.org/10.3390/app11177886

Second Article – Published: 02 September 2022.

Article Type	Research Article
Title	Comparative study of continuous hourly energy consumption forecasting strategies with small data sets to support demand management decisions in buildings.
Authors	D. Mariano-Hernández, L. Hernández-Callejo, M. Solís, A. Zorita-Lamadrid, O. Duque-Pérez, L. Gonzalez-Morales, V. Alonso-Gómez, A. Jaramillo-Duque, F. Santos García.
Journal	Energy Science & Engineering
Category	Energy & Fuels (74/119). Journal Citation Report.
Quality Index	Journal Citation Report (JCR) 2021 - Impact Factor (IF): 4.035 (Q3) Scimago Journal Rank (SJR) 2021 - 0.69 (Q2)
DOI	https://doi.org/10.1002/ese3.1298

Third Article - Published: 12 May 2022.

Article Type	Research Article
Title	Analysis of the Integration of Drift Detection Methods in Learning Algorithms for Electrical Consumption Forecasting in Smart Buildings.
Authors	Mariano-Hernández, D., Hernández-Callejo, L., Martín, S., Zorita-Lamadrid, A., Gonzalez-Morales, L., Duque-Pérez, O., Santos García, F., Jaramillo-Duque, A., Ospino-Castro, A., Alonso-Gomez, V., & J. Bello, H.
Journal	Sustainability 2022, 14(10), 5857.
Special Issue	Artificial Intelligence and Sustainable Energy Systems.
Category	Environmental Sciences (157/324). Journal Citation Report.
Quality Index	Journal Citation Report (JCR) 2021 - Impact Factor (IF): 3.889 (Q2) Scimago Journal Rank (SJR) 2021 - 0.66 (Q2)
DOI	https://doi.org/10.3390/su14105857

In addition to the aforementioned articles, Annex A also includes other works carried out within the framework of this line of research and contributed to the development of this doctoral thesis.

First Additional Article - Published: 24 July 2020.

Article Type	Review Article
Title	A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis.
Authors	Mariano-Hernández, D., Hernández-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., & Santos García, F.
Journal	Journal of Building Engineering 2021, 33, 101692.
Category	Construction & Building Technology (9/89). Journal Citation Report.
Quality Index	Journal Citation Report (JCR) 2021 - Impact Factor (IF): 7.144 (Q1) Scimago Journal Rank (SJR) 2021 - 1.16 (Q1)
DOI	https://doi.org/10.1016/j.jobe.2020.101692

Second Additional Article - Published: 24 November 2020.

Article Type	Review Article
Title	A Review of Energy Consumption Forecasting in Smart Buildings: Methods, Input Variables, Forecasting Horizon and Metrics.
Authors	Mariano-Hernández, D., Hernández-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., & Santos García, F.
Journal	Applied Sciences 2020, 10(23), 8323. (2020)
Special Issue	Artificial Intelligence in Smart Buildings.
Category	Engineering, Multidisciplinary (39/92). Journal Citation Report.
Quality Index	Journal Citation Report (JCR) 2021 - Impact Factor (IF): 2.838 (Q2) Scimago Journal Rank (SJR) 2021 - 0.51 (Q2)
DOI	https://doi.org/10.3390/app10238323

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Abstract

Among the sectors with the highest energy consumption are transport, industries, and buildings. Buildings are responsible for the third part of energy consumption and almost 40% of CO_2 emissions worldwide. The search to improve the comfort of the occupants inside the buildings has brought a consequence that buildings are increasingly equipped with devices that help to improve the thermal comfort, visual comfort, and air quality inside the buildings, causing more energy demand regardless of the type of building making buildings an untapped efficiency potential. This doctoral thesis presents a model for forecasting electricity demand in buildings based on machine learning for load-shifting strategies, which can be implemented in building energy management systems. The forecast model developed allows forecasting the electricity demand for the next 24 hours starting at any time of the day. To achieve this forecast, not only electricity consumption was considered, but also climatic variables, calendar variables, and past time values. Different types of machine learning algorithms were compared using performance measures resulting in tree decision and deep learning algorithms performing better with the developed model.

Resumen

Dentro de los sectores de mayor consumo energético se encuentran: el transporte, las industrias y los edificios. Siendo los edificios responsables de una tercera parte del consumo de energía y casi un 40% de las emisiones de CO_2 a nivel mundial. La búsqueda por mejorar el confort de los ocupantes dentro de los edificios ha traído como consecuencia que los edificios estén cada vez más equipados con dispositivos que ayudan a mejorar el confort térmico, el confort visual y la calidad de aire dentro de los edificios. Causando que cada vez más la demanda de energía de los edificios independientemente del tipo de edificio que sean se encuentre en crecimiento y haciendo que los edificios sean un potencial de eficiencia sin explotar. Esta tesis doctoral presenta un modelo para pronóstico de la demanda eléctrica en edificios basado en aprendizaje automático para estrategias de desplazamiento de cargas, el cual puede ser implementado en sistemas de gestión energética para edificios. El modelo de pronóstico desarrollado permite pronosticar la demanda eléctrica de las próximas 24 horas a partir de cualquier hora del día. Para lograr este pronóstico no solo se consideró el consumo eléctrico sino también variables climáticas, de calendario y valores de tiempo pasado. Diferentes tipos de algoritmos de aprendizaje automático fueron comparados usando medidas de desempeño resultando que los algoritmos de árboles de decisión y de redes profundas presentaban mejor rendimiento con el modelo desarrollado.

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Chapter I. Introduction

1.1. Conceptual Framework

There is an overall agreement in the world that human activities are contrarily affecting the climate and have sped up both global warming and environmental change [1]. Greenhouse gas emissions are an emerging problem that poses a serious environmental problem and threatens the entire world. The electricity production process is considered among the main CO_2 emitters since it is largely based on non-renewable sources such as coal and natural gas [2].

Worldwide economic development and the expansion of the total population have unequivocally impacted the pattern of worldwide energy consumption. In 2018, China, the US, and India together represented more than two-thirds of the worldwide expansion in energy demand, with US consumption growing at its quickest rate for a long time [3].

A country's total energy demand can be assessed by collecting three fundamental monetary areas: buildings, industry, and transport. As indicated by the World Watch Institute information, buildings as the biggest energy consumers representing 40% of the worldwide yearly energy utilization and 36% of the total carbon emissions [4].

Buildings can go about as intelligent systems that work with the shift towards a more feasible energy use worldview. Buildings can strengthen the accelerated understanding of sustainable technologies and decrease energy use, CO_2 emissions, and operating expenses [5]. Notable advances in energy efficiency in the previous year have favored progress in dissociating energy consumption from the buildings sector. However, since 2010, rising demand for energy services in buildings, especially in electrical energy for powering cooling equipment, appliances, and connected devices has been outpacing energy efficiency and decarbonization gains [6].

The field of building automation is not new; but as detecting, computing, and activating advancements have developed the scope of control has extended. The utilization of more wide sensor/actuator networks has made it more possible to consider automation overshadowing inhabitant control, considering agreeable conditions to be kept up without inefficient practices from occupants [7]. A rising requirement for the decrease in energy consumption levels and continuing growth of energy use by buildings have made a need to create new techniques to decrease and enhanced building energy utilization [8].

Building energy management systems (BEMS) play a significant part in decreasing energy use in buildings. BEMS enable buildings to be smarter through automatic, real-time monitoring and control and optimize their use of energy [9,10]. BEMS can be classified as active and passive. Passive gather climate information, device data, and past energy use in smart buildings. Active BEMS work with a degree of automation and intelligence. BEMS have meters, sensors, and gadgets to control building in real-time to reduce energy consumption [11].

Based on management strategies, active BEMS can be classified into fault detection and diagnosis, model predictive control, optimization, and demand-side management [12]. Fault detection and diagnosis is a strategy for recognizing and isolating flaws in BEMS for the protection of a system from additional damage [13]. Model Predictive Control can anticipate the reaction of the building to control demands, and by understanding the method for following it, it can act to perform the necessary operation [14]. Optimization expects that the veritable possibility of scattering of questionable data should be known or surveyed. If this condition is met and the reformulation of the uncertain improvement issue is computationally manageable [15]. Demand-Side Management is an adjustment of actions to improve the energy system on the client side. It goes from improving energy efficiency by using further developed assets, over smart energy rates with motivators for certain use adjustments, up to modern continuous management of allocated energy assets [16].

Demand-Side Management (DSM) plays a very important role in the future energy system for demand-side flexibility [17] and is one of the most prominent strategies for smart buildings and smart grids [18]. DSM is a field of research involved in planning, scheduling, and controlling electrical loads to level the grid, using more renewable energy sources, and reducing overall CO_2 emissions from the grid. DSM inspires end-clients to use less power during peak intervals or shift energy consumption to off-peak hours determined by the term peak-to-average ratio [19,20].

Industrial and commercial consumers often pay for energy consumption (kWh) and peak electricity demand (kW). This charging structure does not necessarily motivate to shift the maximum load on the network, but it does provide a significant motivation to shift the maximum load to consumers. Commercial and industrial consumers can shift the peak load, thereby reducing electricity costs without reducing overall energy consumption [21]. Particularly, decreasing peak electricity demand is a reasonable way to accomplish monetary and ecological benefits. For instance, peak demand is recognized as the principal driver for the developing interests in network framework which applies strain on electricity costs [22].

Energy management is becoming crucial for buildings all over the planet, and energy forecasting is fundamental as an initial step to build an energy management system [23]. Throughout recent many years, forecasting building electricity consumption has acquired significance [24], especially for demand limiting and load shifting control [25].

Building electrical energy use has considerable energy reserve funds potential, yet it requires an accurate forecast since the prediction will straightforwardly impact the control strategies and the building's potential energy reserve funds [26].

1.2. Justification

Building energy consumption has dangerously expanded because of climate issues, and people's rising demand for buildings [27]. Increasing building energy efficiency has turned into an outstanding issue around the world. There is currently high interest in the thermal renovation of building envelopes and choosing the ideal insulation thickness. Nonetheless, energy efficiency measures should not be restricted to the building's envelope but should also consider measures to raise the energy efficiency of building systems [28].

With the popularity of building automation systems, it has become possible to collect a massive amount of building operation information. Provides the opportunity to use a data-driven approach for building electric energy consumption forecasts [29] due to its ease of use, adaptability, practicability, and high forecasting accuracy [30]. The data-driven approach relies on time-series measurable investigations and artificial intelligence to evaluate and estimate electricity consumption [31]. In this sense, a dependable and accurate forecast of building electricity consumption is becoming essential in improving building energy efficiency [32]. Recently, due to their significant application in different fields including electricity consumption in buildings, data-driven models such as machine and deep learning models have become especially well known and are being used to increase forecast accuracy [33,34].

Researchers suggest that building an energy system with accurate forecasting is projected to save somewhere in the range of 10 and 30% of total energy utilization in buildings. Subsequently, a constant attempt to increase the building energy forecast is crucial [35]. Accurate forecasting of building electricity consumption is commonly difficult because building electric energy utilization shows a variety of patterns over time, and external aspects, for example, climate conditions and exceptional occasions can cause changes in the demand curve [36].

Short-term electricity consumption forecasting has been drawing a lot of interest due to its role in infrastructure development, operation, and energy budget planning [37]. The short-term horizon is firmly connected with the everyday operation model of energy systems, which can give helpful direction to establishing cost-effective and energy-saving measures [38]. Facility managers rely on real-time, exact, and comprehensive information to perform everyday activities and to give precise data to top administration [39], increasing the importance of short-term electricity consumption forecasting for daily activities [40].

Due to the aforementioned, this doctoral thesis focuses on the development of a forecast model for short-term electrical energy consumption in buildings to help facility managers achieve savings in the cost of electricity through the use of strategies that can be applied from the information offered by the model.

1.3. Hypothesis & Objectives

Hypothesis

The integration of an hourly electricity consumption forecast model in building energy management systems helps improve demand-side management in buildings, making them more energy efficient.

Main Objective

Develop an electricity consumption forecasting model with a data-driven approach for load displacement strategies in building energy management systems.

Partial Objectives

PO1. Study the state of the art of the different methods used in forecasting energy consumption in building energy management systems, including their different objectives and future challenges.

PO2. Develop a demand forecasting model for applications in building energy management systems.

PO3. Develop an energy consumption forecasting methodology that allows energy consumption to be estimated using a multi-step direct forecasting strategy.

PO4. Integrate change detection methods into the short-term demand forecasting model for forecasting the electricity consumption of entire buildings.

PO5. Validate the electricity consumption forecast model developed using real data from several buildings.

1.4. Main Contributions

The main contributions of the research carried out during the development of this doctoral thesis are the following:

- A strategy that allows forecasting the consumption of electrical energy in buildings for the next 24 hours from any time of the day.
- A methodology for building energy consumption forecasting that incorporates input variables such as historical data, calendar data, climatic data, and past series values.
- A data-driven approach that can be used to forecast continuous hourly electricity consumption to support demand management decisions in buildings with limited time-series data.
- An analysis of the integration of drift detection methods in decision trees and deep learning algorithms for forecasting the electricity consumption of the entire building.

1.5. Methodology

This doctoral thesis was developed in three stages, which led to the construction of the forecast model and then to its validation. In the first stage, a study of the state of the art was carried out, which began with a review of the literature on the different strategies used in building energy management systems, which helped to know which models were used for residential and non-residential buildings in each strategy. Followed by a review of the literature on the different methods used for building energy consumption forecasting. The literature reviews helped to know which algorithms, variables, and prediction horizons would be suitable for the model creation. Similarly, the review of the literature help to select the performance metrics that should be used to evaluate the model. The second stage corresponds to the creation of the model, where different algorithms and variables were analyzed for its elaboration. The third and last stage consisted of the validation of the model in two buildings located on the campus of the University of Valladolid, Spain.

1.5.1 Literature Review

The literature review consisted of two parts, in the first part, it investigated which BEMS strategies could benefit from a forecast model that could have good accuracy in terms of forecasting the electrical consumption of the entire building. Four strategies that are used in BEMS were identified, which were model predictive control, demand-side management, optimization, and fault detection & diagnosis (see Figure 1).

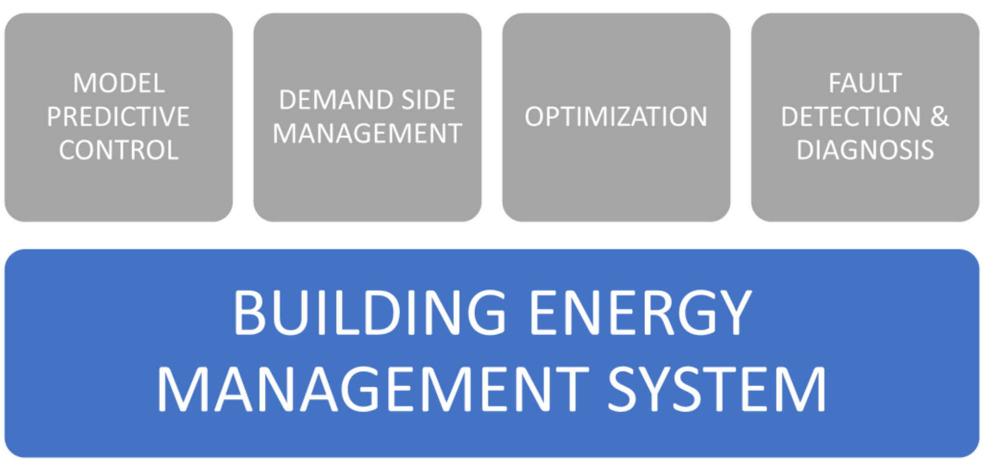

Figure 1. Strategies used in building energy management system.

Of the four strategies, two of them benefited directly from the forecast models, as is the case of model predictive control and demand-side management as presented in the work [34]. However, in the case of the predictive control model, the forecast model would be the first step since a control system is also required. While in demand-side management, the forecast model helps building energy managers make decisions immediately. Due to this, the proposed electricity consumption forecasting model was focused on the demand-side management strategy.

Once the strategy was identified, the second part of the literature review began, where a study of the state of the art of methods, input variables, forecast horizon, and performance metrics was carried out. From this literature review, it was obtained that the forecast of electrical energy in non-residential buildings focuses on the electrical energy consumption of the entire building. Regarding the methods, the data-driven method is the most used in a short-term horizon.

Of the input variables, the most used for the electricity consumption forecast models were historical, climatic, and calendar variables, as shown in Figure 2. With this information obtained through the work [41], the First Partial Objective (PO1) of this thesis could be achieved.

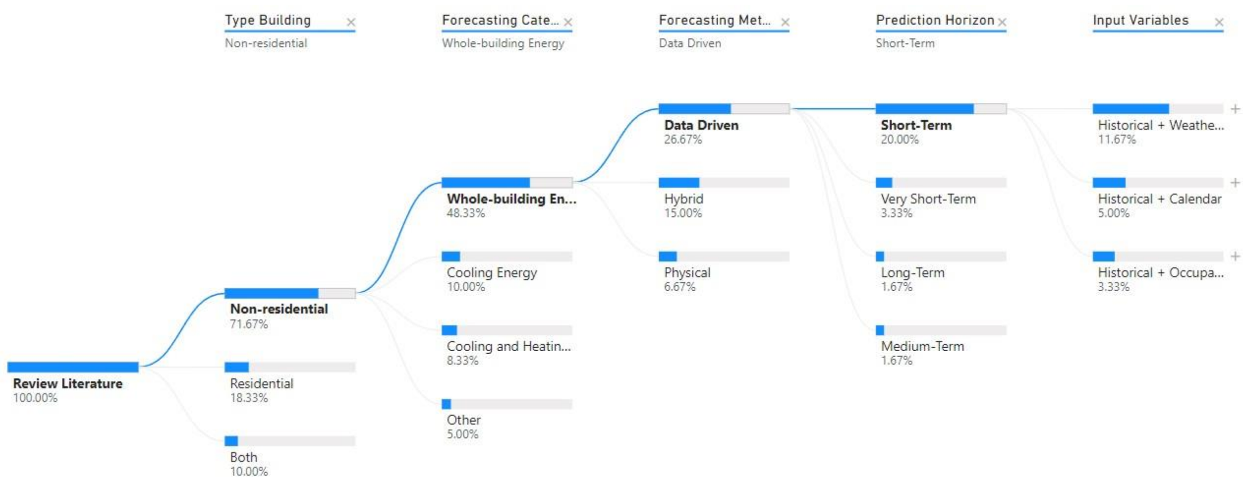

Figure 2. State of the art of models for forecasting electricity consumption in buildings.

1.5.2 Tools and Software

Different tools and software were used to develop the model (see Figure 3). Python was used as the programming language, which is a high-level general-purpose language that is popular in data science applications because it has a wide variety of libraries necessary to develop forecast models. Python codes were executed with the help of the integrated development environment (IDE) Jupiter Notebook and Visual Studio Code editor, which help to program and debug the codes efficiently. Regarding the Python libraries, the following libraries were used for the development of the model:

- Pandas for data analysis and manipulation.
- Matplotlib and Seaborn for data visual analysis.
- TensorFlow, scikit-learn, PyTorch, Keras, and XGBoost to train, test, and validate the machine learning models used.
- Joblib to run python functions like pipeline jobs.
- Scikit-multiflow to detect a sudden change in the data distribution.

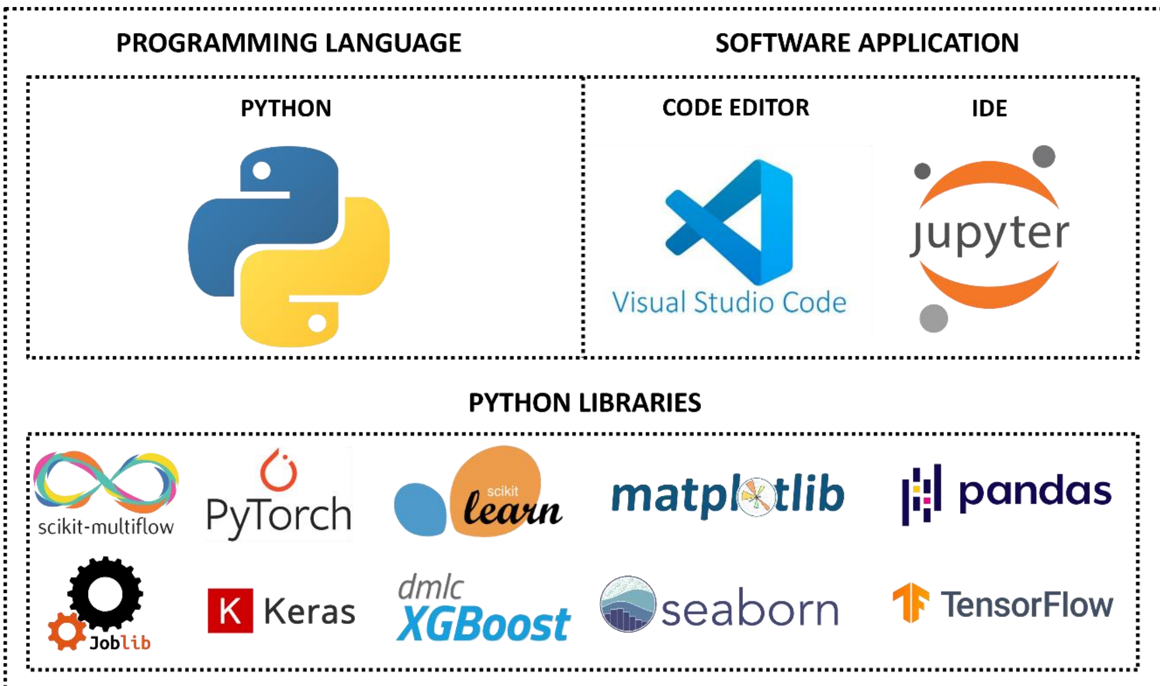

Figure 3. Tools and software used to develop the proposed model.

1.5.3 Model Development

Before developing the model, which buildings would be used to apply the electricity consumption forecast model were selected. Two buildings located on the campus of the University of Valladolid were selected. One of the buildings is dedicated to administrative work while the other is used for both administrative and teaching activities.

Once the buildings were selected, the corresponding data was obtained from them to create the dataset that would be used to train the model. Considering the literature review previously carried out, it was decided that the dataset would contain historical, climatic, and calendar variables. Additionally, since we are working with time series, a specific amount of lags was considered concerning the prediction time in the construction of the dataset.

The historical variables corresponding to the electrical consumption of the buildings were obtained through network analyzers that are installed in each of the buildings. Climate variables were obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program (https://power.larc.nasa.gov/, accessed on 04 March 2021). Because the model that was developed focuses on sustainable buildings, variables that influence occupant comfort within buildings were considered. The following variables were considered for the training of the models: precipitation, relative humidity at 2 meters, the temperature at 2 meters, the minimum temperature at 2 meters, the maximum temperature at 2 meters, heating degree days below 18.3°C, cooling degree days above 0°C, cooling degree days above 10°C, and all-sky surface longwave downward irradiance. Due to the variety of climatic variables that can influence buildings, a correlation analysis was performed using Pearson's correlation coefficient (see Equation 1) to determine which variables could have the greatest influence on the forecast of the electrical energy variable.

$$r = \frac{\sum(x_i - \bar{x}\,)\,(y_i - \bar{y}\,)}{\sqrt{\sum(x_i - \bar{x}\,)^2\ (y_i - \bar{y})^2}} \tag{1}$$

Where, r = correlation coefficient, x_i = values of the x-variable in a sample, $\bar{x}$ = mean of the values of the x-variable, y_i = values of the y-variable in a sample, $\bar{y}$ = mean of the values of the y-variable.

Since we are working with a time series, it was used to obtain the calendar variables, which were extracted from the time and date register kept by the energy meter. Creating the hour, weekday, and month attribute in the dataset. Additionally, because during the year there are holidays as well as periods when classes are not taught, which would affect electricity consumption, an attribute of holidays was added with which the model could learn this behavior.

The variables corresponding to past time values were obtained based on an autocorrelation analysis. Using autocorrelation and partial autocorrelation analyses, the number of lags to include in the dataset to be used for the forecast model was determined. For this analysis, the autocorrelation and partial autocorrelation of the historical data were plotted to select the number of lags to use for past values (see Figure 4).

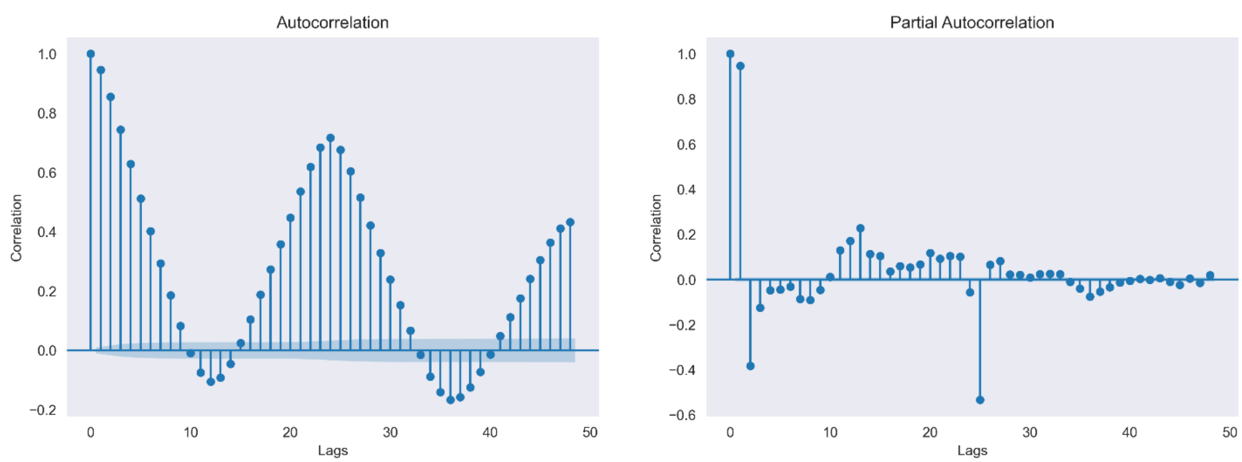

Figure 4. Autocorrelation and partial autocorrelation analysis.

After the aforementioned steps were carried out, the dataset that would be used in the model was built. This dataset was composed of data corresponding to historical variables, calendar variables, climatic variables, and past values. The next step in model development was to split the dataset into a training dataset and a test dataset to train the algorithm that would be used for the model. Since data was available from 2016 to 2019, it was decided that the years 2016 to 2018 would be used for the training dataset, while 2019 would be used for the test dataset.

Once the datasets were distributed, the Random Forest (RF) algorithm was selected as the reference algorithm to be the basis for comparison between other algorithms and to determine which algorithms best fit the developed model. The reason why RF was selected was that it is an algorithm that allows us to have a forecast using a little computational resource. In addition, this algorithm has the function of feature importance, which allows us to evaluate after making the forecast which variables help to improve the forecast of the model.

After the selection of the reference algorithm, a strategy was implemented that would allow the model to perform multi-step forecasting. This strategy consisted of the model being able to forecast the next 24 hours from any hour of the day. The reason for implementing this type of strategy was so that the model would have the versatility to be used at any time of the day. Something that is not common in electricity consumption forecast models.

To optimize the multi-step forecasting model, as mentioned, the RF feature importance function was used, obtaining the results shown in Figure 5. These were compared with the correlation analysis carried out before building the dataset, giving results that The climatic variables that help the model the most are the temperature at 2 meters, the maximum temperature at 2 meters, and all-sky surface longwave downward irradiance.

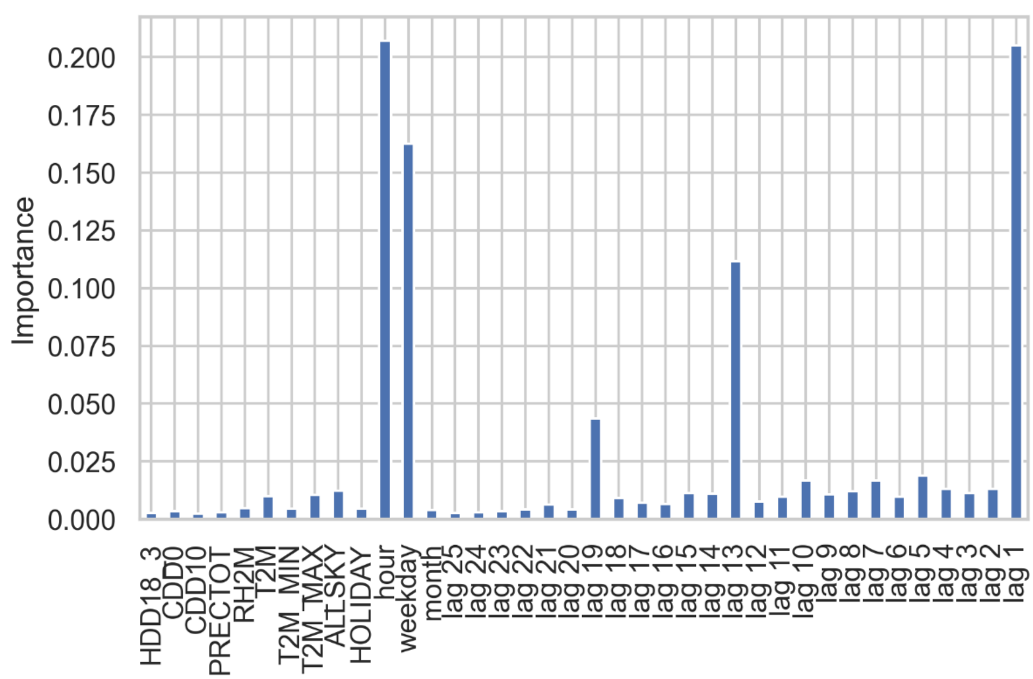

Figure 5. Random forest feature importance [42].

For the comparison between algorithms, both shallow learning algorithms and deep learning algorithms were selected. The shallow learning algorithms used Multiple Linear Regression (MLR), Multi-Layer Perceptron (MLP), and eXtreme Gradient Boosting (XGBoost) while the deep learning algorithms used Long-Short Term Memory (LSTM), Convolutional Neural Network (CNN), Temporal Convolutional Network (TCN), Temporal Fusion Transformer (TFT) by the deep learning algorithm. The algorithms utilized were customized in Python using the Scikit-learn, XGBoost, TensorFlow, and Keras libraries. In addition, for algorithms that were not capable of multi-step forecastings, such as MLR and XGBoost, a multi-output function available in the Scikit-learn library was used.

Before running the models for the 2019 forecast, cross-validation known as backtesting was used. Backtesting was used to find out which were the optimal hyperparameters for each of the algorithms. This process consisted of using the years 2016 and 2017 for the training set and 2018 for the testing set. Dividing the year 2018 into five parts, evaluating the algorithms at different stages of the year as can be seen in Figure 6.

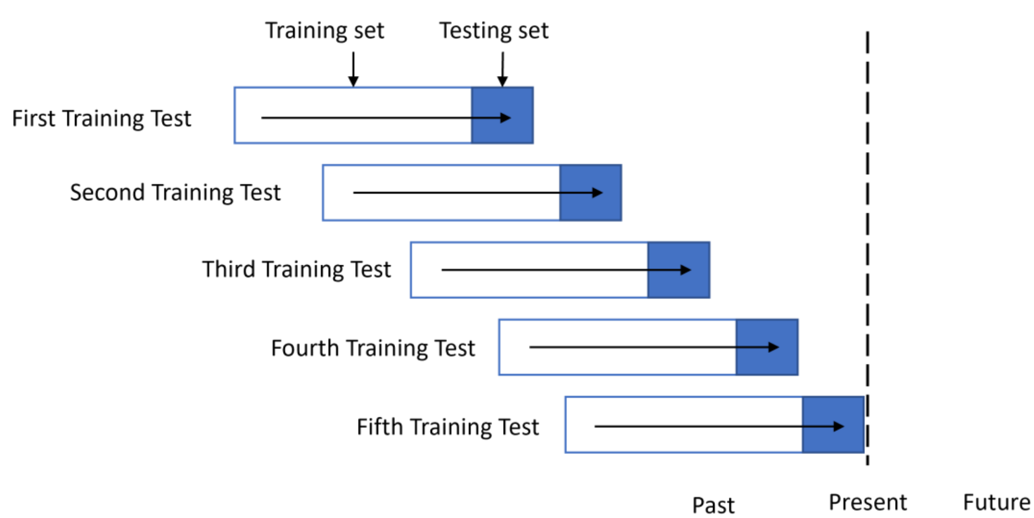

Figure 6. Backtesting with sliding windows procedure [43].

Obtained the best combinations of hyperparameters through the backtesting procedure for each of the selected algorithms, and the development model was complete. During the development of the model, concern arose as to what would be the best approach to use multi-step forecasting, so two approaches were proposed. The first approach was to forecast the next 24 hours for all hours of the day while the second approach was to forecast the next 24 hours from a specific hour (see Figure 7).

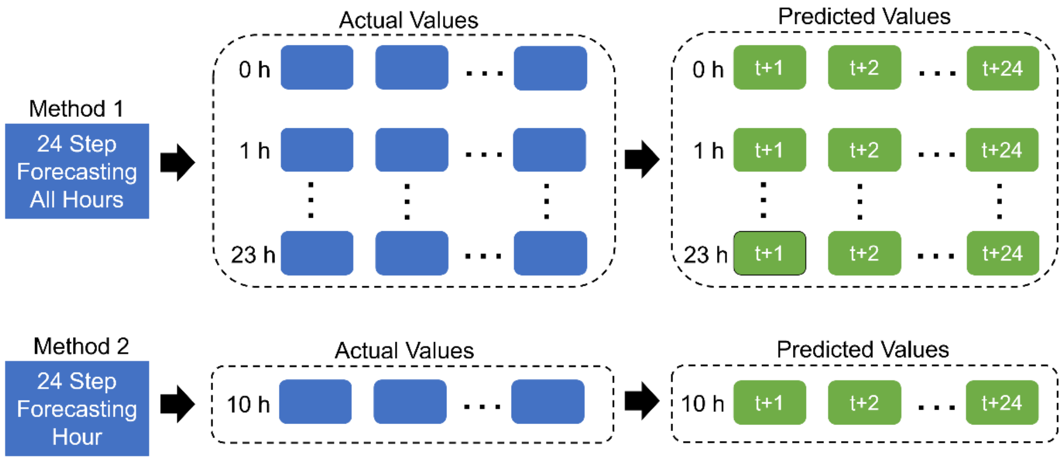

Figure 7. Schematic diagram of the two methods compared [44].

The algorithms that were used to compare the two different multi-step forecasting methods were RF, XGBoost, CNN, and TCN because these were the algorithms that obtained the best results when evaluating the performance of the model. With the results of this comparison study, the Second Partial Objective (PO2) and Third Partial Objective (PO3) of this thesis were achieved.

Normally the models that are developed for the forecast of electricity consumption are offline models, which over time end up being obsolete, being the case of electricity consumption in buildings, normally, energy efficiency measures are implemented that over time change the consumption of buildings. Due to this, drift detection methods (DDM) were integrated into the developed model, which allowed the model to decide to retrain itself when faced with a change in the behavior of electricity consumption and thus maintain its accuracy over time. Figure 8 shows the methodology that was used to implement the DDM in the model.

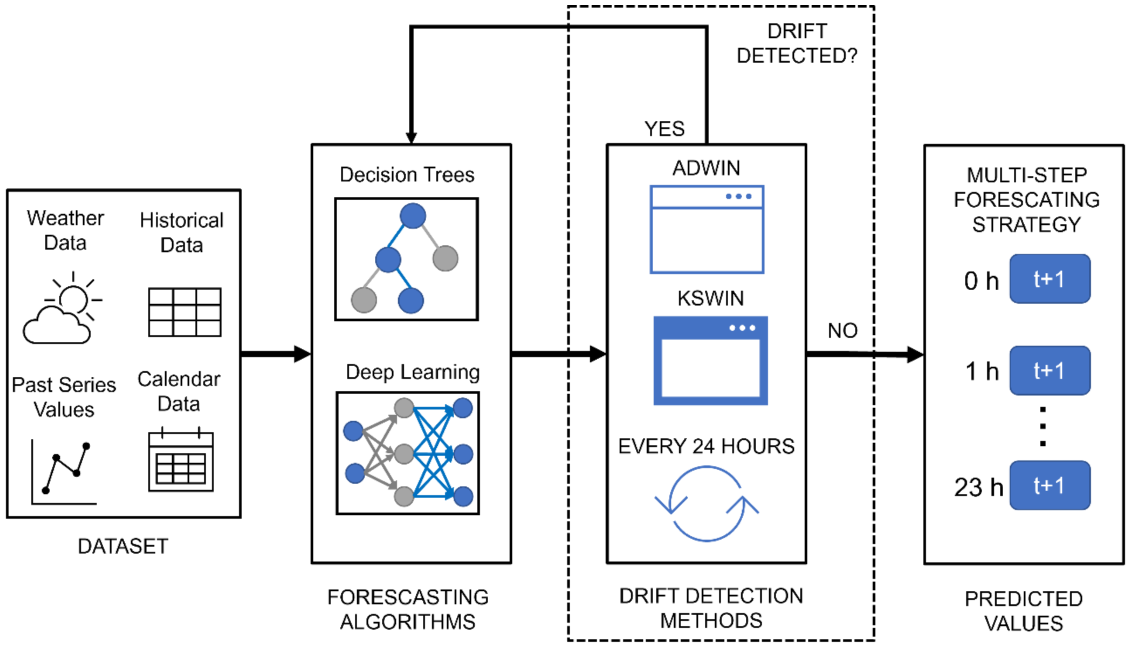

Figure 8. Methodology used for the analysis of the integration of DDM [43].

In the implementation of drift detection methods, two types were used, which were active and passive methods. The passive method consisted of the algorithm retraining every 24 hours regardless of whether a change occurred, while the active methods used were window-based methods such as Adaptive Window (ADWIN) and Kolmogorov-Smirnov Window (KSWIN), which retrain each time a change is detected. With the integration of the drift detection methods into the developed model, the Fourth Partial Objective (PO4) of this thesis was achieved.

1.5.4 Model Validation

As the last stage, the validation of the developed model was carried out using the real data of the electrical consumption of two buildings located on the campus of the University of Valladolid, Spain (see Figure 9). The selection of these buildings was due to the desire to test the model under two different electricity consumption profiles. The first profile corresponding to Building 1 presented a similar consumption during the four years of data that were obtained. The second profile corresponding to Building 2 presented an electrical consumption that was decreasing over the years due to the implementation of energy-saving measures.

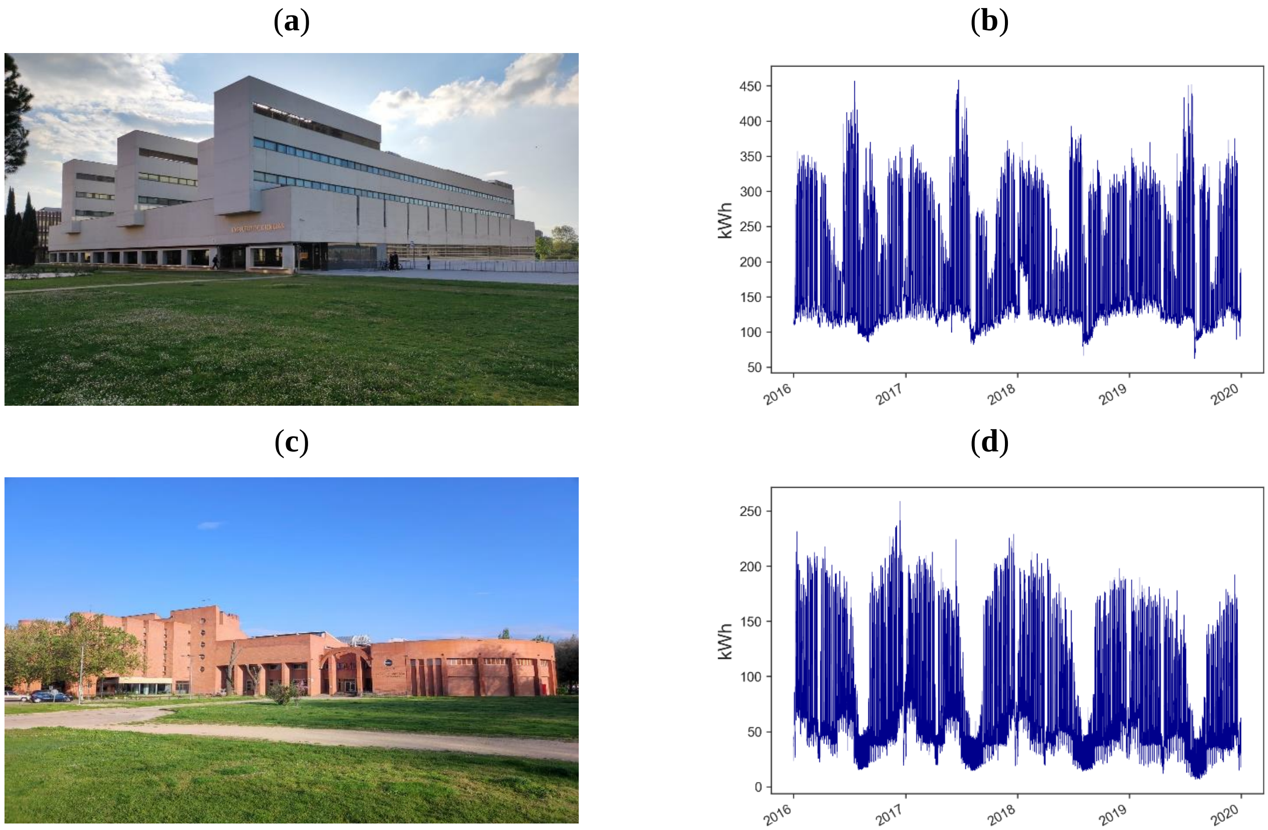

Figure 9. (a) View of Building 1. (b) Hourly electricity consumption for Building 1. (c) View of Building 2. (d) Hourly electricity consumption for Building 2 [43].

The metrics used to evaluate the performance of the model were coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The reason for using these four metrics is because in the case of R^2 it indicates whether or not the model fits the observed values, in the case of the MAE it shows how much inaccuracy we should expect from the forecast on average, in the case of the RMSE because it is in the same unit as the forecast value and in the case of the MAPE it shows a percentage value of the error that facilitates the comparison between algorithms. With the real data of the two buildings as case studies and the selected performance metrics, the Fifth Partial Objective (PO5) of this thesis was fulfilled.

1.6. Results and Discussion

With the investigations that concluded with the review papers [12,41], it was possible to accomplish the PO1, which consisted of the study of the state of the art of the different methods used in forecasting energy consumption in building energy management systems, including their different objectives and future challenges.

Some information of interest that can be obtained from the literature review based on building energy management systems published in the review paper [12] are:

- Non-residential and residential buildings have a typical factor that should be considered for proficient utilization of energy, which is the tenant conduct, which will decide how the system should function.
- About 71.74% of the investigated research endeavors focused on developing building energy management strategies for non-residential, 21.74% focused on residential buildings, and just 6.52% on residential/non-residential buildings.
- About 56.52% of the reviewed investigations in the non-residential concentrate on an HVAC system, which could be because the comfort inside a building relies regularly upon three elements: visual comfort, air-quality comfort, and thermal comfort. Since two of the three components rely upon the HVAC system and the main building energy use happens from cooling and warming systems, it is necessary to improve the usage.
- For residential buildings, just 4.35% concentrate on the HVAC system. Alternately, the investigations concentrate on the whole building or electrical device utilization, this could be because electrical devices are used relying upon the need given by occupants to each load paying little mind to the occasion.

From the review paper [41], which was about a literature review based on energy consumption forecasting in buildings, obtaining the following information:

- About 71.67% of the reviewed studies concentrate on creating building energy forecasting strategies for non-residential, 18.33% concentrate on residential buildings, and just 10% on both.

- Inside the forecasting categories for building energy utilization, the most examined were entire building energy with 63.3%. For entire building energy about 48.3% concentrate on non-residential buildings, 13.3% concentrate on residential buildings, and 1.7% on both. The following categories contemplated were cooling and heating energy with 13.2%. For this category about 8.3% concentrate on non-residential buildings, 3.3% concentrate on residential buildings, and 1.6% on both.
- For the forecasting horizon, about 58.3% of the reviewed studies concentrate on forecasting the short-term, 23.3% concentrate on the long-term, 13.4% concentrate on the very short-term, and 5% on the medium-term.
- About 53.4% of the reviewed research concentrates on utilizing chronicle data and schedule data on the forecasting approach, 41.7% concentrate on utilizing chronicled, climate, and schedule data, 3.3% concentrate on utilizing chronicle, occupancy, and schedule data, and just 1.6% utilize chronicle, climate, occupancy, and schedule data.

With the investigations that concluded with the research paper [42], it was possible to accomplish the PO2, which consisted of the develop a demand forecasting model for applications in building energy management systems.

From the research paper [42], which consisted of the development of a data-driven approach capable of forecasting electricity consumption using historical data, calendar data, climatic data, and past series values as input variables. In addition, a methodology was developed that allowed the developed model to forecast the next 24 hours of electricity consumption from any time of the day, obtaining the following information:

- Using the MAPE as a reference, it is observed that in the first building of the case study the models that gave the best results with the proposed strategy were XGBoost with 8.83%, and TCN with 9.02% while in the second building were CNN with 16.96% and TCN with 17.74%.
- After analyzing all models' behavior for each day, it was found in overall manner that the models keep up with a similar pattern aside from Linear Regression (LR) and Neural Network (NN). For LR, it is because it displays linear connections, which is unmistakably in a tough spot before different models that can catch non-linear connections, while for the NN, it couldn't catch the non-linear connections on explicit days of the week.

- To further develop the outcomes acquired by the models with the proposed strategy, different tests were carried out. The tests consisted of combining the different models to obtain an assembled model. As a general rule, assembled models get better outcomes than single models. The assembled model with a mix of five models was the best one for the first building use in the case study with a MAPE of 7.85% and the second building use in the case study got a MAPE of 15.14% with the mix of four models.

With the investigations that concluded with the research paper [42,44], it was possible to accomplish the PO3, which consisted in the develop an energy consumption forecasting methodology that allows energy consumption to be estimated using a multi-step direct forecasting strategy.

From the research paper [44], which consisted of the comparison between the decision tree algorithm and deep learning algorithm using different multi-step forecasting methods with limited time series data, the following results were obtained:

- Decision tree algorithms trained with small data sets perform better with the method that focuses on forecasting from a particular hour because the data used in the training stage are more specific. Deep learning algorithms trained with small data sets perform better with the method that focuses on forecasting from any hour of the day because the data used in the training stage have a greater variety of data.
- In buildings that are starting to record electricity consumption and the distribution of data remains without sudden changes, decision tree algorithms can be used to forecast electricity consumption to implement demand-side management strategies.
- If the data distribution could present abrupt changes due to energy improvements, the deep learning algorithm would be a better choice since they adapt better to sudden changes.

With the investigations that concluded with the research paper [43], it was possible to accomplish PO4, which consisted of the integration of change detection methods into the short-term demand forecasting model for forecasting the electricity consumption of entire buildings. Additionally, with this article and the two aforementioned articles, it was possible to achieve the PO5, which consisted of the validation of the electricity consumption forecast model developed using real data from several buildings.

From the research paper [43], which consisted of the integration of active and passive drift detection methods into the multi-step forecasting developed model, the following results were obtained:

- The findings show that models based on decision tree algorithms benefited from the integration of passive and active drift detection methods, showing improvement in the results. However, in the case of models based on deep learning algorithms, active drift detection methods only worsened the performance of the algorithms.
- Although the passive method has shown better performance, it cannot be certified with the conviction that it would be better to use it since it is assumed that the behavior of the data would be at a fixed moment, which in reality would not be valid given that the reality could eventually show behavior by different events.
- The results show that the integration of the drift detection methods into the proposed model can maintain or even improve the performance of learning algorithms in situations where there are constant changes in the behavior of electricity consumption in buildings.

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Chapter II. Published Papers

2.1. A Data-Driven Forecasting Strategy to Predict Continuous Hourly Energy Demand in Smart Buildings

This article presents an alternative strategy that uses all the data and makes a forecast for the next 24 hours at any hour of the day and a comparative analysis from a statistical point of view of various machine learning and deep learning models. This research has been published in the following article:

Mariano-Hernández, D., Hernández-Callejo, L., Solís, M., Zorita-Lamadrid, A., Duque-Perez, O., Gonzalez-Morales, L., & Santos-García, F. (2021). A Data-Driven Forecasting Strategy to Predict Continuous Hourly Energy Demand in Smart Buildings. Applied Sciences, 11(17), 7886. https://doi.org/10.3390/app11177886

Published in: Applied Sciences.

Volume: 11, August 2021, 7886.

Received 03 August 2021, Revised 23 August 2021, Accepted 25 August 2021, Available online 26 August 2021.

(This article belongs to the Special Issue on Artificial Intelligence (AI) in Smart Buildings).

Abstract

Smart buildings seek to have a balance between energy consumption and occupant comfort. To make this possible, smart buildings need to be able to foresee sudden changes in the building's energy consumption. With the help of forecasting models, building energy management systems, which are a fundamental part of smart buildings, know when sudden changes in the energy consumption pattern could occur. Currently, different forecasting methods use models that allow building energy management systems to forecast energy consumption. Due to this, it is increasingly necessary to have appropriate forecasting models to be able to maintain a balance between energy consumption and occupant comfort. The objective of this paper is to present an energy consumption forecasting strategy that allows hourly day-ahead predictions. The presented forecasting strategy is tested using real data from two buildings located in Valladolid, Spain. Different machine learning and deep learning models were used to analyze which could perform better with the proposed strategy. After establishing the performance of the models, a model was assembled using the mean of the prediction values of the top five models to obtain a model with better performance.

Keywords: energy consumption; forecasting models; multi-step forecasting; short-term forecasting.

2.2. Comparative Study of Continuous Hourly Energy Consumption Forecasting Strategies with Small Dataset to Support Demand Management Decisions in Buildings

This article presents a data-driven approach that can be used to forecast continuous hourly electricity consumption to support demand management decisions in buildings with limited time-series data and a comparison analysis between a method that forecasts the next 24 hours for all hours of the day and a method that forecasts the next 24 hours for a particular hour. This research has been published in the following article:

Mariano-Hernández, D, Hernández-Callejo, L, Solís, M, et al. Comparative study of continuous hourly energy consumption forecasting strategies with small data sets to support demand management decisions in buildings. Energy Sci Eng. 2022; 1- 14.
https://doi.org/10.1002/ese3.1298

Published in: Energy Science & Engineering.

Volume: 2022, 1-14.

Received: 29 March 2022, Revised: 30 May 2022, Accepted: 22 August 2022, Published: 02 September 2022.

Abstract

Abstract Buildings are one of the largest consumers of electrical energy, making it important to develop different strategies to help to reduce electricity consumption. Building energy consumption forecasting strategies are widely used to support demand management decisions, but these strategies require large data sets to achieve an accurate electric consumption forecast, so they are not commonly used for buildings with a short history of record keeping. Based on this, the objective of this study is to determine, through continuous hourly electricity consumption forecasting strategies, the amount of data needed to achieve an accurate forecast. The proposed forecasting strategies were evaluated with Random Forest, eXtreme Gradient Boost, Convolutional Neural Network, and Temporal Convolutional Network algorithms using 4 years of electricity consumption data from two buildings located on the campus of the University of Valladolid. For performance evaluation, two scenarios were proposed for each of the proposed forecasting strategies. The results showed that for forecasting horizons of 1 week, it was possible to obtain a mean absolute percentage error (MAPE) below 7% for Building 1 and a MAPE below 10% for Building 2 with 6 months of data, while for a forecast horizon of 1 month, it was possible to obtain a MAPE below 10% for Building 1 and below 11% for Building 2 with 10 months of data. However, if the distribution of the data captured in the buildings does not undergo sudden changes, the decision tree algorithms obtain better results. However, if there are sudden changes, deep learning algorithms are a better choice.

Keywords: building energy consumption; forecasting; learning algorithms; multistep forecasting; short-term forecasting.

2.3. Analysis of the Integration of Drift Detection Methods in Learning Algorithms for Electrical Consumption Forecasting in Smart Buildings

This article presents analysis of the integration of drift detection methods in decision trees and deep learning algorithms for whole-building electricity consumption forecasting in smart buildings. This research has been published in the following article:

Mariano-Hernández D, Hernández-Callejo L, Solís M, Zorita-Lamadrid A, Duque-Pérez O, Gonzalez-Morales L, et al. Analysis of the Integration of Drift Detection Methods in Learning Algorithms for Electrical Consumption Forecasting in Smart Buildings. Sustainability 2022;14:5857. https://doi.org/10.3390/su14105857

Published in: Sustainability.

Volume: 2022, 14(10), 5857.

Received: 6 April 2022, Revised: 6 May 2022, Accepted: 10 May 2022, Published: 12 May 2022.

(This article belongs to the Topic Artificial Intelligence and Sustainable Energy Systems).

Abstract

Buildings are currently among the largest consumers of electrical energy with considerable increases in CO_2 emissions in recent years. Although there have been notable advances in energy efficiency, buildings still have great untapped savings potential. Within demand-side management, some tools have helped improve electricity consumption, such as energy forecast models. However, because most forecasting models are not focused on updating based on the changing nature of buildings, they do not help exploit the savings potential of buildings. Considering the aforementioned, the objective of this article is to analyze the integration of methods that can help forecasting models to better adapt to the changes that occur in the behavior of buildings, ensuring that these can be used as tools to enhance savings in buildings. For this study, active and passive change detection methods were considered to be integrators in the decision tree and deep learning models. The results show that constant retraining for the decision tree models, integrating change detection methods, helped them to better adapt to changes in the whole building's electrical consumption. However, for deep learning models, this was not the case, as constant retraining with small volumes of data only worsened their performance. These results may lead to the option of using tree decision models in buildings where electricity consumption is constantly changing.

Keywords: drift detection; electrical consumption forecasting; energy forecasting; machine learning; smart buildings.

Chapter III. Conclusions and Future Work

For the preparation of this doctoral thesis, five scientific articles helped to meet the objectives (see Figure 10). The first and second articles published were two literature reviews, which, although not part of the main core of the thesis, were the bases that allowed the development of the model for forecasting electricity consumption in buildings and helped to achieve the PO1. The third and fourth articles corresponded to the development of the model based on a data-driven approach using a multi-step forecasting strategy so that the developed model was capable of forecasting the following 24 hours, thus achieving the PO2 and PO3. The fifth article corresponding to the integration of drift detection methods allowed the model to be retrained in case the data suffered a sudden change in its behavior, preventing it from becoming obsolete, which helped to achieve the PO4. Regarding the PO5, it was achieved with the third, fourth, and fifth articles, since in each one of them each of the characteristics that were integrated into the model was validated with real data from buildings. By achieving the five partial objectives, the main objective of the thesis could be achieved, which consisted of the development of a model based on a data-driven approach that could be used for load displacement.

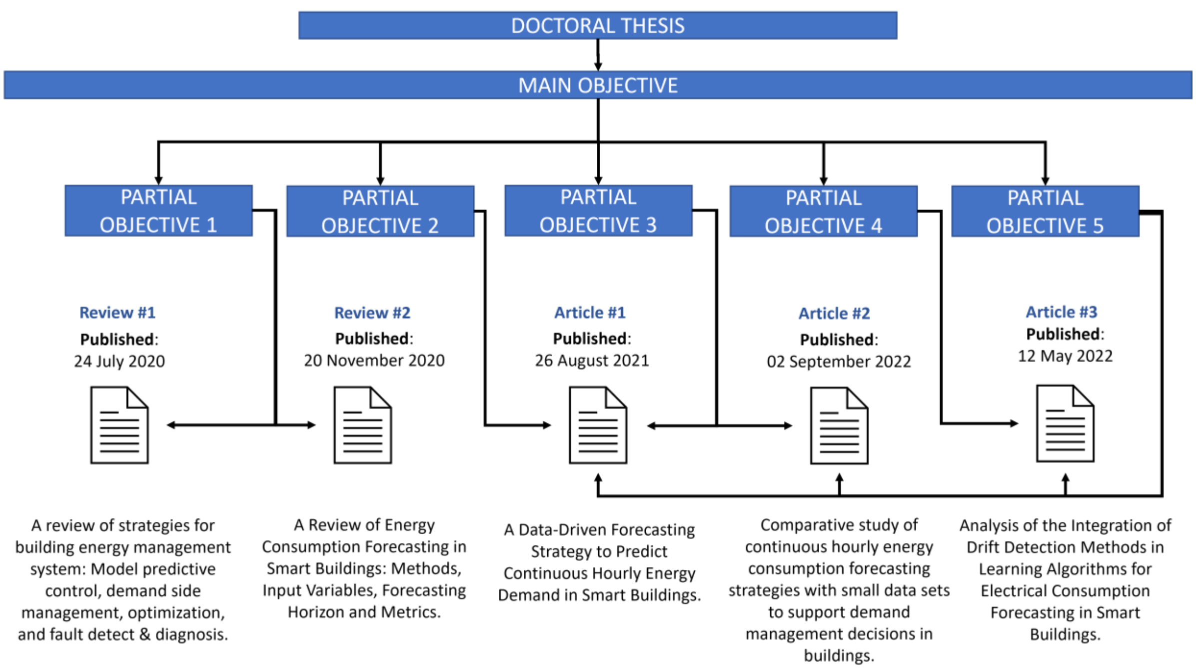

Figure 10. Relationship between the objectives of the doctoral thesis and the articles published.

The research carried out in the first review included in Annex A sought to analyze the different management strategies that are used in the building energy management system in both residential and non-residential buildings. With this article, it was possible to know strategies that were used in buildings and which ones could benefit from an electricity consumption forecasting model. The main conclusions of this review are:

- Most of the studies focused on HVAC systems, prioritizing only decreasing the energy consumption of these systems but leaving aside other buildings subsystem, which may represent a higher consumption depending on the purpose of the building.
- Some research areas may require more consideration: energy consumption prediction models for different subsystems, demand management considering new loads such as electric vehicles, methods that include the behavior of the occupants based on real data, and methodologies that can be applied to both residential and non-residential buildings.

The research carried out in the second review included in Annex A sought to analyze the energy consumption forecasting methods, input variables, forecasting horizon, and metrics that are used in building to improve their energy efficiency. In addition, analyzing the contributions and limitations of different studies focused on each of the energy consumption forecasting methods. With this article, it was possible to observe the different objectives of forecasting in buildings, comparing which types of forecasting categories within the buildings were most used and which methods within the buildings were the most studied. The main conclusions of this review are:

- Most of the studies focused on non-residential buildings utilizing hybrid and data-driven techniques that focus on energy for the whole building, so that all systems in the buildings can be studied, yet utilizing just chronicle data and schedule data as input variables to forecast system utilization.
- Some research points in building energy consumption forecasting might require further reflection, like tenant conduct, which is critical for a more precisely foreseen energy utilization.

The research carried out in the first article that constitutes Chapter II presents a data-driven forecasting approach that allows forecasting continuous hourly energy demand. In addition, different machine learning and deep learning models were compared to analyze which could be better for the proposed approach. With this article, it was possible to develop a strategy that used a dataset composed of historical, climate, calendar, and past series values. It is to later be analyzed in different forecasting models so that it could know its performance and limitations. The main conclusions of this article are:

- Machine learning and deep learning models are significant strategies for building energy consumption forecasting, so important to go with them with procedures that can make the most of these models.
- The proposed technique in the published paper is not the same as other techniques since it can foresee the energy utilization of the following 24h at any hour of the day, which is important to smart buildings and microgrids.

The research carried out in the second article that constitutes Chapter II presents a comparative study to determine, through continuous hourly electricity consumption forecasting strategies, the amount of data needed to achieve an accurate forecast. In addition, analyzes the model developed to support demand management decisions in buildings with limitations in terms of the amount of data. With this article, it was possible to analyze if the developed model could be used in buildings that were beginning to capture historical data on electricity consumption in a building. The main conclusions of this article are:

- For buildings where data distribution does not suffer sudden changes during data capture, a model based on decision tree algorithms would be better to use than models based on deep learning algorithms.
- For the cases where the forecast horizon is one week, it is possible to obtain satisfactory results with 6 months of data. However, in the case where the forecast horizon is one month, 10 months of data is needed.

The research carried out in the third article that constitutes Chapter II evaluated the integration of drift detection methods in models for electric energy consumption forecasting in buildings so that these models can adjust to the changing conduct that has been happening in buildings due to energy-saving measures. In addition, comparison analysis between active and passive drift detection methods for building electricity consumption forecasting. With this article, it was possible to ensure that the developed model could automatically adapt to sudden changes that occurred in the data set, retraining itself at the appropriate times. The main conclusions of this article are:

- In the case of models based on decision tree algorithms, the incorporation of drift detection methods not only allows them to keep up with changes in the data distribution but also improves their accuracy. However, in the case of models based on deep learning algorithms, the incorporation of drift detection methods did not turn out to be as favorable.
- The passive method of drift detection methods was shown to be more effective than the active methods, however, the passive methods require assumptions based on a known prior data distribution, which in some cases would not be possible.

Although it is considered that the objective of the thesis has been achieved, there are still future works that can be carried out. Some of them:

- Improve prediction accuracy through improvements in the composition of the dataset with occupancy data inclusions to improve the adaptability of the forecast when there are radical changes.
- It would be necessary to focus on the integration of drift detection methods that do not computationally penalize models based on deep learning algorithms.
- Implementation of improved forecasting techniques to improve the composition of the dataset so that the algorithms used can better capture the behavior of the time series corresponding to electricity consumption.

Annex A. Additional Publications

A Review of Strategies for Building Energy Management System: Model Predictive Control, Demand Side Management, Optimization, and Fault Detect & Diagnosis

This article presents a literature review on the strategies used in building energy management systems, the limitations of the existing studies on each of the strategies, and the future challenges for the applications of the strategies in smart buildings. This research has been published in the following article:

Mariano-Hernández, D., Hernández-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., & Santos García, F. (2021). A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis. Journal of Building Engineering, 33, 101692. https://doi.org/10.1016/j.jobe.2020.101692

Published in: Journal of Building Engineering

Volume: 33, January 2021, 101692

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Abstract

Building energy use is expected to grow by more than 40% in the next 20 years. Electricity remains the largest energy source consumed by buildings, and that demand is growing. To mitigate the impact of the growing demand, strategies are needed to improve buildings' energy efficiency. In residential buildings home appliances, water, and space heating are answerable for the increase of energy use, while space heating and other miscellaneous equipment are behind the increase of energy utilization in non-residential buildings. Building energy management systems support building managers and proprietors to increase energy efficiency in modern and existing buildings, non-residential and residential buildings can benefit from building energy management system to decrease energy use. Based on the type of building, different management strategies can be used to achieve energy savings. This paper presents a review of management strategies for building energy management systems for improving energy efficiency. Different management strategies are investigated in non-residential and residential buildings. Following this, the reviewed researches are discussed in terms of the type of buildings, building systems, and management strategies. Lastly, the paper discusses future challenges for the increase of energy efficiency in building energy management system.

Keywords: Building energy management system; Building management strategies; Energy efficiency; Energy management system; Energy savings; Smart buildings.

A Review of Energy Consumption Forecasting in Smart Buildings: Methods, Input Variables, Forecasting Horizon and Metrics

This article presents a literature review on energy consumption forecasting in smart buildings, different types of methods used in the forecasting of energy consumption, and current state and future challenges for the forecasting of building energy consumption. This research has been published in the following article:

Mariano-Hernández, D., Hernández-Callejo, L., García, F. S., Duque-Perez, O., & Zorita-Lamadrid, A. L. (2020). A Review of Energy Consumption Forecasting in Smart Buildings: Methods, Input Variables, Forecasting Horizon and Metrics. Applied Sciences, 10(23), 8323. https://doi.org/10.3390/app10238323

Published in: Applied Sciences.

Volume: 10, November 2020, 8323.

Received 19 October 2020, Revised 19 November 2020, Accepted 20 November 2020,
Available online 24 November 2020.

(This article belongs to the Special Issue Artificial Intelligence in Smart Buildings).

Abstract

Buildings are among the largest energy consumers in the world. As new technologies have been developed, great advances have been made in buildings, turning conventional buildings into smart buildings. These smart buildings have allowed for greater supervision and control of the energy resources within the buildings, taking steps to energy management strategies to achieve significant energy savings. The forecast of energy consumption in buildings has been a very important element in these energy strategies since it allows adjusting the operation of buildings so that energy can be used more efficiently. This paper presents a review of energy consumption forecasting in smart buildings for improving energy efficiency. Different forecasting methods are studied in nonresidential and residential buildings. Following this, the literature is analyzed in terms of forecasting objectives, input variables, forecasting methods and prediction horizon. In conclusion, the paper examines future challenges for building energy consumption forecasting.

Keywords: building energy consumption; energy forecast; forecasting methods; smart building.