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Design and performance of an office building in Oslo

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Abstract. With the emerging of smart grids as an answer to the need of sustainability, it rises in relevance the ability to predict the consumption of a building. This is particularly true for offices, where the consumption to guarantee visual and thermal comfort are constantly high. A reliable forecast of electricity usage helps now the energy manager to adjust the scheduling and reduce wastes and in the next future, it will allow the grid operator to prevent peak usage and push demand-response policy. In this paper, we analyzed the strategies already proposed to predict multiple consumption, with a small time granularity. We modelled an office in a building in Oslo by using DesignBuilder software, and exploited EnergyPlus to collect simulated measurements of internal energy absorption from the year 2017 to the year 2019. Firstly, we applied the Energy Signature method twice: with a simple linear regression model and with a multilinear regression model, having the difference between indoor and outdoor temperatures and global horizontal solar radiation as independent variables. The analysis was applied on data sampled at different time intervals: 10 minutes, hourly, daily and weekly. The results show that the best model is the multi linear one obtained with a weekly resolution, with an adjusted coefficient of determination R^2_{adj}=0.93 for cooling consumption and R^2_{adj}=0.90 for heating consumption. Then we built our version of a state-of-the-art deep neural network, composed of a convolutional model and a long short term memory one, trained to predict the next hour given the past one. Lastly, we simultaneously extended both the past window and the forecast period finding that it is possible to predict the next week with **MAE 0.04 kWh** for heating consumption and **MAE 0.02 kWh** for cooling and internal light electricity consumption.

Contents

1 Introduction

In recent years, the attention towards climate change and CO2 overproduction has significantly grown, so it has become more and more important to find ways to minimize waste and increase efficiency when consuming energy.

The object of this study is to find the optimal values for some of the building parameters, such as the windows-to-wall ratio (WWR) or its orientation, with the objective of minimizing its consumption tasking as case study an office located in Oslo (Norway). In order to model the office, we have used the software DesignBuilder: a 3D modeler which integrates EnergyPlus for the simulation of the energy consumption.

After obtaining the optimized office model, we used a combination of a Convolutional Neural Network (CNN) and a Long Short-Term Network (LSTM) for the prediction of 4 variables (heating consumption, cooling consumption, lighting consumption and mean indoor operative temperature), which could be useful to implement automatic heating and cooling systems able to quickly react to environmental changes.

2 Related Work

A lot of studies have been conducted to extract features from energy consumption data and predict electrical energy consumption. There are three categories used for energy consumption forecasting: statistical-based modeling, machine learning-based modelling and deep learning-based modeling.

Amber K.P et al. [3] used multiple regression (MR) and genetic programming (GP) models for the forecasting of daily electricity consumption of an administration building. Both models integrate five important independent variables, i.e. ambient temperature, solar radiation, relative humidity, wind speed and weekday index. They claimed that the GP model performs better with a Total Absolute Error (TAE) of 6% compared to TAE of 7% for MR model. In general, GP model achieved slightly better forecasts, but the training time consumed by the GP model was more than the MR model.

Fumo N. et al. [6] used a multiple linear regression approach to predict the residential energy consumption. Their result shows that time resolution of the observed data strongly affects the performance of the predictive model. The linear regression is straightforward and eliminates unnecessary variables to improve predictive performance stability. However the correlation between independent variables used for prediction might lead to multicollinearity problems.

Mynhoff P. A. et al. [9] did a comparison between the statistical methods and the deep learning based ones, showing how the latter outperforms the former.

Different deep learning neural networks are proposed in literature. A FCM-GWO-BP neural network is proposed by Tian Y. et al. [10], where the fuzzy C-mean clustering algorithm (FCM) helps cluster historical data while the BP neural network prediction is established, optimized by a grey wolf algorithm (GWO-BP) which showed good results in the short term predictions.

Another popular option is the Long Short-Term Memory which has proved suitable for both medium term and short term forecasting. D. Marino et al. [8] analyzed two LSTM-based architectures: a standard one and an LSTM-based Sequence to Sequence architecture. The results show that the standard LSTM has low accuracy in one-minute forecasts while performing well with one hour time steps. The S2S architecture instead performed well with both time steps.

Lastly a group of Seul researchers, compared many famous deep models with an innovative one they proposed [7]. They claim their adaptation of the standard LSTM model into a stacked CNN-LSTM neural network outperforms all the others. In particular this variation shows better results with respect to a Sequence to Sequence architecture for minutely, hourly, daily and weekly time steps. The idea of the model is to use a convolutional neural network (CNN), whose purpose is to pre-process the sequences of the several features and then feed the LSTM layer that will find temporal correlation.

3 Methodology

3.1 Building Design

As case study, a generic office in Oslo has been considered, modelled on DesignBuilder. It was a block of 18m ×8m ×3.5m with two rooms of $64m^2$ and a corridor of $16m^2$. We considered three window configurations to study the effect of their U-value: *single, double* and *triple* glazing. All the surfaces are adiabatic except the ceiling, the internal walls and the walls with windows in them. Two different orientations have been tested: toward North (shown in **Fig.** 1) and toward East. The preferred ventilation of the building is *natural.* It is ON from April 15 until October 15, from 7:00 PM up to 7:00 AM, while the cooling system of the office was set to be active in the same period of the year but from 7:00 AM to 7:00 PM, with set-point equal to 24°C and set-back equal to 28°C. On the other hand, the heating system in the modeled office was scheduled active from September 15th to May 15th, from 5:00 AM to 7:00 PM. Its set-point and set-back were respectively 21°C and 12°C. Additionally, the lights were set be turned ON or OFF automatically depending on the lighting conditions.

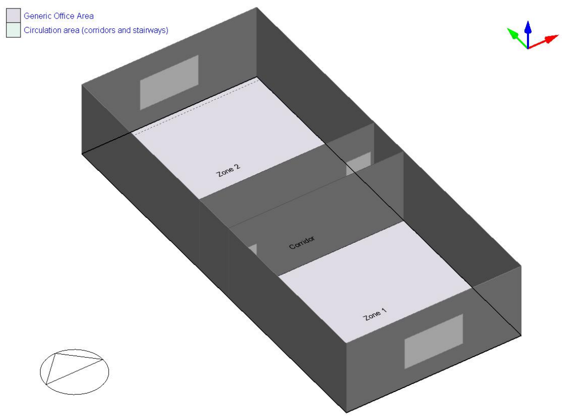


Figure 1: Building envelope of the case study (Oslo Office)

3.2 Parameter Optimization

To obtain the best design in terms of energy consumption we looked into four parameters:

- **Insulation thickness**. This is a proxy of the *U-value* which is the reciprocal of the thermal resistance. A lower U-value also means better insulation. The total thermal resistance R_T can be understood as the sum of the individual thermal resistances of the materials and assemblies (such as windows) who build the layers plus the heat transfer resistances of the external and internal surface, respectively R_{se} and R_{si}.

$$U = \frac{1}{R_T} = \frac{1}{R_{se} + \sum_{i=1}^{n} \frac{d_i}{\lambda_i} + R_{si}} \tag{1}$$

  where λ_i and d_i are the thermal conductivity and the thickness of the $i-th$ layer and n being the number of layers. The insulation thickness chosen for the optimization varied in a range between 0 m and 0.35 m.

- **Window to Wall ratio** (WWR). It is the measure of the percentage area of the building's total glazed area with respect to the exterior envelope wall area. The tested configurations are 15%, 50% and 90%.
- **Orientation**. Different scenarios of orientation of the building. It could be oriented towards North or East.
- **Ventilation**. If the ventilative cooling is On or Of. If the ventilation is ON, it is assumed that the flowrate in each room is maximum.

3.3 Energy Signature

As described in Annex B of the International Standard EN ISO 15603:2008, the **Energy Signature** is an evaluation method that graphically correlates energy consumption with climatic variables. Its scope is that of representing the actual energy behaviour of the building. Indeed, it is also called: thermal performance line or building energy performance line or heat balance equation.

The most common analysis used to perform the Energy Signature is the regression analysis, in which a relationship among *regressand* or *dependent variable* and *regressors* or *independent variables* is found. When dealing only with one regressor, the regression analysis is called *univariate regression*; while when dealing with two or more regressors, the regression is called *multivariate regression*. For the case of Energy Signature, such a relationship is generally modelled with a linear regression: *simple* if the energy consumption is dependent by only one regressor; *multiple* if the energy consumption is dependent by two or more regressors. In the univariate model, the outdoor temperature is considered the most important variable as regressor, but it is also possible to substitute the outdoor temperature with the difference ΔT between indoor and outdoor temperature. Multivariate versions include as further regressors also global horizontal solar radiation (GHI) as well as other weather variables such as wind effects.

The regressand energy consumption can be divided into two main parts: heating and cooling. This is useful to observe the energy performance in two different seasons: summer and winter, in which respectively the heating and the cooling systems are off.

The slope of the regression lines is an important parameter to be considered, since it represents the **Heat Loss Coefficient** K [kWh/°K], that is a measure of the heat lost through the building's envelope.

3.4 Convolutional NN/Long short-term memory

Once investigated the previous work in **Section 2** we decided to build the model proposed by Seoul researchers in [7] that best performed. To understand the reason why they proposed such a peculiar network is worth recall the main functions of the two architectures that they combined.

When referring to *Recurrent Neural Network* (**RNN**) we address a family of architecture that are provided with an internal state. Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs (recursion) that are related with the previous one. Nevertheless, their working iteratively often lead to the phenomenon said "vanishing gradient" due to the explosion of the error, which is amplified at every iteration. *Long Short-Term Memory* (**LSTM**) networks are a modified version of RNN usually composed of a cell, an input gate, an output gate and a forget gate (architecture reported in **Fig. 2**). The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell, understanding what information must be remembered and what can be forgotten. Thank to the regulation obtained with the three gates, the vanishing gradient problem is overcome.

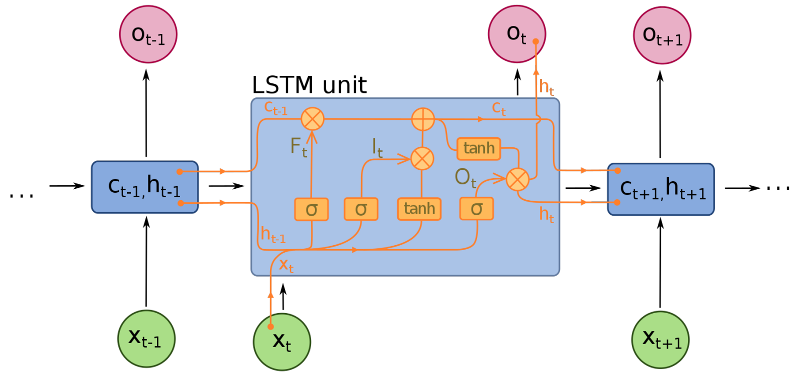


Figure 2: Standard LSTM unit representation

For what concerns the *convolutional neural network* (**CNN**), it is a particular feedforward network in which at least one layer exploits convolution between the input and a set of filters (or kernels). The output of the convolution is activated (and often down-sampled) before being passed to the following layer. This kind of model is famous for its ability in extracting abstract features from the input.

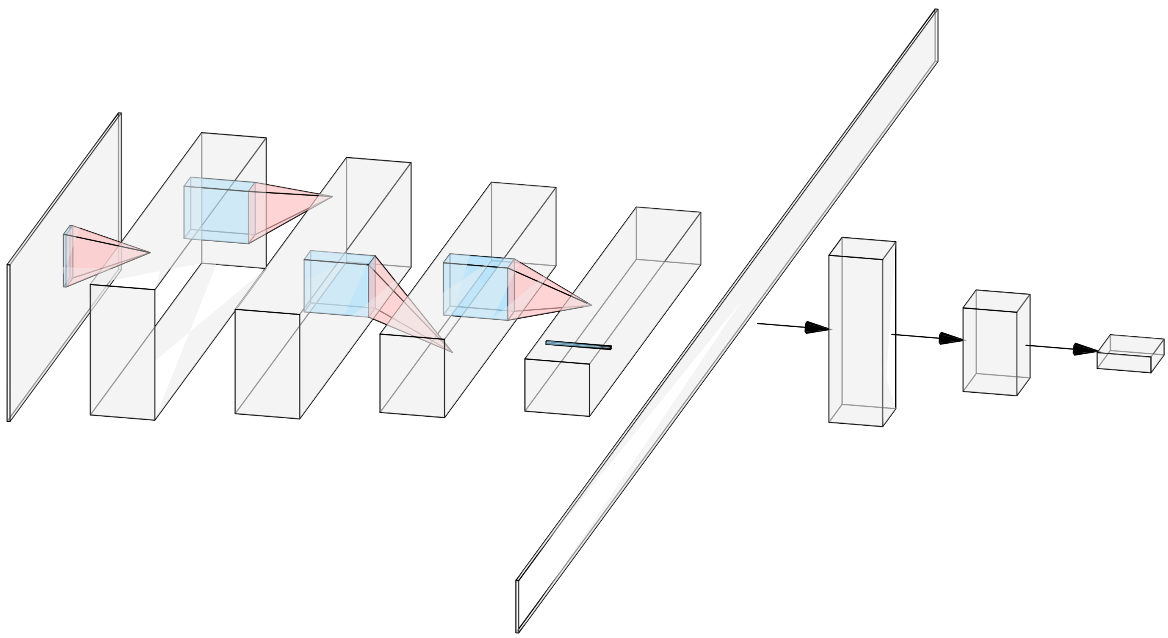


Figure 3: Our proposed model architecture, where the LSTM is fed with the output of the CNN model

The combination of the two models is displayed in **Fig. 3**. As input to the model we will provide a list of past samples (window). The features we are using, are reported in **Tab. 1** and regard weather data, the internal temperature and consumption of the office. Then the convolutional model apply small filters on the columns, generating abstract features from data of the same nature to get rid of trends and spatial correlations. The output of the CNN is flattened

Table 1: The features used to feed the model

#	Attribute	Description
1	Day	An integer value between 1 and 31
2	Month	An integer value between 1 and 12
3	Year	An integer value between 2017 and 2019
4	Hour	An integer value between 0 and 23
5	Minute	An integer value between 1 and 60
6	Outdoor Air Dry-Bulb Temperature [C]	Average temperature measured outside the site
7	Outdoor Air Dewpoint Temperature [C]	Average temperature measured outside the site
8	Outdoor Air Barometric Pressure [Pa]	Average pressure measured outside the site
9	Wind Speed [m/s]	Measured outside the site
10	Wind Direction [deg]	Measured outside the site
11	Diffuse Solar Radiation [W/m2]	Radiation rate per area on windows
12	Direct Solar Radiation [W/m2]	Radiation rate per area on windows
13	Solar Azimuth Angle [deg]	Measured over the site
14	Solar Altitude Angle [deg]	Measured over the site
15	Internal Temperature [C]	Average temperature measured inside the office
16	Heating Setpoint [C]	Minimal temperature desired inside the office
17	Heating Consumption [J]	Office overall consumption for heating

into a smaller number of samples but with many more features and it is provided to the LSTM that will then learn from it the temporal characteristics of the series. Lastly a couple of fully connected layers progressively reduce the number of outputs and perform regression. In **Tab. 2**

Table 2: The proposed CNN-LSTM architecture

Layer (type)	# Filter	Kernel size	Stride	Output shape	# Param
Reshape	-	-	-	(6, 17, 1)	0
Convolution	64	(2, 1)	(1, 1)	(5, 17, 64)	192
Activation (ReLU)	-	-	-	(5, 17, 64)	0
Pooling	-	(2, 1)	(1, 1)	(4, 17, 64)	0
Convolution	64	(2, 1)	(1, 1)	(3, 17, 64)	8256
Activation (ReLU)	-	-	-	(3, 17, 64)	0
Pooling	-	(2, 1)	(1, 1)	(2, 17, 64)	0
TimeDistributed	-	-	-	(2, 1088)	0
LSTM (64)	-	-	-	64	295168
Activation (tanh)	-	-	-	64	0
Dense (32)	-	-	-	32	2080
Dense (6)	-	-	-	6	198
Activation (ReLU)	-	-	-	6	0
Total number of parameters					305894

we report the overall architecture of the proposed network. As discussed in **section 2**, we are adapting to our need the one built from researchers from Seoul. Therefore the input size will be a batch of samples shaped (6,17) and the output will be a list of 6 forecasts obtained throughout the dense layer. Moreover, we added a final ReLU activation layer to force the predictions to be always positive, since our time series never get negative.

4 Results

4.1 Parameter Optimization

4.1.1 Study on Window Glazing

Table 3: Comparison between results of the besos optimization using single, double and triple glazing windows

	U-Value $\left[\frac{W}{m^2 \times K}\right]$	**Lighting** $[kWh]$	**Heating** $[kWh]$	**Cooling** $[kWh]$	**Total Consumption** $[kWh]$
Single Glazing	4.513	6056.01	5606.29	2494.50	14156.81
Double Glazing	2.045	6224.84	5076.79	2608.15	13909.78
Triple Glazing	1.058	6385.55	4787.13	2664.70	13837.39

One of the components of a building which most influences its energy consumption is the glazing. The changes in energy consumption, according to the number of layers in the glazing, are shown in the **Tab. 3**. Each parameter is affected differently according to different types of glazing. In other words, different glazing configurations could bring improvements for specific parameters, while introducing drawbacks in others.

For the interior light, for example, an increase in the number of layers lead to an increase in the electricity consumption of the lighting system because multi-layering prevents the diffusion of light inside the office, so additional lighting is needed and therefore more electricity is consumed.

Heating and Cooling consumption are two other variables which are affected by multi-layered glazing. Heating consumption is inversely correlated with the number of layers. Therefore, if the number of layers in windows is higher, there is less need for heating, which also means a lower energy consumption. On the contrary, having windows with more layers would lead to an increase in the cooling consumption.

To sum up, the effect is not the same for every parameter. That's why total consumption is analyzed in order to finally determine how glazing system affect to the whole system in terms of energy consumption. As it can be seen from the **Tab. 3**, total consumption decreases as more layers are added to the windows (up to the triple-layer configuration). Therefore, the triple glazing system is the one we chose for the windows in our office.

4.1.2 Consumption optimization

A first idea on how each parameter impacts the optimization of the different energy consumption is given by the heatmap in **Fig. 4**.

From the heatmap we can see some strong inverse correlations between couple of variables. The first notable one is between lighting consumption and Window to Wall Ratio that shows how, increasing the window size helps in reducing the consumption, due to more natural light coming through. Another important correlation is between heating consumption and insulation thickness. The ability of a room to retain the heat with the help of the wall insulation helps in reducing the energy consumption due to heating devices. The last strong correlation is between ventilation and cooling consumption. If ventilation is allowed within the building, it helps with reducing the energy consumption due to the cooling systems.

Furthermore, some minor direct correlations can be seen between insulation thickness and cooling consumption for example. Increasing the insulation thickness, while helping retain heat,

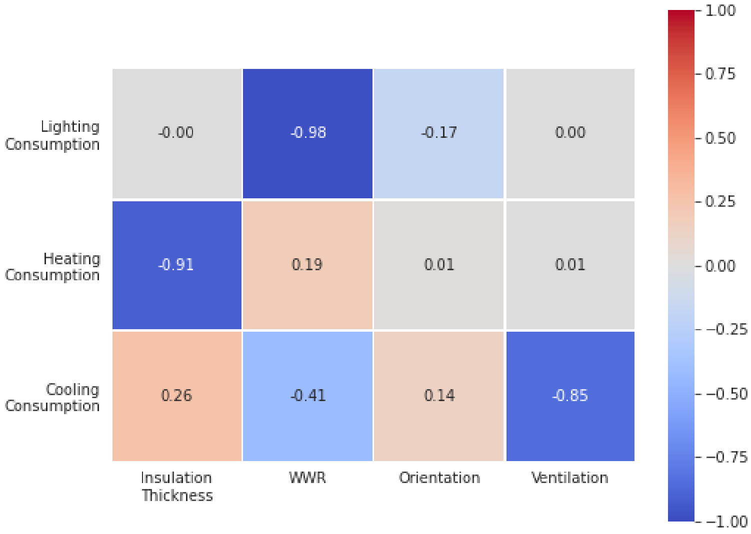


Figure 4: Correlation Heatmap between the power consumption and the analyzed parameters (triple glazing windows)

doesn't allow the space to disperse it, increasing ever so slightly the need of cooling systems. Also the heating consumption is directly correlated to the window to wall ratio since windows are worse insulator than walls and disperse the heat faster. Hence, the higher the width of the windows, the higher is the need of a heating system to keep the space warm.

The orientation of the building also has a slight impact on the energy consumption, notably in the lighting consumption and in the cooling consumption. How much natural light comes though the window and how much of the heat produced by the sun can warm up the room is affected by where the windows are positioned (north or east).

The optimization gave as result:

- **Insulation Thickness**: 0.35 m
- **WWR**: 0.9
- **Orientation**: 90° (East)
- **Ventilation**: ON

    Room 1: 0.665074 m^3/s
    Room 2 : 0.653072 ACH
    Corridor: 0.265087 ACH

This results are coherent with the correlation shown in figure 4. We reach the lowest energy consumption when both *Insulation Thickness* and and *WWR* are set to the maximum of the considered values. The consumption is minimized also by the usage of ventilation, which lowers the need of the cooling system and by the east orientation of the building so that both the rooms can receive as much natural lighting as possible.

4.2 Energy Signature

To perform the **Energy Signature** method, we simulated with EnergyPlus the energy consumption of the best possible building, obtained after the parameter optimization (**Section 4.1**). The weather data file used for the simulation was a modified version of the epw available on the EnergyPlus website [1]. The new weather data were related to the whole 2017 and have been downloaded freely from Weather Underground [2].

From the EnergyPlus output file, we extracted heating, cooling and indoor temperature for each of the three zones of the building and we used the average value among the zones for each variable to perform regression. The available data as well as weather variables values (solar radiation and outdoor temperature) were sampled each 10 minutes.

As shown in [4], to achieve a better linear regression it is useful to consider weekly data of power consumption since it produces a smoothing effect which removes outliers and temporary exceptional behaviors. Therefore, to perform the Energy Signature at different time resolution and comparing results, the available data at 10 minutes of resolution have been resampled and averaged over each time period to obtain the hourly, daily and weekly data for the total energy consumption and weather parameters.

The energy consumption was transformed from Joule to kWh; the difference between internal and external temperatures ΔT was computed in °C and the GHI (Global Horizontal Irradiance) was used in W/m^2.

In this paper, we performed the Energy Signature method twice. Firstly, by modelling separately heating and cooling energy consumption as function only of ΔT. Thus, with a simple linear regression model. Secondly, by adding the global horizontal solar radiation as second regressor. Thus, with a multilinear regression model.

To evaluate the quality of the models, the coefficient of determination R^2, the adjusted coefficient of determination R^2_{adj} and the Root Mean Square Error (RMSE) were used. See **Appendix A** for a deeper explanation on the used metrics.

4.2.1 Single variate Energy Signature

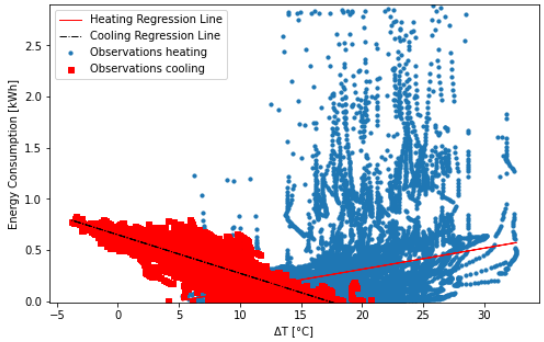
From results in **Tabs 4-5**, we see that quality parameters are best for the model based on weekly time interval. This is true overall for the heating consumption. Indeed, the coefficient of determination passes from 0.064 to 0.871. As also reported in **Section 4.2**, this can be explained because as the resolution in time increases, anomalous climatic conditions and the discrepancies among individual effects in shorter time periods are averaged over longer time periods. **Fig. 5** shows single-variate Energy Signature for different resolutions, from 10 minutes to weekly.

Table 4: Model evaluation for cooling consumption

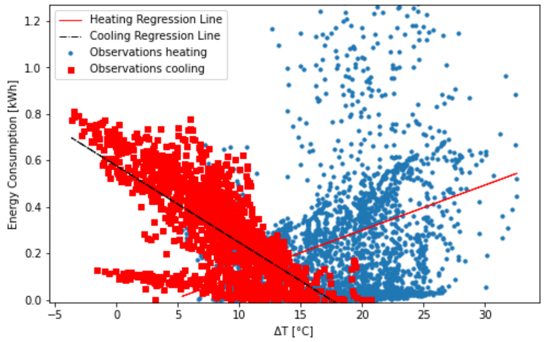
	10 minutes	Hourly	Daily	Weekly
R^2	0.693	0.485	0.702	0.867
RMSE [kWh]	0.105	0.145	0.042	0.018

Table 5: Model evaluation for heating consumption

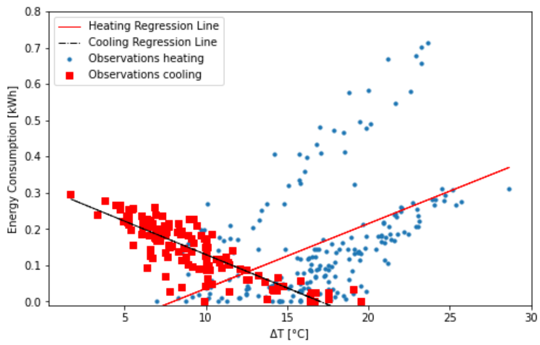
	10 minutes	Hourly	Daily	Weekly
R^2	0.064	0.064	0.239	0.871
RMSE [kWh]	0.372	0.348	0.135	0.030



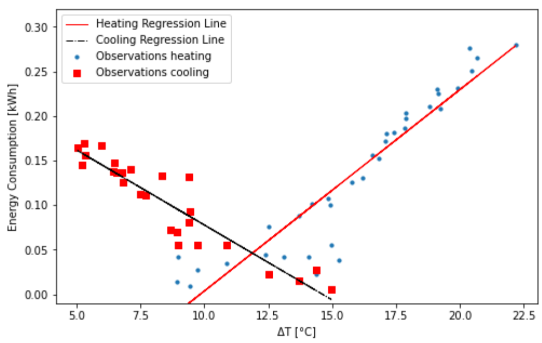
(a) Energy Signature: 10 minutes resolution



(b) Energy Signature: 1 hour resolution



(c) Energy Signature: 1 day resolution



(d) Energy Signature: 1 week resolution

Figure 5: Single Variate Energy Signature

4.2.2 Multivariate Energy Signature

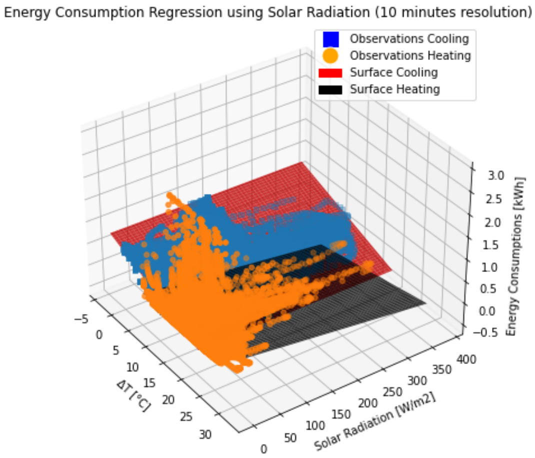
As also stated by Fumo N et al. [6], the multiple linear model using the difference between indoor and outdoor temperatures and solar radiation as regressors offers a better quality with respect to single linear models, as it can be noted from **Tabs 6-7**. Indeed, with a weekly data resolution, the adjusted coefficient of determination reaches values equal to 0.93 and 0.90 respectively for cooling consumption and heating consumption. **Fig. 6** shows the multivariate Energy Signature for different resolutions, from 10 minutes to weekly.

Table 6: Model evaluation for cooling consumption

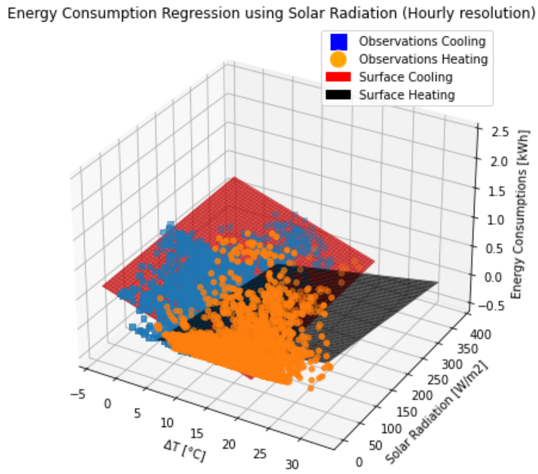
	10 minutes	Hourly	Daily	Weekly
R^2_{adj}	0.693	0.489	0.754	0.933
RMSE [kWh]	0.105	0.144	0.038	0.012

Table 7: Model evaluation for heating consumption

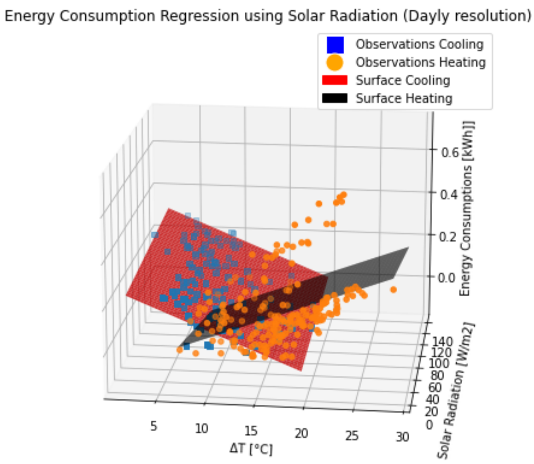
	10 minutes	Hourly	Daily	Weekly
R^2_{adj}	0.087	0.088	0.267	0.902
RMSE [kWh]	0.367	0.343	0.131	0.025



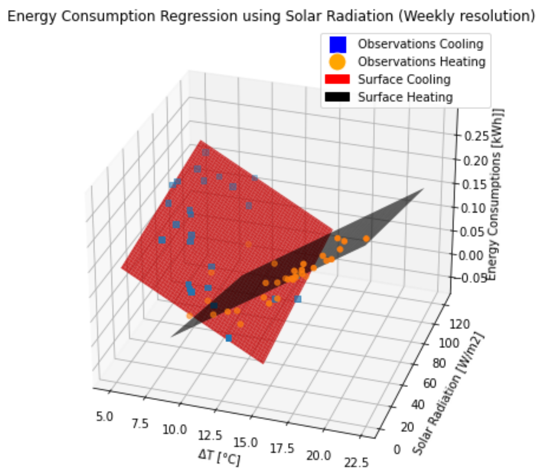
(a) Energy Signature from observed values. 10 minutes of resolution



(b) Energy Signature from hourly resolution



(c) Energy Signature from daily resolution



(d) Energy Signature from weekly resolution

Figure 6: Multiple Variate Energy Signature

4.3 Convolutional NN/Long short-term memory

As mentioned in **Section 3.4**, our prediction task was focused on the following hour, with a sampling resolution of 10 min and keeping a symmetric lag window (i.e. the number of past samples to observe for the prediction), therefore our model had to predict 6 future samples by looking at the previous 6. The training was executed on the years 2017 and 2018, while the test was performed on the year 2019.

In order to have a better understanding of the capabilities of our model we focused our study on the prediction of 4 different variables (having a different network for each one of them):

- Heating consumption [kWh]
- Cooling consumption [kWh]

- Lighting consumption [kWh]
- Mean indoor operative temperature [°C]

As for measuring the performance of the prediction, we have used two types of errors: the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), whose formulae are listed in **Appendix A**.

4.3.1 Dataset creation and training phase tuning

We provided Energy-Plus with the weather data from years 2017-18-19 and with the best performing office idf file; as output we obtained the exact consumption for those years with a time step of 10 minutes. In order to build a proper dataset suitable for the supervised training we extracted from the energy plus output the columns regarding the features and the target values (heating consumption, cooling consumption, energy consumption for interior lights, internal mean temperature). To each entry we also added as extra feature the date and time and the set-points, leading us to a 16 dimension time series. All those features are reported in **Tab. 1**. It is worth mentioning that attributes (15) and (16) were relative to the study of a specific regressed value and were changed according to it.

At this point we have a multivariate time series with the realization of all the variables every 10 minutes, but to feed a neural network it is necessary to provide a test set and list of true target values to evaluate a loss function. In other words, it is necessary to reshape the sequential problem into a supervised one. To obtain a proper dataset we associated a number of samples to the next same number of realization of the consumption. Our first target was to predict one hour given the previous one, then both the window and the number of forecast steps is 6. Then the window was slid by one step, and a new entry of the dataset was generated. From this list of window-forecasts we randomly took out the samples that compose the validation set. Both set were normalized with the "min-max normalization" that already proved to be most suitable for this kind of problem [5].

The training phase was performed applying a shuffle to all the data of the training set after every epoch, and afterwards extracting bathes of size 10 samples. This was meant to force the model to learn from the features and not only from the sequence. The training lasted 30 epochs and was early interrupted only in case the loss over the validation set stopped decreasing for a while.

4.3.2 Heating consumption

As it can be seen from **Fig. 7a**, the network had a good prediction despite struggling with the highest consumption peaks registered at the beginning of each week. Moreover, the noise lead the network to predict some consumption even in the periods in which the heating system was supposed to be inactive. Having a look at **Fig. 7b** it is possible to check the good overall ability of the network to properly model the heating consumption. In fact, the performance metrics, which are displayed in **Tab. 8**, are quite good and satisfactory for the prediction of this particular parameter.

Table 8: Performance metrics on the prediction of the heating consumption

MAE [kWh]	RMSE [kWh]
0.0167	0.0827

4.3.3 Cooling consumption

As mentioned in **Section 3.1**, in order to reduce the consumption of the A/C system, we adopted a cooling strategy based on natural ventilation, which is activated when the office is empty (i.e. at night and during weekends). For this reason, unlike what happened with the heating, there was not a consumption peak at the beginning of the week because the office was already cooled down. As it can be seen in **Fig. 8a**, the network did a good job at modeling the cooling consumption, without making any severe errors. Also analyzing a shorter period of time, like in **Fig. 8b**, we find that the predicted values are very close to the real ones, with only some minor errors with the network predicting little consumption during weekends, even if the system is off. Despite this, the performance metrics in **Tab. 9** are still good for the prediction of A/C system.

Table 9: Performance metrics on the prediction of the cooling consumption

MAE[kWh]	RMSE[kWh]
0.0034	0.0155

4.3.4 Lighting consumption

As mentioned in **Section 3.1**, the lighting strategy for the office was to use an automated system which turned on or off the lights depending of the illumination conditions. Considering that the location of the studied office is Oslo, during the Winter we expect only few hours -if any- where the natural light would be enough. On the other hand, during Summer, it is more likely that the artificial lighting would not be necessary for most of the day. The aforementioned difference is clearly spotted in **Fig. 9a**, where a slight decrease in the consumption happens during Summer. Regarding the prediction of such consumption, it can be seen that the network well performed, with only some overestimation, especially in the second semester. Taking a closer look at the consumption in the month of July in **Fig. 9b**, we notice that also in this case some consumption was predicted during weekends where the lights were supposed to be always off. Despite some minor errors tough, the performance metrics in **Tab. 10** demonstrate that the prediction was good, also due to the high periodicity of this particular variable.

Table 10: Performance metrics on the prediction of the lighting consumption

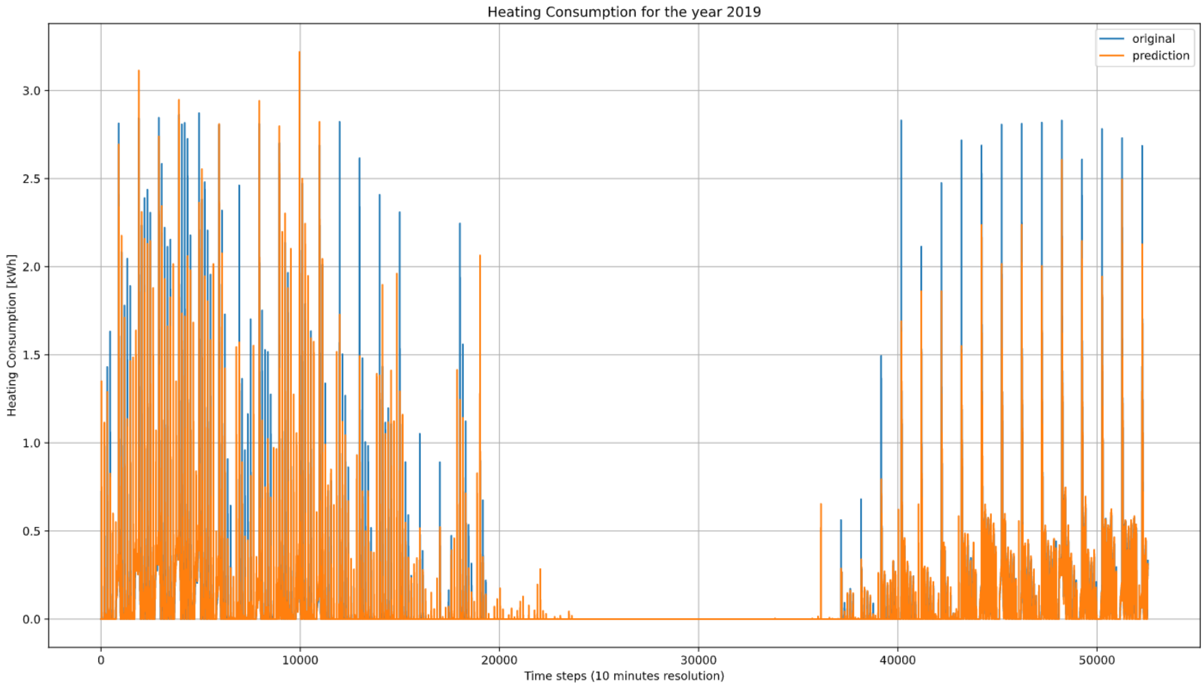
MAE [kWh]	RMSE [kWh]
0.0076	0.0378

4.3.5 Mean indoor operative temperature

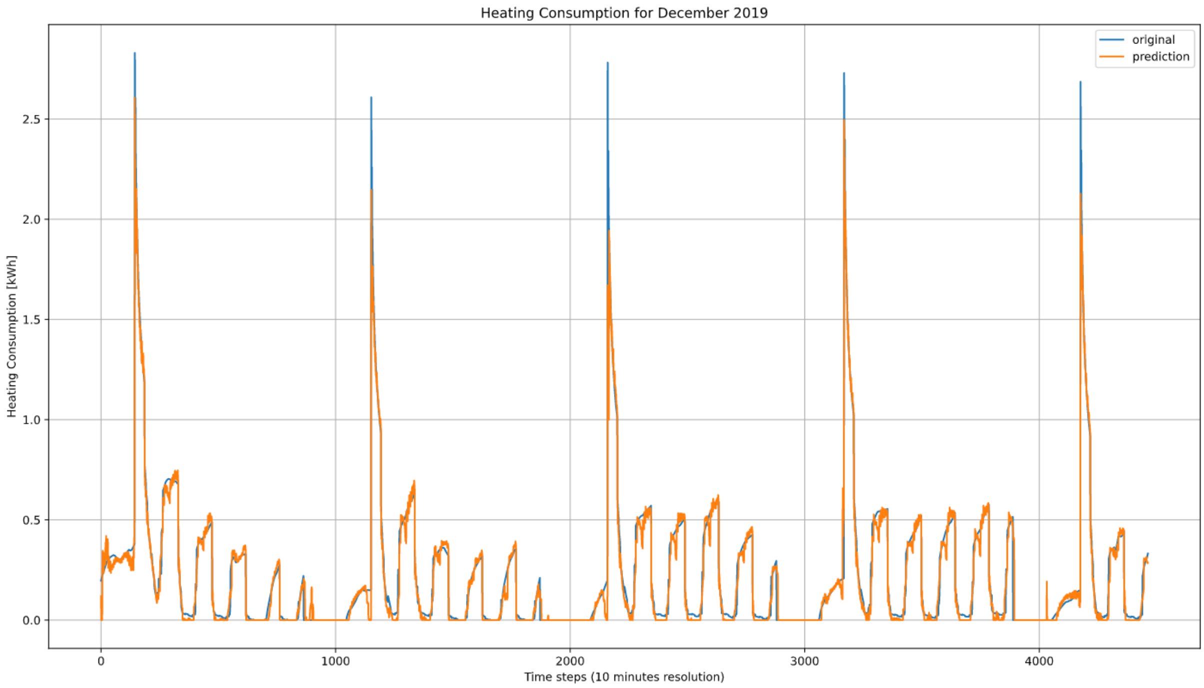
The mean indoor operative temperature was computed as the mean of the operative temperatures of the 3 zones in our office. This parameter is of great importance as it is one of the key elements to be properly controlled in order to have an adequate level of comfort. As it can be seen in **Fig. 10a**, unlike in the prediction of the consumption parameters, in this case the network was able to perform an almost perfect prediction. In fact, also looking at a smaller period in **Fig. 10b**, it can be seen that the predicted values and the real values are very close and the errors are almost negligible. This statement is also supported by the performance metrics listed in **Tab. 11**.

Table 11: Performance metrics on the prediction of the mean indoor operative temperature

MAE [°C]	RMSE [°C]
0.1098	0.2537

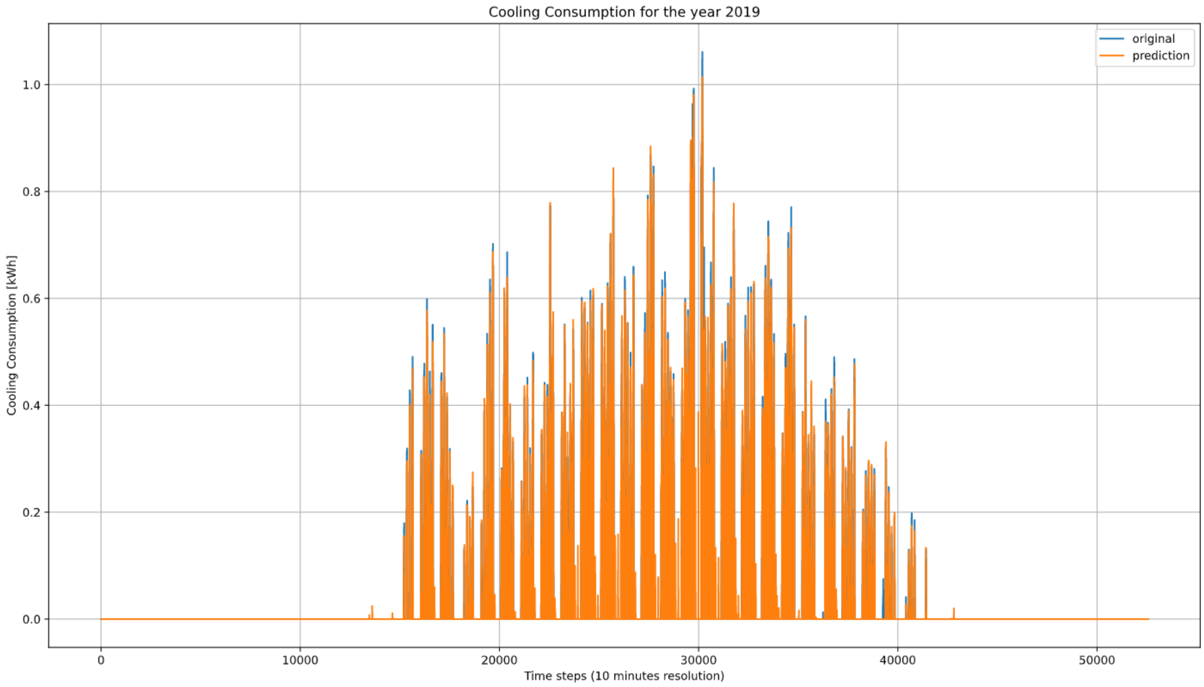


(a) Heating Consumption for the year 2019

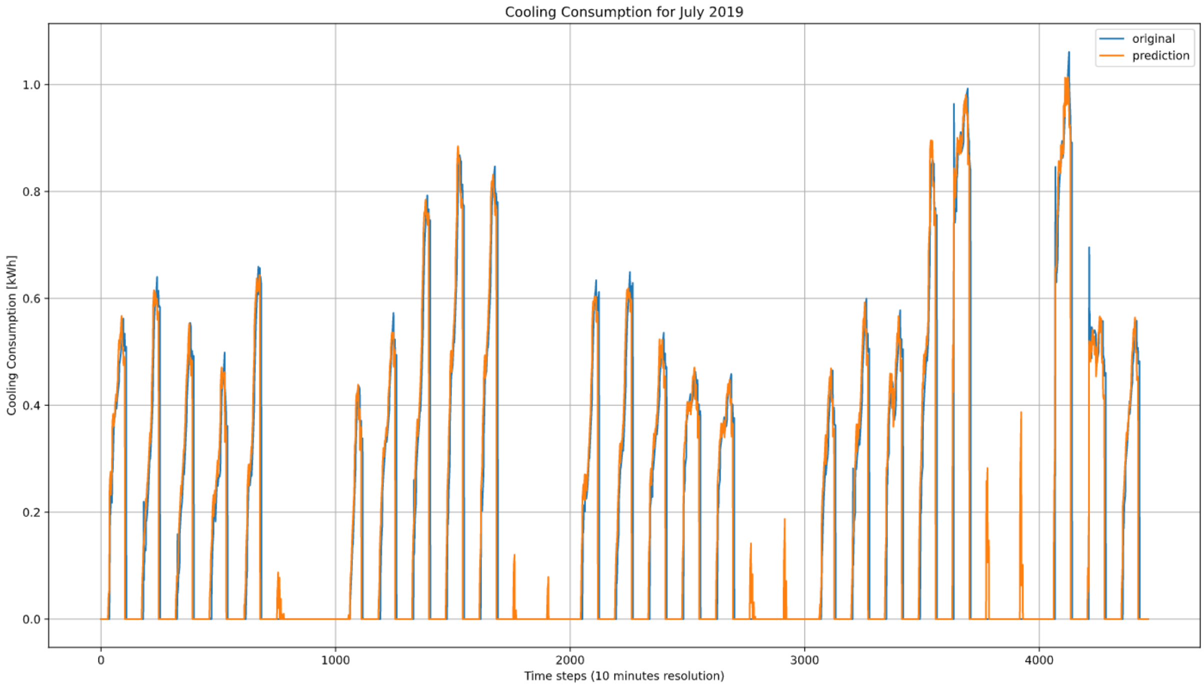


(b) Heating Consumption for December 2019

Figure 7: Heating consumption predictions versus true values

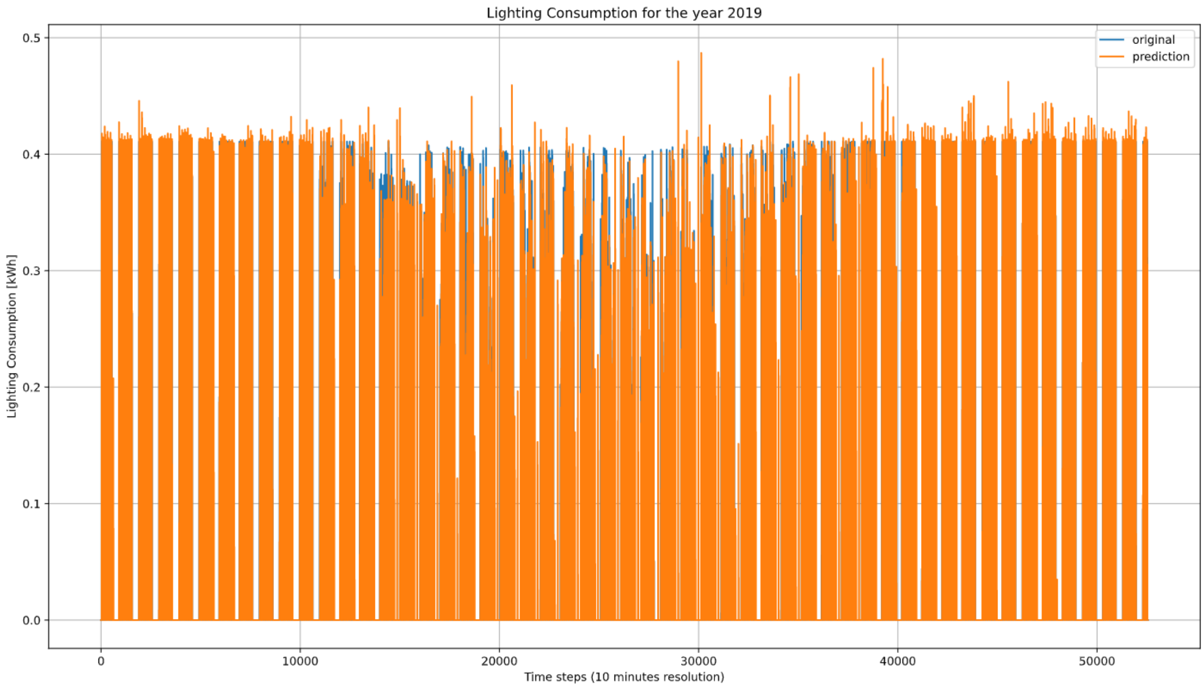


(a) Cooling Consumption for the year 2019

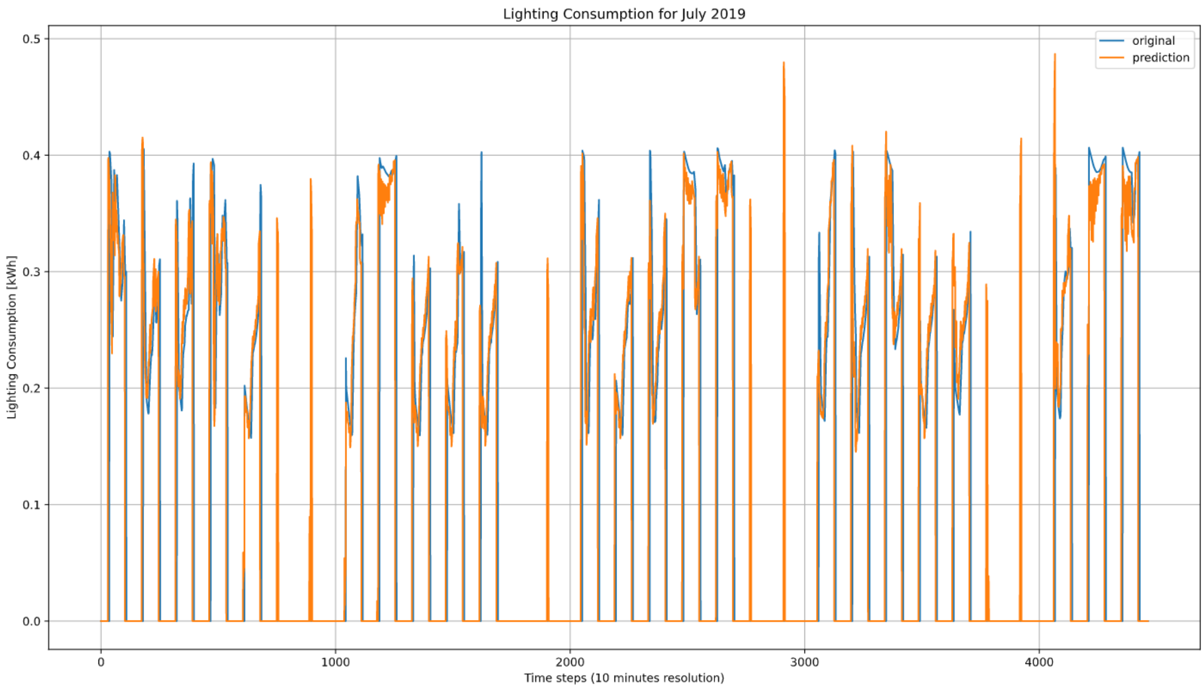


(b) Cooling Consumption for July 2019

Figure 8: Cooling consumption predictions versus true values

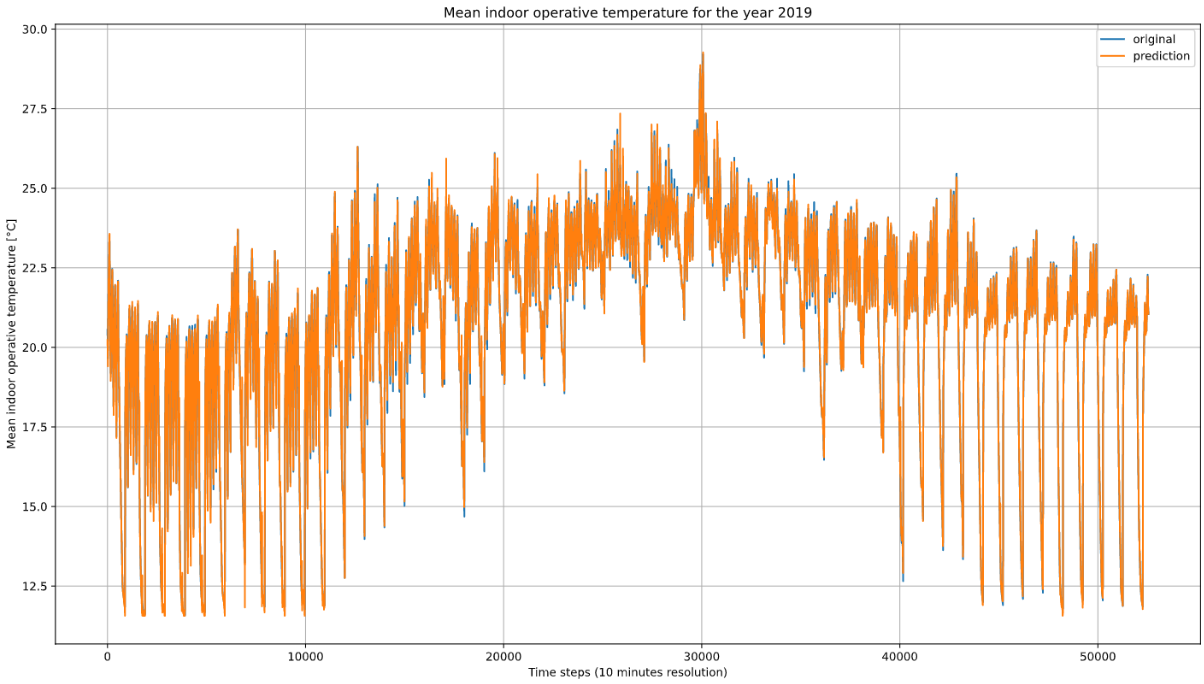


(a) Lighting Consumption for the year 2019

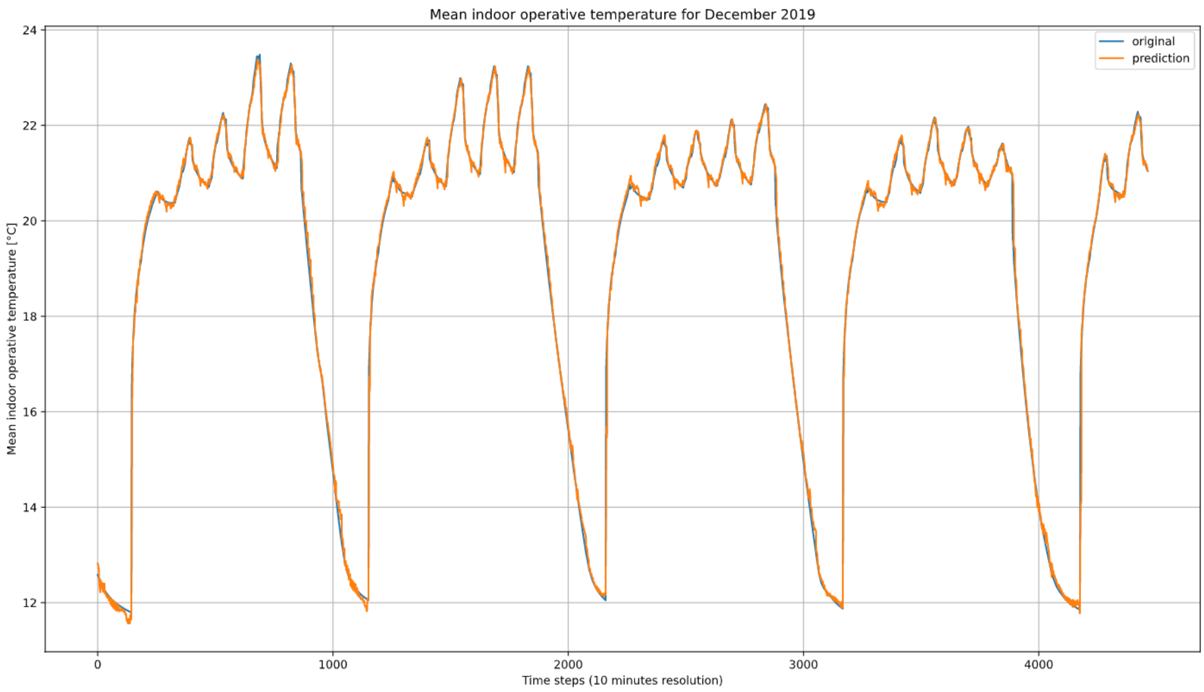


(b) Lighting Consumption for July 2019

Figure 9: Lighting consumption predictions versus true values



(a) Mean indoor operative temperature for the year 2019

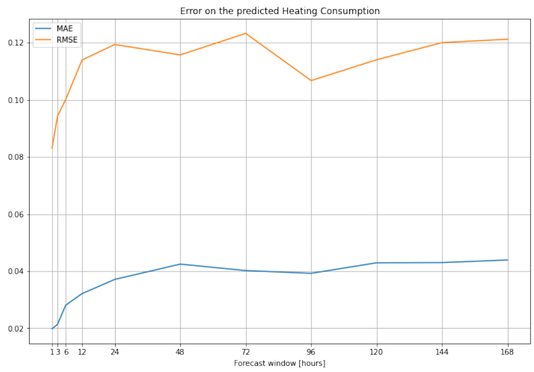


(b) Mean indoor operative temperature for December 2019

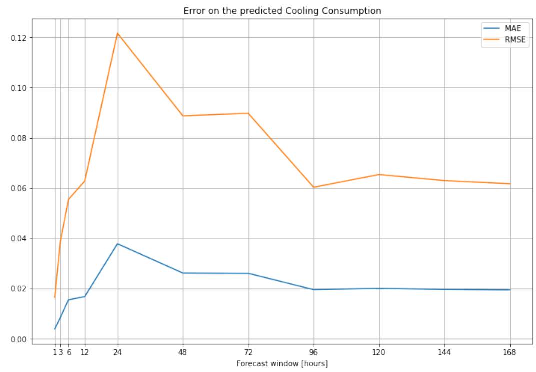
Figure 10: Mean indoor operative temperature predictions versus true values

5 Discussion

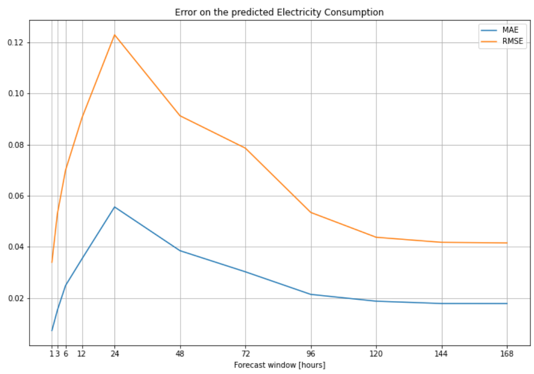
In the emerging smart grids network it will be useful to be able to predict with good confidence the next future consumption, this is particularly crucial for the demand-response approach to prevent peak of usage. There are many proposed approach, some of which are direct, with the grid operator forcefully capping the consumption, while other are indirect, pushing users to save energy during peak hours with adaptable price tables. We tried then to extend the prevision window to understand how our model behave in more demanding situation. The chosen windows were 1h, 3h, 12h, 24h, 48h, 72h, 96h, 120h, 144h and 168h.



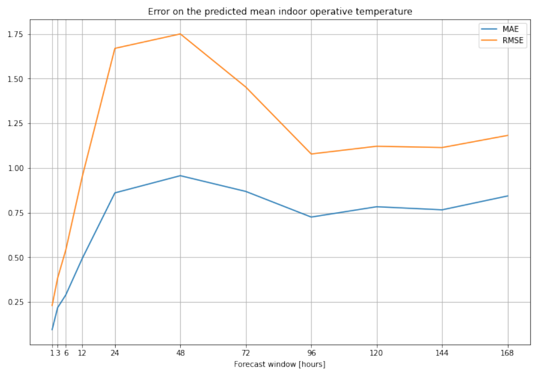
(a) Errors on the Heating Consumption prediction



(b) Errors on the Cooling Consumption prediction



(c) Errors on the Lighting Consumption prediction



(d) Errors on the mean indoor temperature prediction

Figure 11: Errors on the prediction of the 4 variables for different forecast windows

Looking at **Fig. 11**, an interesting trend can be spotted. In fact, with the exception of the heating consumption's, all the other predictions presented an initial increase of the error, followed by a decrease when the forecasting window was greater than 24/48h. It should be mentioned that our approach was to keep the look-back window symmetric to the forecasting one, i.e. the number of past samples given as input to the LSTM was kept the same as the number of forecast samples. It is highly likely that due to the periodic behaviour of the predicted variables, once more samples are given as input, it becomes easier to make a longer term forecast. On the other hand, the heating consumption does not show this trend, probably due to its higher variability, which also led to worse results in the previous sections. Nevertheless, from the obtained results, it is evident that our model can also be used for mid to long-term predictions, keeping in mind that the error would be slightly higher.

6 Conclusions

This paper presents a model, i.e. a CNN-LSTM neural network, aimed at the forecasting of energy consumption of an administration building. Our case study referred to an office located in Oslo (Norway). We designed the office based on optimized U-value and WWR. The optimized parameters where, as expected, the highest possible, since the higher the insulation and the window to wall ratio, the better the heat is retained and there is lower need for heating and cooling systems.

We performed the Energy Signature method for the optimized building, with data sampled at four different resolutions: 10 minutes, every hour, every day and every week. As illustrated from the results, as the time interval of the observed data increases, the quality of the models improves. This is explained by the fact that for longer time periods, the discrepancies among individual effects in shorter time periods are averaged over longer time periods. Moreover, the solar radiation as a second predictor variable shows improvement of the coefficient of determination.

The proposed neural network had good predictions with respect to Mean indoor operative temperature ($MAE = 0.1096$ kWh) and cooling consumption ($MAE = 0.0034$ kWh). Further analysis on features might increase the prediction accuracy due to null values in the time series that might skew the results, even if it didn't affect that much our outcome. Actually most of the noise in predictions is probably due the high variance in Oslo weather. Moreover, given the trends observed in **Fig. 11**, we can suppose that a training window longer than 24 hours would have led to better results even on short time prediction. The crucial result is that the neural network performed only slightly worse by increasing the prediction horizon. Indeed, the MAE over the predicted internal temperature after 168h (1 week) is less than 1 °C. This might be useful for more elastic applications.

A Model evaluation parameters

As parameter to evaluate the quality of the simple linear model of fitting to the given set of observed data, the coefficient of determination R^2 can be considered:

$$R^2 = [Corr(Y, \hat{Y})]^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \tag{2}$$

where:

$[Corr(Y, \hat{Y})]^2$ is the *correlation coefficient*

$\sum(y_i - \hat{y}_i)^2$ is called *sum of squared errors*

$\sum(y_i - \bar{y}_i)^2$ is called *total sum of squares.*

The value of R^2 varies between 0 and 1.

For the multiple linear regression model instead, the adjusted coefficient of determination R^2_{adj} can be considered. It is defined as:

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-(k+1)} \tag{3}$$

where:

n is the number of sample data contained in the dataset

k is the number of regressors (2 in the case of this paper)

As further parameters to measure the quality of the fitting, the root mean square error (RMSE) and mean absolute error (MAE) are also calculated. The former is computed as:

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \tag{4}$$

The latter is computed as:

$$MAE = \frac{\sum|y_i - \hat{y}_i|}{n} \tag{5}$$

where:

y_i is the true value of the data

$\hat{y}_i$ is the regressed value of the data

n is the number of sample data contained in the dataset

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