Optimization and prediction of the energy consumption and internal temperature of a residential building in Torre Pellice

ICT in Building Design - A.Y. 2021-22

Professors

Giacomo Chiesa

Lorenzo Bottaccioli

Student Group 3

Huang Kai s273741

Ni Maoquan s295796

Wang Di s275509

Yu Yenchia s287513

Master Degree in ICT4SS, Politecnico di Torino

February 13, 2022

Contents

Abstract

The energy consumption in buildings accounts for a significant part of total global energy use. In order to reduce the energy consumption, the optimized architectural characteristics is essential. In this paper, we have studied the effects of several parameters and then find the optimum solution through BESOS that minimize the energy consumption, using a residential building located in Torre Pellice as study case. Furthermore, we have visualized the energy behavior in terms of energy signature and performed 1-hour ahead prediction of the energy consumption using different models including Recurrent Neural Network(RNN) based on Long Short-TermMemory(LSTM) layer, Convolution Neural Network(CNN) and Prophet.

Keywords: Energy consumption; BESOS; Energy signature; Energy consumption prediction; Artificial neural networks; LSTM; Prophet.

1 Introduction

As the exponential population growth and urbanization increase since the last century, the present way of living of human beings rises an important issue of climate change and energy crisis. Therefore, environmental sustainability has become an indispensable topic world-widely at nowadays. Sustainability encourages us to switch to renewable energy, as well as to reduce the consumes and waste by using the energy in a more efficient and effective way. As well-known, the building sector has a large part of responsibility of the overall energy consumption (approximately 40% of energy consumption and 36% of CO2 emissions in the EU (European Commission, 2018)). Umberto Berardi [2] has pointed out the global energy demand in buildings could be doubled by 2050, as well as the insufficient of current policies to significantly reduce the building energy consumption. Hence making efforts to increase the energy efficiency and reduce the energy consumption in this sector have great potential benefits for sustainability.

Buildings can differentiate into variety types such as office buildings and residential buildings. For office buildings the energy consumption is concentrated in working hours while for residential buildings that is higher in the morning before going to work and at evening after work time. In any case, the purpose of the energy consumption is to provide the thermal comfort, a better indoor air quality as well as the visual comfort by means of heating, ventilation, and air conditioning(HVAC) systems, shading, glazing and other architectural characteristics. Moreover, the environmental parameters such as air temperature, humidity of air, air relative velocity, mean radiant temperature(MRT), outdoor light level, etc. also play a significant role in energy consumption of buildings. It is worth to mention that, building as a system, whose functions of each component are inter related, every choice of a single component may influence other components and many functions.

In this view, focusing on a residential building located in Torre Pellice as study case, the objective of this paper is to study the effects of several architectural characteristics including the insulating layer(U-value), window glazing, shading, ventilation and to find an optimum solution from the point of view of minimizing the energy consumption. The energy behavior of the building in terms of energy signature then were presented by simulating of the smart meter. Furthermore, to predict the the energy consumption using different methods, to compare and to visualize the results, which would be helpful to the advance of energy efficient, are also main objectives. For the prediction we adopt several models including Recurrent Neural Network(RNN) based on Long Short-Term Memory(LSTM) layer, Convolution Neural Network(CNN) and Prophet. Finally we had some discussions based on the results of the experiment.

2 Literature review

In recent years there have been many studies devoted to energy consumption and forecasting in building sector.

The analysis of building energy consumption can start from building attributes. Barbaresi [1] assessed the influence of five architectural characteristics on the thermal performance including external walls, roof, glazing, shading and building orientation in a case study industrial building, it turns out the influence of each characteristic is effected in a significant way by the chosen temperature range and by the conditioned or unconditioned scenarios. Angel Rico [7] introduced entropy generation rate to describe energy efficiency in buildings and found out the sun irradiance is the most important entropy generation source, from which the importance of shading system can be evidently seen. Rajeev Kamal [5] exhibited strategic controls by shifting peak electricity demand of a HVAC system utilizing thermal energy storage to lower operational costs. This study discovered a 10-17 percent total cost reduction and a 25-78 percent yearly peak shifting. Both suppliers and consumers profited from the cost savings without incurring any performance penalties. The internet of things(IoT) has recently contributed to the advancement of technologies to manage the consumption of the building energy systems. Giacomo Chiesa [3] has developed a smart ventilation system, the system has adopt a data-driven approach, using distributed IoT platform to control and monitor the indoor air quality(IAQ), it achieved an objective of ensuring IAQ comfort levels at low cost not only from an economic point of view but also from the energy consumption point of view.

In term of energy prediction, Marjan Ilbiegi [4] has proposed a deep learning neural network to forecast and optimize energy consumption. Several artificial neural network(ANN) models were trained to calculate the required energy, which was then optimized using the Galapagos plugin's Genetic Algorithm approach. The results showed that the Genetic Algorithm saves 35% of energy. While X.J. Luo [6] has proposed a novel clustering-enhanced adaptive artificial neural network (C-ANN) model to forecast day ahead building cooling demand. In this model the annual datasets are categorized into featuring clusters, each cluster is adopted to train one ANN sub-model, the optimal structure and parameters of each ANN sub-model are selected according to its featuring training datasets, thus the ANN sub-models are adaptive. The model has been tested that having 4.2% and 3.1% improvement in mean absolute percentage error of the training and testing cases compared to conventional ANN model with a fixed structure. On the other hand R.sendra-Arranz's purpose [8] was to anticipate short term forecast of the power time series based on the previous data in order to feed a future demand-side management system. The prediction models are RNNs based on LSTM layers. The results demonstrate that forecasting power consumption one day ahead of time has lower accuracy than forecasting power consumption one hour ahead of time, yet the error is acceptable. The findings are positive in terms of predicting real-time energy use in buildings.

3 Methodology

3.1 Building design

As case study, a residential building located in Torre Pellice(residential 3) has been considered. The building has been modeled on DesignBuilder software as shown in Figure 1. The building is divided into ten zones including one bedroom, one kitchen, one lounge, two bathrooms and one corridor zone, as well as three spare rooms could be considered as study or storage rooms. Note that there are two types of external wall having different thickness, the thickness of the uninsulated Wall for zone 3 and zone 8 is 30cm, while for other zones the thickness is 53cm.

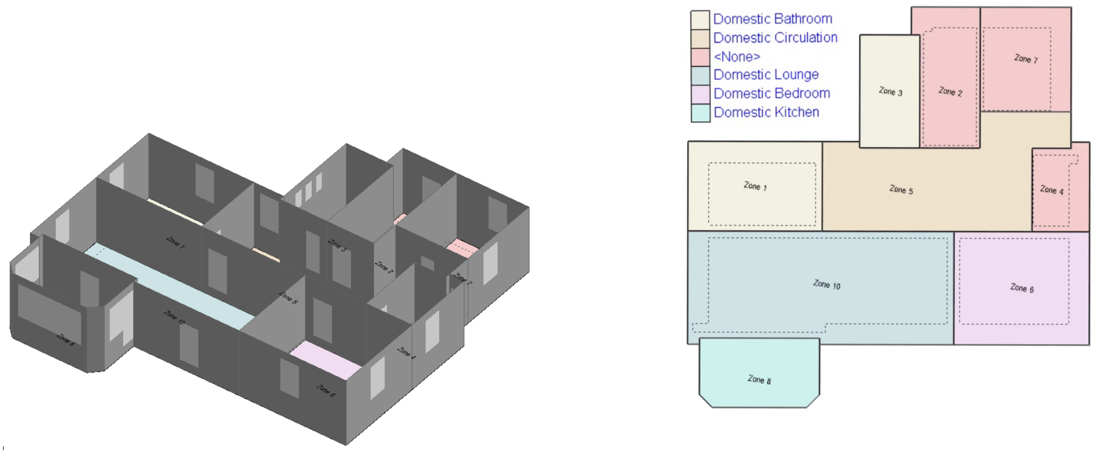


Figure 1: Case study - Residential 3

Considering the specific climate in Torre Pellice, schedules of the HVAC system of the building been adopted are shown in Table 1. Noted that, the heating system in winter are scheduled as from 15th Oct. to 30th Apr. and the cooling system in summer are scheduled as from 1st May. to 14th Oct..

3.2 Parameters optimization

The energy consumption of a building is for sure influenced by its components, in this project we focus on the following elements:

Table 1: Schedules of the HVAC system

	For weekdays	For weekends	For holidays
Winter heating	Until: 05:00, 0.75 Until: 10:00, 1 Until: 15:00, 0.75 Until: 24:00, 1	Until: 07:00, 0.75 Until: 23:00, 1 Until: 24:00, 0.75	Until: 07:00, 0.75 Until: 21:00, 1 Until: 24:00, 0.75
Summer cooling	Until: 05:00, 0.5 Until: 10:00, 1 Until: 15:00, 0.5 Until: 24:00, 1	Until: 07:00, 0.5 Until: 21:00, 1 Until: 24:00, 0.5	Until: 07:00, 0.5 Until: 21:00, 1 Until: 24:00, 0.5

- External wall. By changing the thickness of the insulating layer for the external walls, it is able to change the U-value of the walls. Different values of thickness in domain [0-0.35m] are adopted, and the related U-values are calculated.
- Window glazing. For windows we have tried single, double and triple glazing windows, and the related U-values are calculated.
- Shading system. The shading system has two states, ON and OFF. It will on OFF state until the predefined threshold is reached. We have adopted two strategies of shading thresholds. One is to set the threshold according to temperature, which is in range 20°C - 28°C, the other one is according to the solar irradiation, which is in range 80W/m^2 - 300W/m^2.
- Ventilation system. Natural ventilation has been considered and different values of ACH in domain [0-6] are adopted.

For each possible combination of these elements we have obtained an idf file, then together with the weather data we have performed simulation using EnergyPlus. By varying different values and different combination through BESOS, the influence of these elements on the energy consumption can be seen, and the optimal parameters that minimize the energy consumption can be chosen accordingly. The according results are shown and discussed in Chapter 4.1.

3.3 Visualization and Energy signature

The visualization of multiple metrics in a building management system (BMS) is a good approach for users to monitor the status of the buildings in real time. The outcome is advantageous for energy conservation, long-term planning, and building maintenance.

3.3.1 Visualization

We developed a simulation of sensors collecting meteorological and energy data and transmitting it over MQTT, with InfluxDB functioning as the MQTT subscriber, at this stage. The temperature of the time series, as well as the amount of heating, electrical, and cooling energy used, are all saved in the database after that. Then, using Grafana as a visualization tool, plot the data's trend over time.

Figure 2 shows the temperature inside the building and outdoor air temperature. We have discovered that the temperature within the house is rather consistent. The temperature differential between indoors and outdoors is significant in the winter. We require heating in winter to keep the indoor temperature within the human body's comfortable zone.

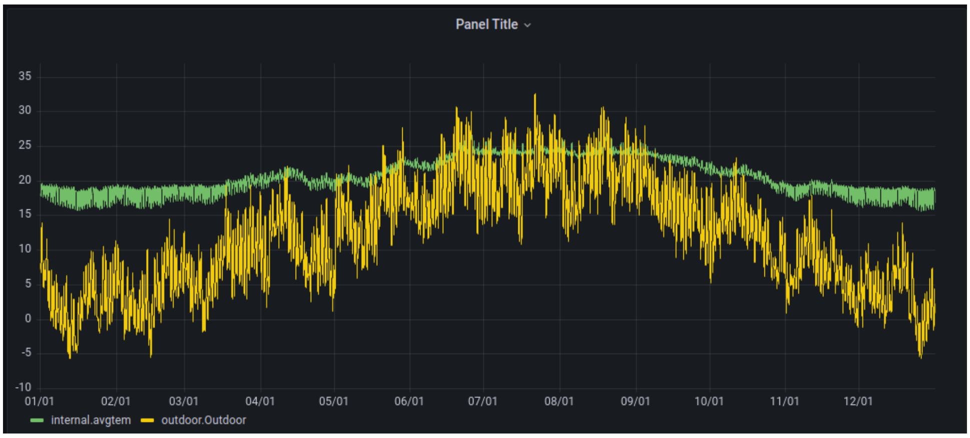


Figure 2: Indoor and outdoor temperature

Figures 3 and Figure 4 depict the annual cooling and heating energy in 2005. Torre Pellice is a northern city with a colder climate, which demands the heating system working longer (from 15/10-30/04). The utilization of cooling systems can be reduced in the summer due to cooler ambient temperatures.

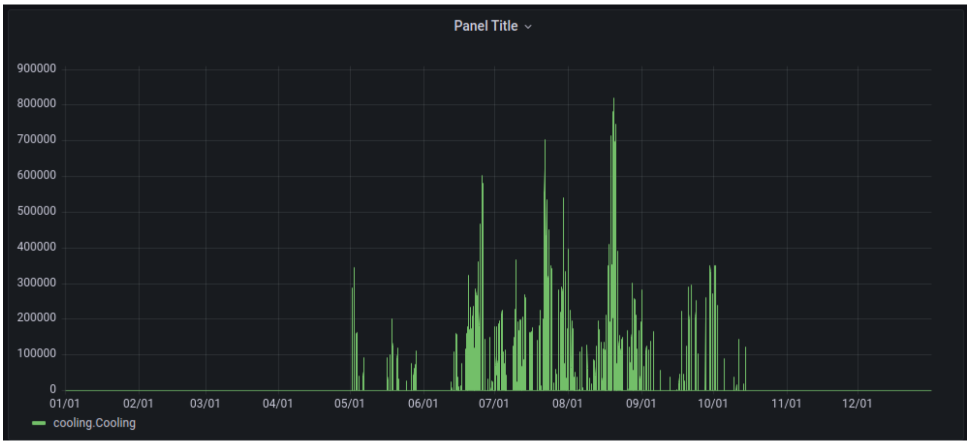


Figure 3: Annual cooling energy consumption in 2005

Figure 5 shows a graph comparing the energy consumption for heating and cooling. In our residential, heating consumes significantly more energy than cooling throughout the summer.

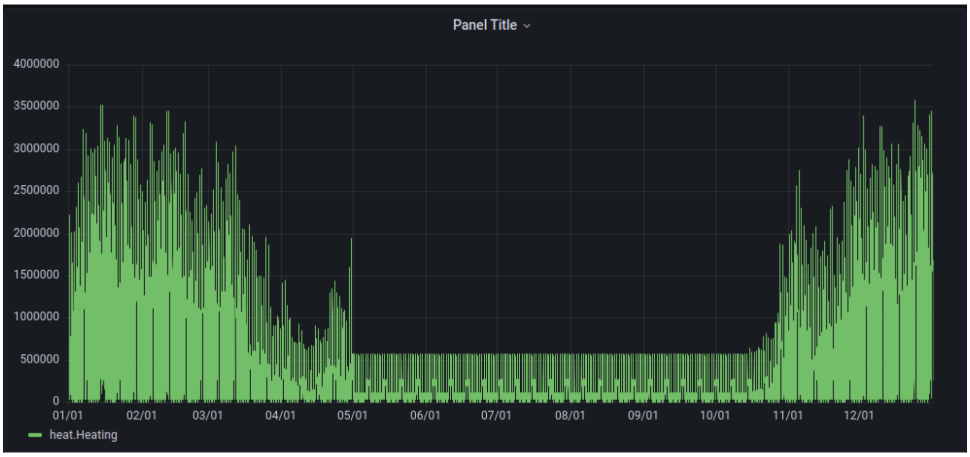


Figure 4: Annual heating energy consumption in 2005

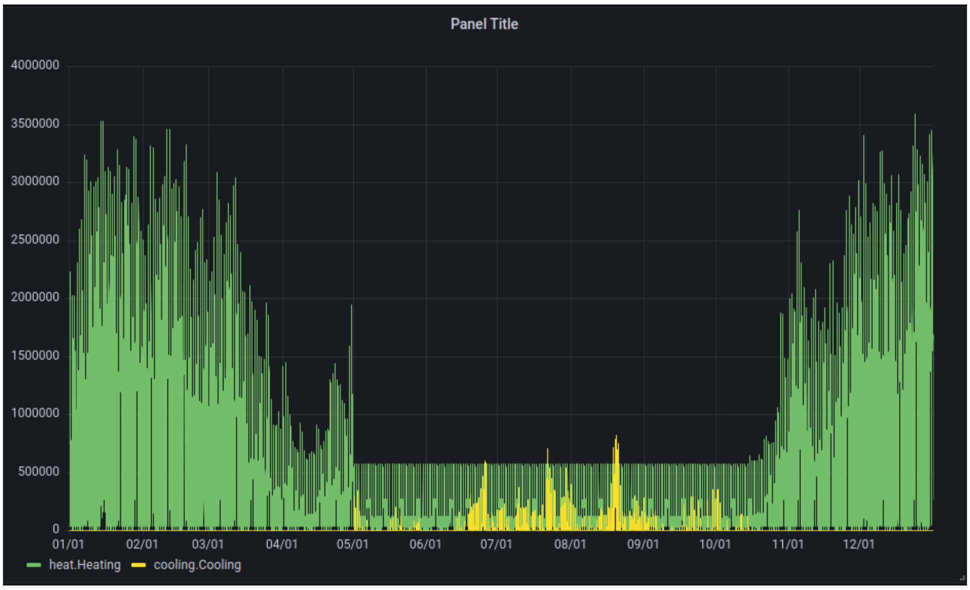


Figure 5: Comparison of the energy consumption for heating and cooling

3.3.2 Energy signature

The Energy Signature is a method of evaluation in which energy usage relates to climatic data in order to show the building's actual energy behavior. We apply these parameters in our building when we've optimized the settings, and then we get updated weather data for the entire year of 2005 from the website Weather underground. From influxDB, we retrieved heating, cooling, and the temperature differential between inside and outside. It is useful to remove outliers if there is no heating schedule in the summer and no cooling schedule in the winter in order to produce a better linear regression. After that, we ran the Energy signature at various time resolutions by resampling the data from hourly to daily and weekly to see how different sample means performed. This stage involves unit conversion: the energy consumption unit is changed from Joule to kWh, and the temperature differential is reported in °C.

3.4 Prediction

To predict the the energy consumption and indoor temperature in the building would be helpful to the advance of energy efficient and thermal comfort. We have adopted several methods to perform prediction, moreover, for each model we have chosen different size of training dataset, i.e. the length of time period in which the data are used for the model to perform prediction, as well as different time horizon of the prediction, i.e. to predict the internal temperature of the following 1 hour, 6 hours and 12 hours. At the end, it is possible to compare the final results.

3.4.1 Recurrent neural network (RNN)

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed or undirected graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. It is a type of neural network well-suited to time series data. RNNs process a time series step-by-step, maintaining an internal state from time-step to time-step. In our implementation, single LSTM(Long Short-Term Memory) layer is used to predict near future(1 hour in the future) as Figure.6 shows. When prediction in the further future is needed, a "single-short" model will be applied to the original neural network in order to make the entire sequence prediction in a single step(as Figure.7 shows).

3.4.2 Convolution neural network (CNN)

A Convolution neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing, classification, segmentation and also for other auto correlated data. Meanwhile, there are many types of CNN models that can be also used for specific types of time series forecasting problem. In our implementation, for near future(1 hour) forecasting problem, a single convolution layer and several dense

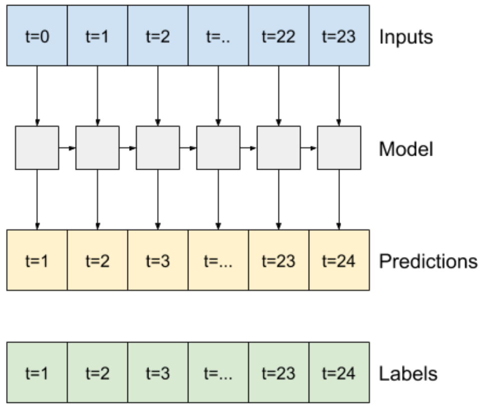


Figure 6: RNN - single step prediction

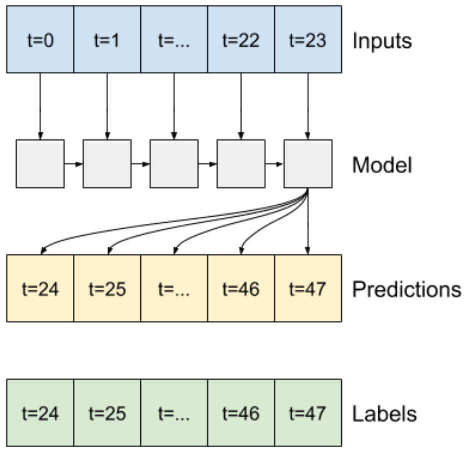


Figure 7: RNN - multiple steps prediction

layers are used to build the neural network. As Figure.8 shows, the convolution layer takes multiple time steps as input to each prediction. In the case of predicting further future, the "single-short" model will also be applied. The convolutional model makes predictions based on a fixed-width history as Figure.9 shows.

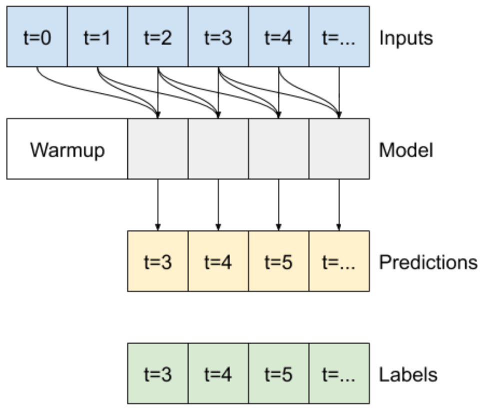


Figure 8: CNN - single step prediction

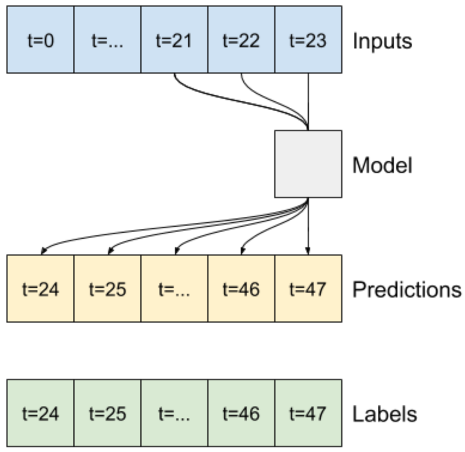


Figure 9: CNN - multiple steps prediction

3.4.3 Prophet

Prophet is a procedure for forecasting time series data proposed by Facebook [9], based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. It is fully automated, and no manual effort is required to obtain an acceptable forecast on messy data. Prophet is also robust to outliers, missing data, and dramatic changes in time series.

The model is mainly composed of three components, as shown in equation 1.

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

$g(t)$ is the trend function which models nonperiodic changes in the value of the time series, $s(t)$ represents periodic changes (e.g., weekly and yearly seasonality), and $h(t)$ represents the effects of holidays which occur on potentially irregular schedules over one or more days. The error ϵ_t represents any idiosyncratic changes which are not accommodated by the model. Other regressors can also be used with this model, but the additional regressor must be known for both the history and future dates. So the regressor must either be something with known future values or something that has been forecasted separately elsewhere. In this case, we didn't use any additional regressors.

4 Results

4.1 Parameters optimization results

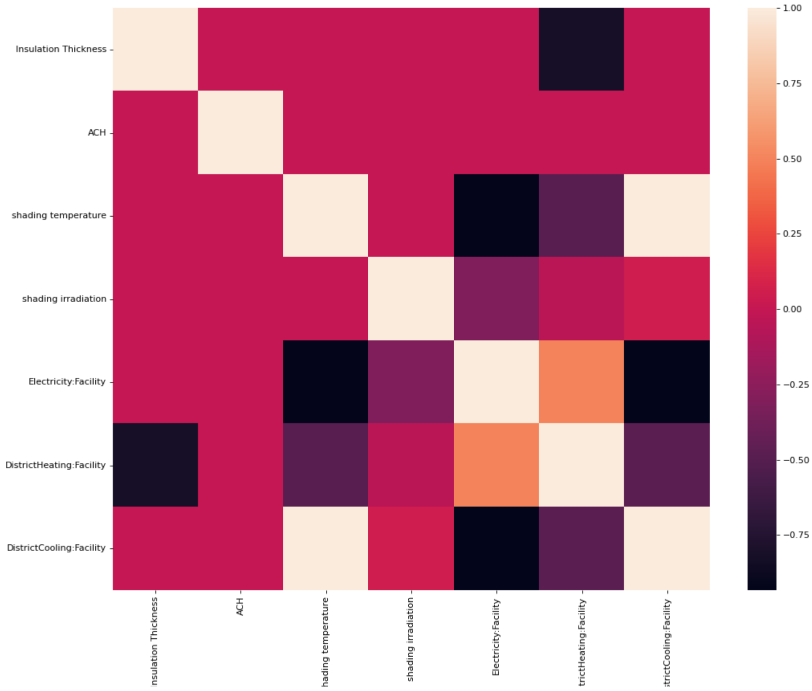
We have simulated different combinations of parameters to obtain the correlation matrix as shown in Figure 10(b) - glazing parameters including U-value, light transmission and solar heat gain coefficient (SHGC) and in 10(a) - other parameters. In Figure 10(a) we can see that insulation thickness have strong correlation to the heating system, the greater the thickness, the better it can insulate the indoor environment so to reduce the heating energy demand. Moreover, the electric usage is strongly correlated to shading system since when the threshold of shading is lower the artificial lights have to be used more to maintain the indoor illumination comfort. The consumption of cooling system is directly related to the shading temperature threshold since in summer the sun irradiance is the most important heat generation source. In Figure 10(b), the glazing parameters are clearly correlated with each other, and they are both correlated to electricity, heating and cooling energy consumption.

The optimized parameters and the corresponding energy consumption are shown in Table 2.

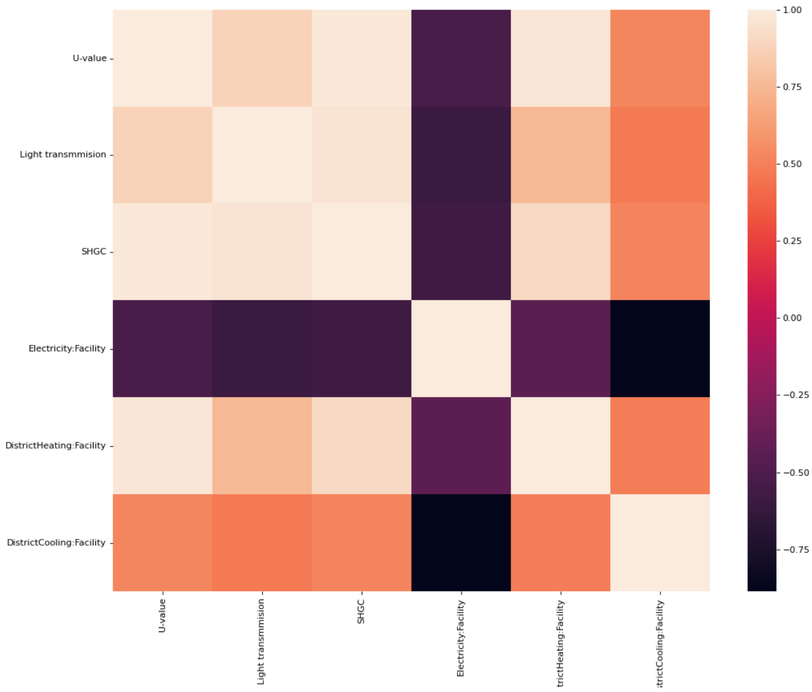
The detailed analysis are reported in Chapter 4.1.1 for insulating layer, Chapter 4.1.2 for window glazing, Chapter 4.1.3 for ventilation and Chapter 4.1.4 for shading system.

4.1.1 Insulating layer

As mentioned in Building design chapter 3.1, there are two types of external wall having different thickness, 30cm for zone 3 and zone 8, 53cm for other zones. Table 3 shows the thickness of insulating layer and the corresponding U-value for both two types of the external wall. From which it can be seen that the thickness of the uninsulated wall would affect the U-value, but the influence is relatively limited compared to the thickness of insulating layer.



(a) Other parameters



(b) Glazing parameters

Figure 10: Correlation heatmap between considered parameters and energy consumption

Table 2: The optimized parameters and annual energy consumption

Insulation Thickness	ACH	shading temperature	shading irradiation	glazing layers
0.35m	6	20°C	120W/m^2	2

Annual energy consumption[KWh]			
Electricity	Heating	Cooling	Total energy consumption
2468.725	6932.033	902.052	10302.809

Table 3: Thickness of insulating layer and corresponding U-value

Thickness of insulating layer[m]	U-value[W/m^2K] (53cm Wall)	U-value[W/m^2K] (30cm Wall)
0.05	0.429	0.490
0.10	0.263	0.285
0.15	0.190	0.201
0.20	0.148	0.155
0.25	0.122	0.126
0.30	0.103	0.106
0.35	0.090	0.092

In the common sense, when the U-value of insulating layer becomes smaller,the better-insulated a structure is, which leads to less energy consumption. To see how exactly the insulation thickness affect the energy consumption of the entire apartment, a controlled variable simulation is done in which the thickness of insulation layer varies from 0.05m to 0.35m and other parameters keep as default value. As Figure.11(left) shows, the total energy consumption of the apartment decreases as the insulation thickness increases. However, it is interesting to see that as the thickness increases, the cooling consumption increases(as Figure.11 right shows).The possible reason could be that the apartment is located in mountain area where the outdoor temperature changes significantly between day and night. When the thickness of insulation layer becomes larger, it is less capable to cool down the apartment using outdoor low temperature, which leads to the increase of cooling energy consumption.

4.1.2 Window glazing

As a component of building envelope, external window affects the performance of several aspects of the building.

Different types of window glazing have different transmittance and U-values. however, due to material limitations, multilayer glazing has a lower visible transmittance and SHGC

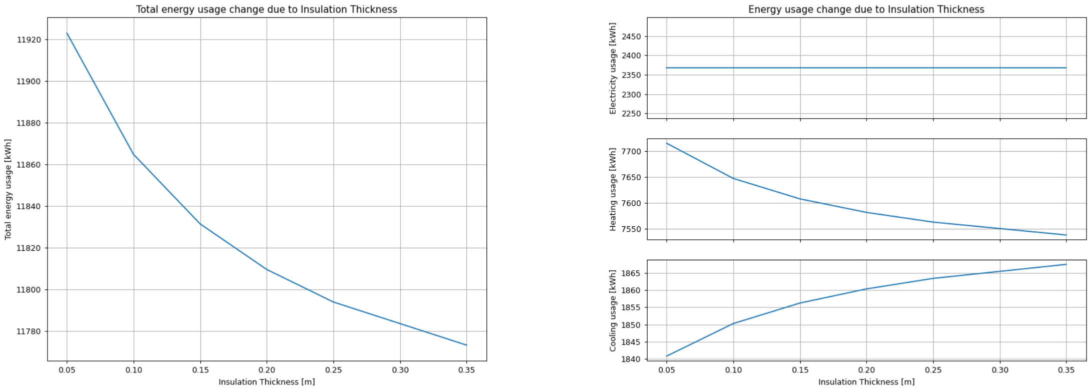


Figure 11: Energy usage change due to insulation layer thickness

while having a lower U-value. The parameters of the three types of chosen glazing are listed in table 4.

Table 4: Parameters of different window glazing

	SHGC	Light transmission	U-value [W/m^2K]
Single glazing	0.768	0.821	3.835
Double glazing	0.597	0.769	1.512
Triple glazing	0.474	0.661	0.780

More glazing layers can lower the amount of light that enters the window from the outside. As a result, more artificial lighting will be required, resulting in an increase in electricity consumption. Window glazing has an impact on heating and cooling energy consumption, but the correlation is more complex. Take heating as an example, with more layers of window glazing, the U-Value will decrease, reducing the building's energy loss and lowering the heating requirement. Conversely, the SHGC will decrease, leading in less solar heat being transmitted and a rise in the demand for heating. Therefore, evaluating the impact of the number of layers of window glazing on the eventual heating consumption is difficult.

Simulate the energy consumption of buildings with different glazing using BESOS, the results are shown in Table 5. As can be observed, the total energy consumption is lowest when double glazing is adopted, hence double glazing is optimized in our instance.

4.1.3 Ventilation

We have considered different values of ACH in domain [0-6]. Figure 12 shows the temperature change due to 4 sample values of ACH in summer season. It can be seen that the influence of ACH is more obvious when the outdoor temperature is relatively high, during months of June, July and August the temperature with ACH=6 is less than

Table 5: Annual energy consumption(unit: Kwh)

	Heating consumption	Cooling consumption	Electricity consumption	Total consumption
Single glazing	7561.99	1061.28	2438.66	11061.93
Double glazing	6932.03	902.05	2468.72	10302.80
Triple glazing	7084.36	705.88	2532.61	10322.85

around 1°C lower than the one with ACH=0, while during when the outdoor temperature is lower than 24°C, note that until the mid of September the temperature difference is still intuitive, this may caused by the high pressure difference between indoor and outdoor in the specific season, which leads to a higher wind airflow. In our case study the influence of ACH on annual energy consumption is not significant, because Torre Pellice is located in a mountainous environment, the outdoor temperature will not be extremely high even in summer.

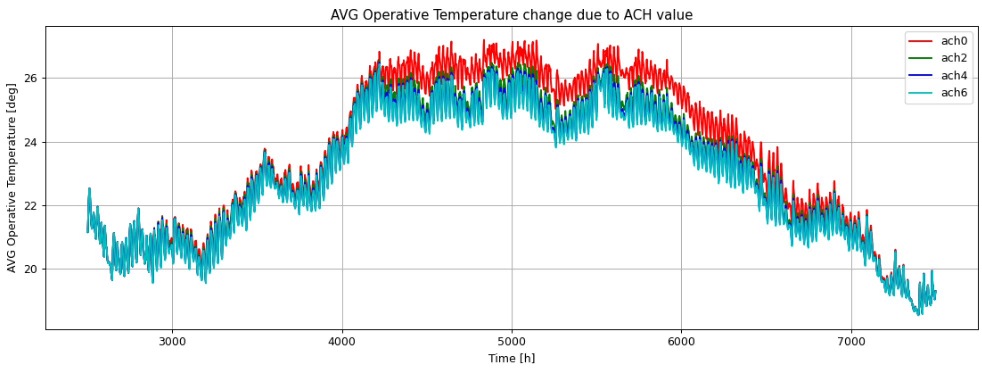


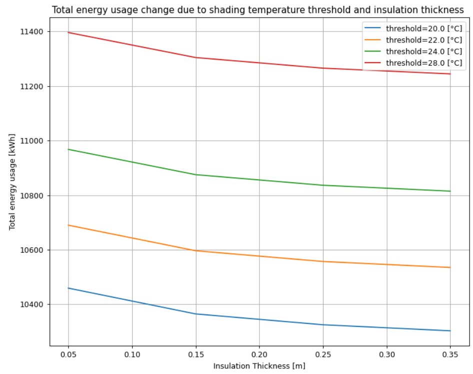
Figure 12: Temperature change due to ACH

4.1.4 Shading

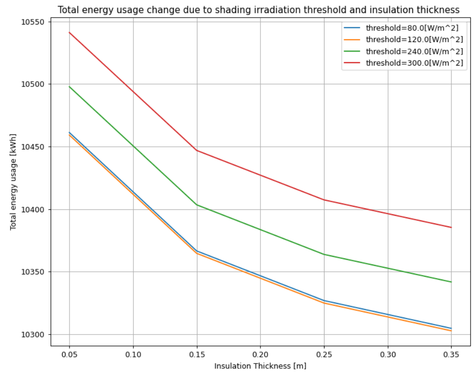
The sun irradiance is one of the most important factor that influences the thermal performance of the building, hence the function of shading system is critical. Figure 13 shows the relationship between the energy consumption and the thresholds of the shading system.

Figure 13(a) and 13(b) tells that in general for both two types of the threshold, the lower the threshold is, the less the total energy consume, and changing irradiation threshold would effect more on the energy usage. Note that for irradiation threshold, the energy consumption with $80W/m^2$ is slightly higher than the one with $120W/m^2$, the reason can be seen from Figure 13(c) and 13(d). Specifically speaking, the electricity usage is inversely proportional to the thresholds, increasing the thresholds will reduce the usage of electricity. But the reduction of the usage of electricity is relatively limited, despite this, when the threshold is low, it can still fetch up the increase of cooling usage.

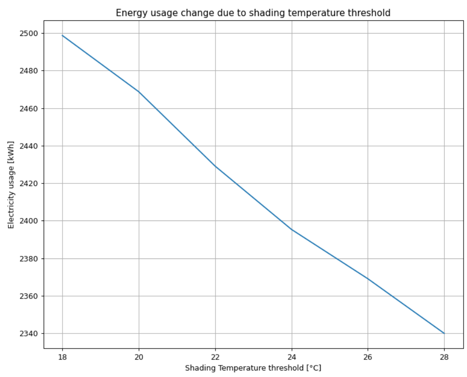
However, as thresholds keep increasing, the reduction of the usage of electricity are unable to cope with the the increase of cooling usage anymore.



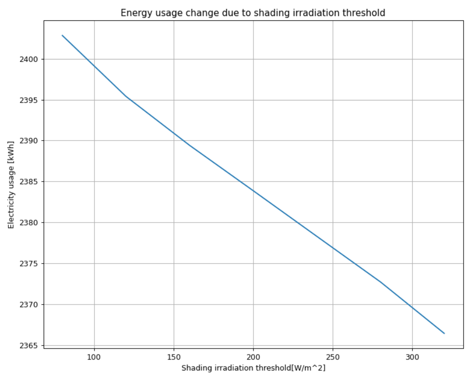
(a) Total energy usage vs Temperature threshold



(b) Total energy usage vs Irradiation threshold



(c) Electricity usage vs Temperature threshold

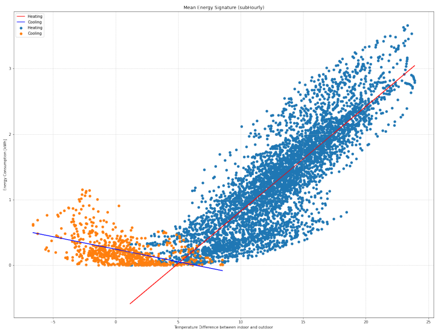


(d) Electricity usage vs Irradiation threshold

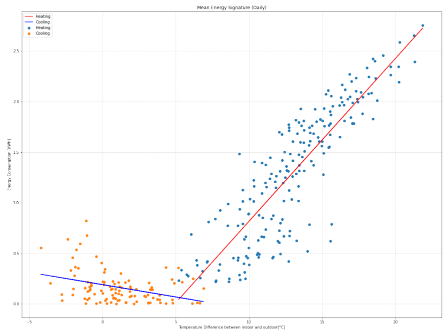
Figure 13: Energy usage change due to shading system

4.2 Energy signature results

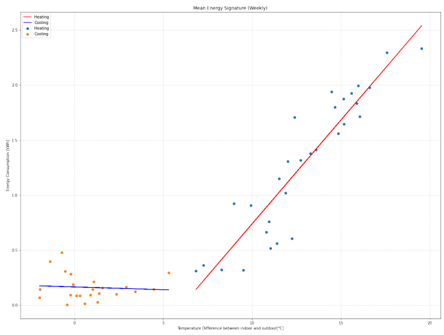
The energy signature is plotted in three separate time samples, as shown in Figure 14(a) - hourly mean data, in 14(b) - daily mean data and in 14(c) - weekly mean data. Environmental variables would have an impact on the first two. Noted that the slope of the linear regression, i.e. the Heat loss factor [W/K], which determines the rate of heat flow through the buildings' envelope when a temperature difference exists between the indoor air and the outdoor air under steady state conditions. K is -0.038 kWh/°C in summer, and 0.16 kWh/°C in winter, indicating that in the winter it requires more energy to adapt each degree of temperature variation. Moreover, in Figure 14(a) there are many points close to the X-axis since we set the cooling schedule to a threshold of 26°C in the summer. It is only necessary to use the air conditioner on occasion to maintain a comfortable indoor temperature in this residential. When people have left the building on weekdays during the winter, we set the heating schedule to 0.75 in order to save energy.



(a) Hourly



(b) Daily



(c) Weakly

Figure 14: Mean Energy Signature

The quality of the basic linear model of fitting to the given set of observable data is represented by R^2. The quality parameters are optimal for the model of weekly time interval, according to the R^2 values in Table 6, although this is only true for heating consumption. The data for cooling use in the table from a weekly period is insufficient to perform a good linear regression. Due to our cooling schedule, data collected on a weekly basis does not adequately reflect the characteristics of the energy we consume when we use air conditioners. Another cause could be that in the summer, the inside and outdoor temperatures are similar.

Table 6: Model evaluation for heating and cooling consumption

	Hourly	Daily	Weekly
R^2 for heating	0.721	0.757	0.851
R^2 for cooling	0.223	0.133	0.006

4.3 Prediction results

As mentioned in 3.4, three different prediction algorithms(RNN, CNN and Prophet) will be used to predict the indoor temperature(average operative temperature) and energy consumption(electricity, heating and cooling) of the apartment. In order to be able to compare the performance of these three algorithms, one week's data (168 samples) are used to be the training set. Due to the fact that the indoor temperature and energy consumption vary according to the season, the original 1-year data set from Energyplus is separated into four subsets including spring(March to May), summer(June to August), autumn(September to November) and winter(December to February).

Due to the fact that the mechanism for the tested algorithms are quite different(as Chapter 3.4 mentioned), this same baseline might not lead to the best performance for each algorithm. In this case, all three algorithms produced good outcomes, but as Figure.15 shows, when the prediction time becomes further, the MSE of indoor temperature prediction becomes larger for all three algorithms, and error of Prophet may increase faster. In the following subsections, the implementation or each algorithm and performances corresponding to 1-hour prediction will be analyzed.

4.3.1 RNN

In the implementation of RNN algorithm, the data in each season will again be divided into three subsets, including 70% of the data to be training set, 20% of data to be the validation set and 10% of data to be test set. For the need of the algorithm, data in each subset will slice again into the length of 168+n samples(data samples + n label samples).

As Table.7 shows, the MSE of indoor temperature prediction in summer and in winter are smaller than the ones in spring and autumn. It is because in summer and in winter, the outdoor and indoor temperature normally stays in a relatively stable value, while in spring and in autumn changes quite significantly. As Figure.16(a) and Figure.16(c) shows,

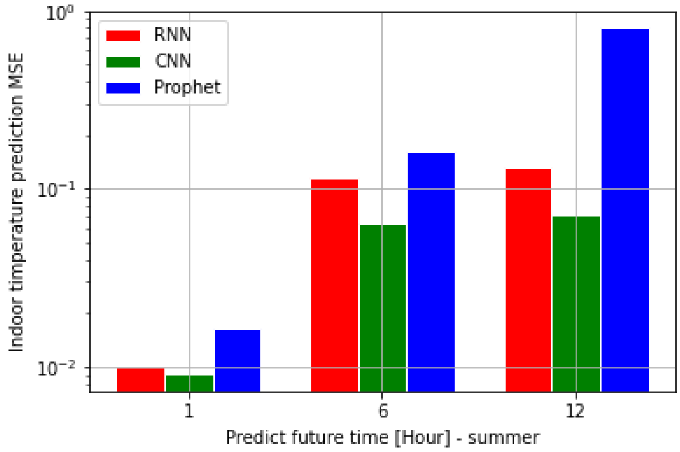


Figure 15: General prediction performance for three algorithms

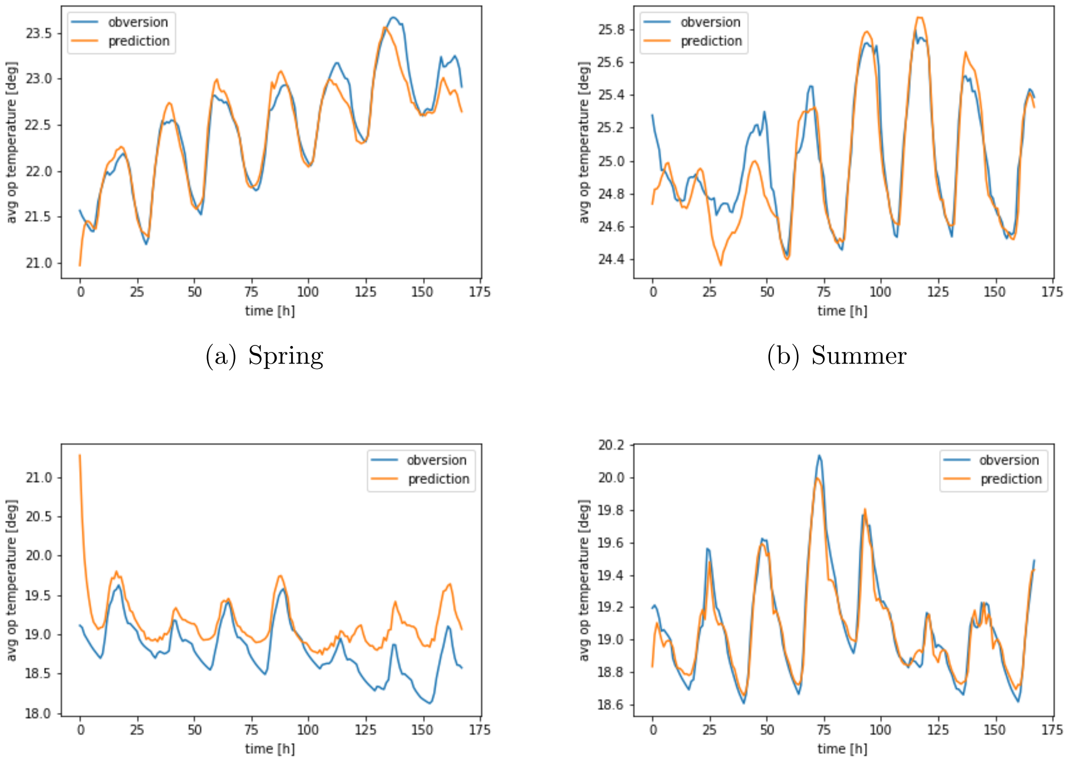
the average temperature in spring has a trend to increase and in autumn has a trend to decrease. It is interesting to find that in spring the predicted temperature often lower than the actual value and in autumn the predicted temperature always higher than the actual value. Which means the algorithm is less sensitive to the change average temperature and normally leads to a delay in prediction. From Table.7, it is interesting to notice that the MSE in the prediction of electricity consumption in winter is twice as much as the MSE in other seasons. According to our setting in DesignBuilder, the main electricity consumption is from the lighting in the apartment. The possible reason could be during the winter time the lighting is more frequently and randomly used.

Table 7: MSE for RNN 1-hour prediction

	Temperature	Electricity	Heating	Cooling
Spring	0.0366	0.0247		
Summer	0.0099	0.0204		0.0021
Autumn	0.0522	0.0228		
Winter	0.0052	0.0447	0.0229	

4.3.2 CNN

In the implementation of CNN algorithm, the data in each season will again be divided into subsets and slice as the pre-process step in RNN algorithm(in Chapter.4.3.1). From Table.8 and Figure.17, the MSEs and prediction trends are basically similar to the result of RNN algorithm(in Chapter.4.3.1). However, from Figure.17 we can notice that the prediction curve produced by CNN algorithm has more sharply changes in the peak or bottom of the actual temperature. The cause of this phenomena need more investigation. However, the result gives a signal that the CNN should be carefully used when dealing with frequently changed time series.



(a) Spring (b) Summer

(c) Autumn (d) Winter

Figure 16: RNN 1-hour prediction in four seasons

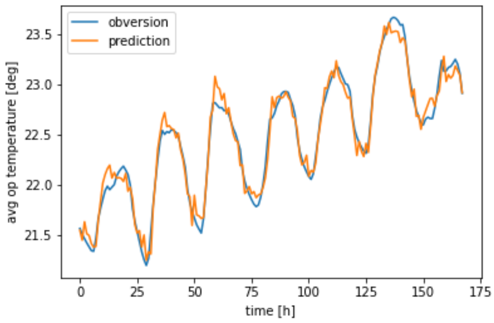
Table 8: MSE for CNN 1-hour prediction

	Temperature	Electricity	Heating	Cooling
Spring	0.0298	0.0534		
Summer	0.0090	0.0554		0.0019
Autumn	0.0408	0.0522		
Winter	0.0068	0.0471	0.0293	

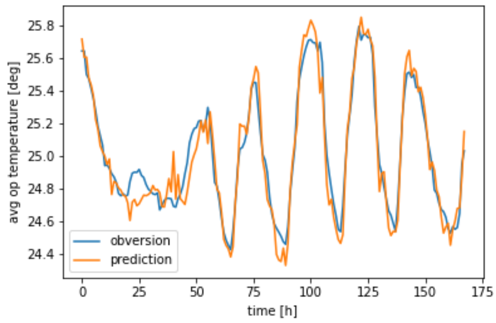
4.3.3 Prophet

Different from RNN(Chapter.4.3.1) and CNN(Chapter.4.3.2) algorithm, Prophet algorithm do not need to have extra data set for training or validating. It fit a serial of data to the model and predict the required future based on it. It has the advantage that the fitting(training) procedure can finish very quickly(comparing to RNN and CNN). However, Prophet has a limit that models can only be fit once, and a new model must be re-fit when new data become available.

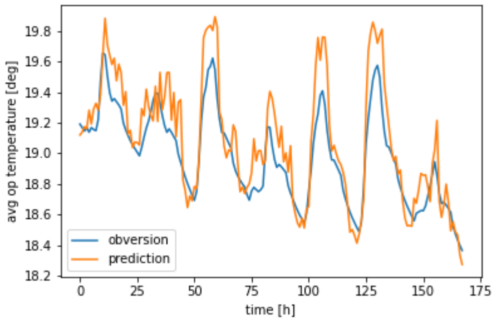
Considering the pros and cons of Prophet algorithm, we randomly selected data of one week to fit the model and predict the internal temperature and power consumption in the next hour. And with the help of a sliding window, we make forecast of 1-hour future in the following 24 samples(24 hours), as shown in figure 18. The performance of forecast is listed in table 9. Comparing the 1-hour prediction of Prophet algorithm with RNN and



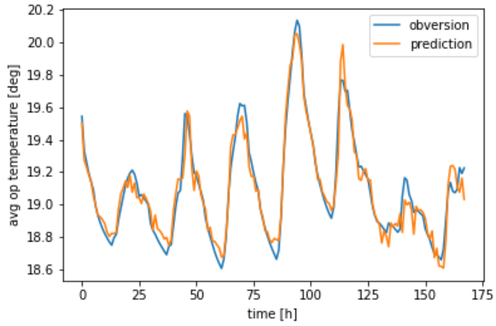
(a) Spring



(b) Summer



(c) Autumn



(d) Winter

Figure 17: CNN 1-hour prediction in four seasons

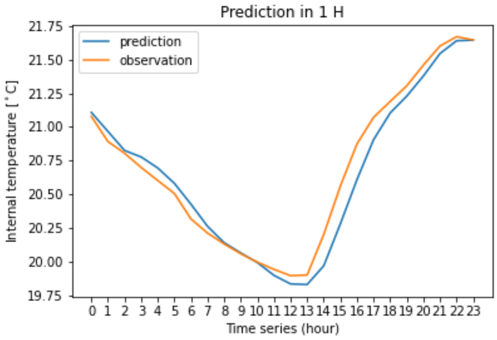
CNN, the performance is similar. However, due to the fact that only a small amount of data was used to fit the model for predicting, as the forecast period progresses, the error increases significantly as Figure.15 shows.

Table 9: MSE for Prophet 1-hour prediction

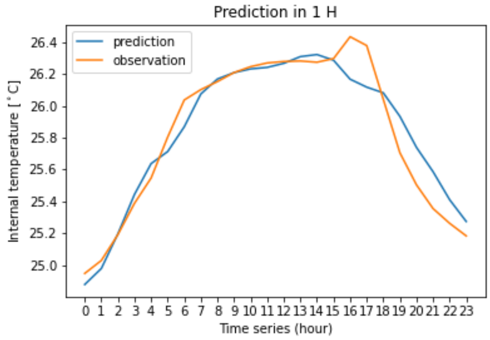
	Temperature	Electricity	Heating	Cooling
Spring	0.0068	0.0205		
Summer	0.0164	0.0329		0.0083
Autumn	0.0038	0.0287		
Winter	0.0070	0.0325	0.0723	

5 Conclusion

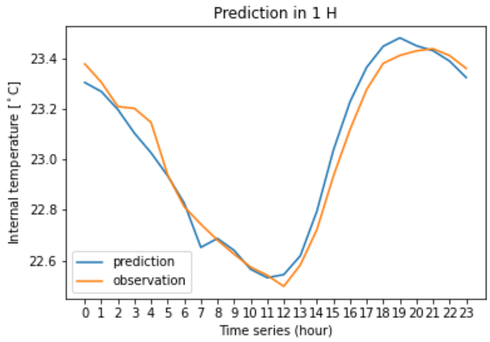
Our case study is based on a residential building located in Torre Pellice. We utilized DesignBuilder to set and adjust a set of parameters (glazing, shading, ventilation, and the thickness of the external wall's insulation layer) and EnergyPlus to simulate internal temperature and energy consumption. Then BESOS can help us better understand the impact of those parameters on energy performance and choose the best parameters.



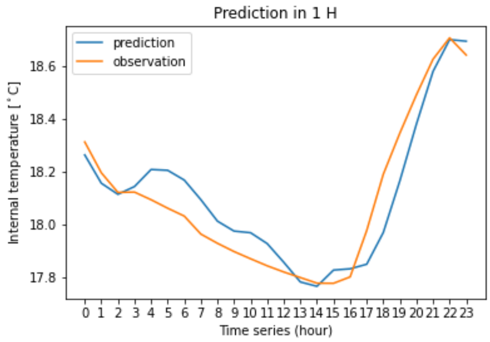
(a) Spring



(b) Summer



(c) Autumn



(d) Winter

Figure 18: Prophet 1-hour prediction in four seasons

After obtaining the optimum parameters and combining them with meteorological data, We produced the simulation in 2005 and use the MQTT protocol to deliver it to influxDB. Grafana is an excellent tool for data visualization, through which it is evident that heating system accounts for the majority of a building's energy usage. The energy signature approach have been used to provide a better approximation of the energy behavior related to temperature by sampling at different time intervals.

Then, using machine learning approaches(RNN, CNN and Prophet), we attempted to predict future energy consumption and internal temperature and reached a good result. Users can use the prediction results to change the configuration of the building system based on various situations in order to save energy and while maintaining comfort.

References

[1] Alberto Barbaresi, Marco Bovo, and Daniele Torreggiani. The dual influence of the envelope on the thermal performance of conditioned and unconditioned buildings. *Sustainable Cities and Society*, 61(May):102298, 2020.

[2] Umberto Berardi. A cross-country comparison of the building energy consumptions and their trends. *Resources, Conservation and Recycling*, 123(Jun), 2017.

[3] Giacomo Chiesa, Silvia Cesari, Miguel Garcia, Mohammad Issa, and Shuyang Li. Multisensor IoT platform for optimising IAQ levels in buildings through a smart ventilation system. *Sustainability (Switzerland)*, 11(20), 2019.

[4] Marjan Ilbeigi, Mohammad Ghomeishi, and Ali Dehghanbanadaki. Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm. *Sustainable Cities and Society*, 61(May):102325, 2020.

[5] Rajeev Kamal, Francesca Moloney, Chatura Wickramaratne, Arunkumar Narasimhan, and D. Y. Goswami. Strategic control and cost optimization of thermal energy storage in buildings using EnergyPlus. *Applied Energy*, 246(February):77–90, 2019.

[6] X. J. Luo. A novel clustering-enhanced adaptive artificial neural network model for predicting day-ahead building cooling demand. *Journal of Building Engineering*, 32(May):101504, 2020.

[7] Angel Rico, Victoria J. Ovejas, and Angel Cuadras. Analysis of energy and entropy balance in a residential building. *Journal of Cleaner Production*, 333:130145, 2022.

[8] R. Sendra-Arranz and A. Gutiérrez. A long short-term memory artificial neural network to predict daily HVAC consumption in buildings. *Energy and Buildings*, 216:109952, 2020.

[9] Sean J. Taylor and Benjamin Letham. Forecasting at Scale. *American Statistician*, 72(1):37–45, 2018.