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Design and performance analysis of an office in Moscow (RU)

Professors
Giacomo Chiesa, Lorenzo Bottaccioli

Francesco Barlocco (s264065), Luca Gioacchini (s257076),
Alan Cedric Grimm (s274507), Stefano Picerno (s265406), Bruno Valente (s263322)

Abstract
In the 2020 European strategy, the European Union aims at achieving a 20% share of renewable energies and the 20% reduction of the overall energy consumption. With a share of 64.1% in the residential sector, heating is one of the largest primary energy consumers [4]. On average, non-residential buildings exceed residential ones by 40% in terms of energy use per m^2.
In order to reduce the overall energy requirement, the optimum building retrofitting design in terms of thermal transmittance (or U-value, which is central in the energy transmission through the building envelope) is essential. Another point of high relevance in the context of renewable energy use is the prediction of energy demand, due to the need for decentralization of the electricity grid and the often time-bound availability of renewable energy sources [10]. Through intelligent networking, load management and demand flexibilization, an efficient integration of renewable energies and a stable grid condition can be achieved in the context of the conversion from the traditional power grid into so-called smart grids [3].
This paper therefore first deals with the optimization of the U-value, the Window to Wall Ratio and the thickness of the windows Argon filled area of an exemplary office building in Moscow and then with the prediction of its monthly energy consumption of the same building. Finally, the forecast of the next hour average internal temperature has been performed through Long Short-Term Memory (LSTM) recurrent neural network to lay the foundation for an automated environmental control system.
Keywords: Energy consumption; Energy demand forecast; Artificial neural networks; LSTM; Energy efficiency; Smart Grid; Smart Building;

1 Introduction

With the proclamation of the climate crisis in the European Parliament, the issue of climate change and the need for CO2 savings is more present than ever on the political agenda. With the formulation of the "green-deal", the road-map for the coming years was essentially set. Buildings and their renovation play an important role alongside other core issues such as mobility, sustainable industry and clean energy with the focus not only on the heating energy consumption as in the past, but also on the cooling one. By counting the 20% of the total energy demand in buildings, cooling already represents a significant share, and the trend is rising [6]. When choosing the construction method and corresponding thermal insulation measures, the influence of increasingly higher outside temperatures and corresponding cooling requirements is therefore becoming more and more relevant.

In the building energy demand calculation it is necessary to differentiate between residential structures, in which the highest primary energy demand is early in the morning and late in the evening, and office buildings, which consume more in regular working hours. In addition to the activity schedule, other parameters such as the ventilation of the building, the waste heat from electronic devices, the lighting, etc. are also strongly correlated to the type of use.

This work focuses on the application and creation of an IT-supported optimization of an exemplary office building envelope in Moscow, whose design and structure can be transferred to other areas and climatic zones. The primary focus of this work was the optimization of the thickness of the insulation. In addition, the thickness of the windows Argon filled area, the orientation, the Window to Wall Ratio (WWR) and the presence of natural ventilation were considered as further variables. Moreover, the monthly energy demand of the building is determined in terms of energy signature by emulating the presence of smart meters. Finally, a LSTM, an artificial recurrent neural network, is implemented to forecast the next hour average internal temperature for a possible automated HVAC control system.

2 Background

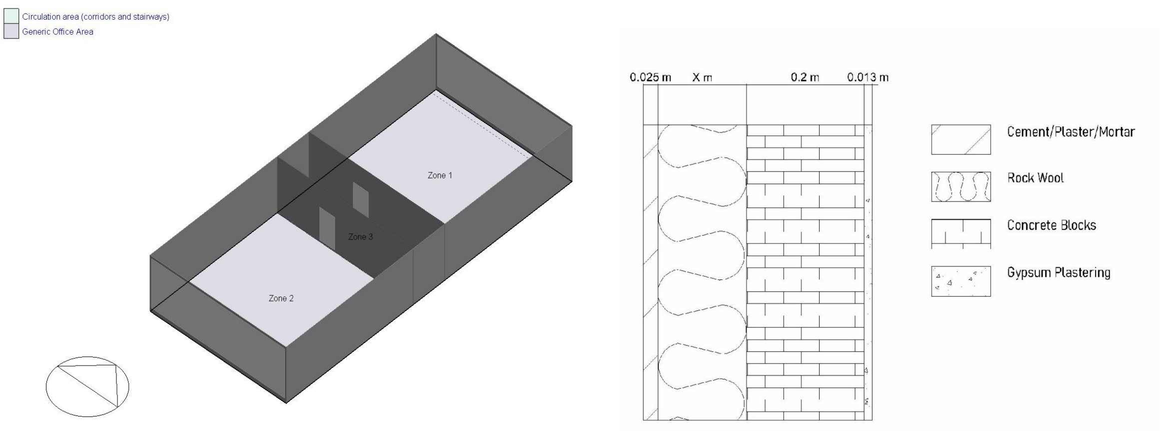
Regarding the deep learning aspect, in literature different models have been tested to forecast environmental parameters in cold regions. In [1] the energy demand of different user clusters is forecasted by obtaining the energy consumption of 609 households through smart meters recording data each 30 minutes. The Long Short-Term Memory model has proved suitable for both medium term (15 days) and short term (3 days) forecasting. The results show an error of 3.15% for the prediction of peak energy demands. A similar approach is reported in [11], in which forecasted building energy consumption using an electrical consumption dataset has been performed. Authors used the gated recurrent unit (GRU) mechanism based Sequence-to-Sequence models to make short (6 hours), medium (2 days) and long term (5 days) predictions stating that GRU S2S models outperformed LSTM S2S, RNN S2S, and Deep Neural Network models for all forecasting intervals. Finally, authors of [8] compared the performance to forecast the aggregated energy demand of several machine learning approaches with the application of deep learning methods. Predictions were made for one day in the future, using data from the past week. The obtained results prove the superiority of the methods of deep learning compared to machine learning methods, when applied to energy prediction.

In the field of optimization of building design, the research related to buildings in similar climatic zones is particularly interesting in the context of this work. While much of the research concentrates on the energy optimisation of buildings for residential use, the following section presents two studies that also investigated office buildings.

Authors of [7] worked on the IT-supported optimisation of design parameters for Norwegian and Australian office space in cold regions by using dedicated software tools (DesignBuilder and EnergyPlus). The results show how important the envelope, or more precisely the combination of thermal storage capacity and high insulation, is to remain in a thermal comfort zone all year round. The energetic optimization is investigated also in [12]. The WWR is identified as most crucial factor for electricity use in large scale Chinese buildings, whereas for well-insulated buildings, the number of floors was identified as most crucial factor. Since heating and electrical energy consumption were considered separately, the degree of insulation had little influence on energy consumption.

3 Building Design and Problems Definition

According to Section 1 a generic office in Moscow has been considered as case study. By using the DesignBuilder software, the envelope is developed as a single rectangular block of 144 m^2 divided in two zones sized 64 m^2 and a 16 m^2 corridor. Double glazing Argon filled windows are on the short sides of the block, the ceilings are 3 m high and all the surfaces are adiabatic except for the long sides and floor. Two orientations have been tested: a north oriented one shown in Figure 1(a) and an east oriented one. Regarding the natural ventilation, when it is set ON, its schedule is from May to September and from 6:00 PM up to 8:00 AM.



(a) Building envelope of an office in Moscow as case study

(b) Wall Section

Figure 1: 3D view of the case study and wall section.

3.1 Parameters Optimization

To obtain the best design in terms of energy consumption four parameters have been investigated:

- U-value. It is the reciprocal of the thermal resistance, therefore a lower U-value also means better insulation. The total thermal resistance R_T can be understood as the sum of the material-specific individual thermal resistances of the materials plus the heat transfer resistances of the external and internal surface, respectively R_{se} and R_{si}.

$$U = \frac{1}{R_T} = \frac{1}{R_{se} + \frac{d_1}{\lambda_1} + \frac{d_2}{\lambda_2} + \cdots + R_{si}} \; [\mathrm{W/m^2K}] \tag{1}$$

  where λ_i and d_i are the thermal conductivity and the thickness of the $i-th$ facade. By analyzing the model under study the thermal resistances due to the horizontal flow used by Energy+ have been set equal to $R_{se} + R_{si} = 0.04 + 0.13 = 0.17\,\mathrm{m^2K/W}$ and the U-value is evaluated by changing the thickness of the rockwool used to insulate the walls in a range between 0.05 m and 0.35 m.

- Window to Wall Ratio (WWR). It is the ratio of the window area to the gross exterior wall one. It is a crucial parameter, since it determines the admitted amount of solar radiation incident on the facades. The tested configurations are 15%, 50% and 90%;

- Argon (Ar) filled area. It is the thickness of the gas filled layer between the two glazings. In order to evaluate its impact on the HVAC power consumption, different window configurations have been investigated. The window U-value can be determined by considering the glass one and the frame one with respect to their surface. Considering that the WWR was changed three times, this would have lead to a high number of plots and a decreasing comparability of the obtained results. For this reason the approximation of the window U-Value was used, neglecting the minor influence of the frame, to determine the thickness of the argon filled area. Therefore the following formula was used:

$$U = \frac{1}{\frac{d_{g1}}{\lambda_{g1}} + \frac{d_{g2}}{\lambda_{g2}} + \frac{d_{Ar}}{\lambda_{Ar}}} \; [\mathrm{W/m^2K}] \tag{2}$$

  Where gi is referred to the $i-th$ glass layer and Ar is referred to the Argon filled section. The used Argon conductivity is $\lambda_{Ar} = 0.016\,\mathrm{W/mK}$ and its section has been changed in the range [0.3, 2.3] cm corresponding to the [0.7, 5] $\mathrm{W/m^2K}$ U-value range. The conductivity of both the glasses has been fixed to $\lambda_{g1} = \lambda_{g2} = 0.9\,\mathrm{W/mK}$ and their thickness has been fixed at 0.3 cm.

- Visible transmittance. The office is developed with a responsive lighting system, so it has been investigated the impact of the WWR and of the Visible transmittance at normal incidence on the lighting consumption. The WWR configurations are the same of the previous analysis, whereas the visible transmittance changes in the [0.0, 0.7] range.

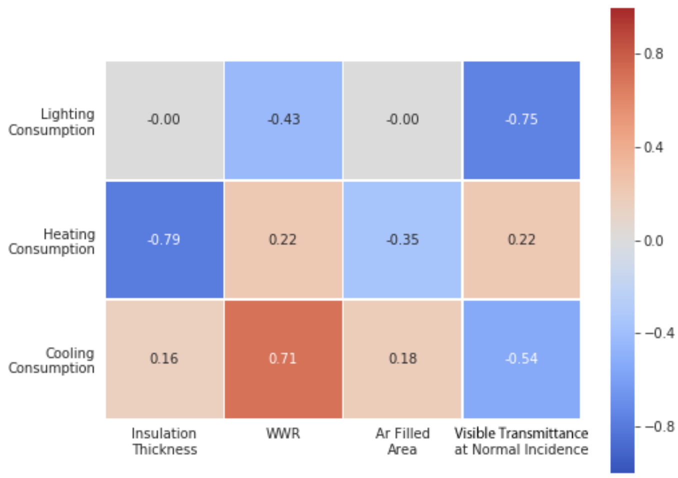


Figure 2: Correlation Heatmap between the power consumptions and the analyzed parameters.

Before proceeding with the implementation, a preliminary analysis on the expected results has been performed by realizing a correlation heatmap between the parameters and the cooling, heating and lighting consumptions.

Figure 2 shows that there is a direct relationship between the insulation thickness, the WWR, the Argon filled area and the cooling consumption. This can be explained by understanding the insulating properties of the considered variables. During summertime those can cause overheating effects on the office, which is exposed to the solar radiation. On the contrary, when increasing the visible transmittance, the lighting consumption is highly reduced, decreasing the heating due to the light bulbs.

An opposite behavior is obtained when the heating consumption is observed. A greater insulation means a warmer internal environment making the HVAC system more efficient.

Finally, the lighting consumption depends only on the WWR and on the visible transmittance with a reasonable inverse relationship. The optimum values of the parameters are found by applying a grid search approach. Several combinations of the explained variables are fed to the Energy+ software in order to perform an annual simulation of the building functioning with the support of the local meteorological data.

The energy consumption returned by the software is evaluated for both the building orientations and for the annual, summertime and wintertime periods. Moreover, the presence of the natural ventilation is investigated to understand its impact on the system.

3.2 Energy Signature

As described in the ISO EN 15603:2008 Annex B, the energy signature of a building is a method which graphically reflects its energy efficiency; especially it expresses the energy sensitivity of the building to changes in temperature. It uses the correlation between climate data and the heating or cooling demand. In the univariate model, the outdoor temperature is considered the most important variable. Multivariate versions include solar radiation, but other data such as occupancy can also enhance the transparency of the results [9].

Depending on the type of building and the application of the multivariate approach, a case-based consideration of the relevant factors should take place. However, usually solar radiation is considered as the second factor: for this reason in this paper only the univariate model is taken into account. To determine the energy signature, the difference between the internal temperature and the external one is defined as ΔT and plotted against the energy used for a defined period of time, obtaining a cloud of points. Then, when applying linear regression, a distinction can be made in principle between three cases:

1. The first case is a function with a slope equal to zero. It represents a temperature range in which no energy is used for heating or cooling. The graph corresponds to the fixed part of the energy used in the building, such as ventilation systems;
2. The second case is a function with a positive gradient. This indicates the energy difference caused by a colder outside temperature; energy is spent to heat the internal environment;
3. The third case occurs when the indoor temperature is above the defined comfort zone and so energy must be used to cool the building inside. Accordingly, the determined function has a negative slope.

In summary, the energy signature can therefore be expressed as a graph in which these three components are superimposed, reflecting the different relationships in different periods of the year. In general, it can be said that the greater the amount of ΔT, the greater the energy consumption of the building. This corresponds to the intuitive assumption that in case of extreme temperatures outside, more energy must be used to keep the inside of the building envelope in the defined comfort zone. Correspondingly, the steepness of the degrees of regression indicates how sensitively the energy consumption of a building reacts to external temperature conditions. The flatter the slope, the better the building is insulated.

As shown in [2], to achieve a better linear regression it is useful to consider weekly data of power consumption rather than daily, hourly or sub-hourly ones, since it produces a smoothing effect which removes outliers and temporary exceptional behaviors.

3.3 Long Short-Term Memory Models

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture, which is a generalization of feed-forward neural network that has an internal memory. This memory is the internal state of each unit which is fed to the next one as additional input. The LSTM advantage is the presence of a sigmoid function in each unit working as a 'forget gate', which detects the less informative features that can be discarded. In this way it is possible to analyze time series by reducing the vanishing gradient effect occurring in other deep learning models.

3.3.1 Internal Average Temperature Forecasting

In order to establish a basis for an automated thermal control system, a stacked LSTM is used to predict the average internal temperature of the office by starting from the environmental data recorded by smart meters. The emulated acquisition is performed every 5 minutes and the model is built to predict the following 15 minutes of the target variable trend. Available data is referred to all the 2017 year.

The input training dataset of the LSTM model $\in \mathbb{R}^{N \mathrm{x} T \mathrm{x} F}$ where N is the number of samples, T is the number of time-steps, or the size of the observation window, and F is the number of features. Since the prediction is referred to the following 15 minutes with a 5 minutes step from the latest observation, the size of the window is $T = 3$.

The neural network is composed of a first unrolled hidden LSTM layer with 100 units, a second bidirectional unrolled LSTM one with 80 units and a time distributed dense output layer with T neurons. To prevent overfitting, each LSTM layer has a 20% of dropout. The designed loss function is the Mean Squared Error (MSE) and the network optimizer is the Adaptive Moment estimator (AdaM)[1].

By considering that the LSTM is sensitive to the features and target range, a Min-Max scaling is performed to make data belonging to the [0,1] range, so, by considering the $i-th$ feature x_i, scaled data is:

$$z_i = \frac{x_i - min(x_i)}{max(x_i) - min(x_i)} \tag{3}$$

Finally, the model validation is performed by splitting the entire dataset. The first 70% of data is used as training dataset and the remaining 30% is taken as test, or validation, one.

3.3.2 HVAC Power Consumption Forecasting

An additional deep learning implementation is developed to forecast the HVAC power consumption defined as the sum of the cooling one and the heating one. The data acquisition frequency and the target time are the same of Section 3.3.1, whereas the dropout has been increased to 30%. Moreover the training dataset is composed by the 60% of the total one and the test one is the remaining 40%. Since the HVAC consumption highly depends on the internal temperature of the building, the external data have been discarded and a binary information of the system status (ON, OFF) with respect to the current hours is added to the dataset.

Finally, by considering that the measured consumption is in the [0,1.5] kWh range, the Min-Max scaling has not been applied.

[1] The AdaM algorithm is an extension to stochastic gradient descent (SGD) used as optimizer in several Deep Learning models. With respect to the SGD, which maintains a single learning rate for all weight updates during all the training procedure, the AdaM optimizer adapts the learning rate during the iterations by analyzing the average first moment (the mean) and the average of the second moments of the gradients (the uncentered variance).

4 Results

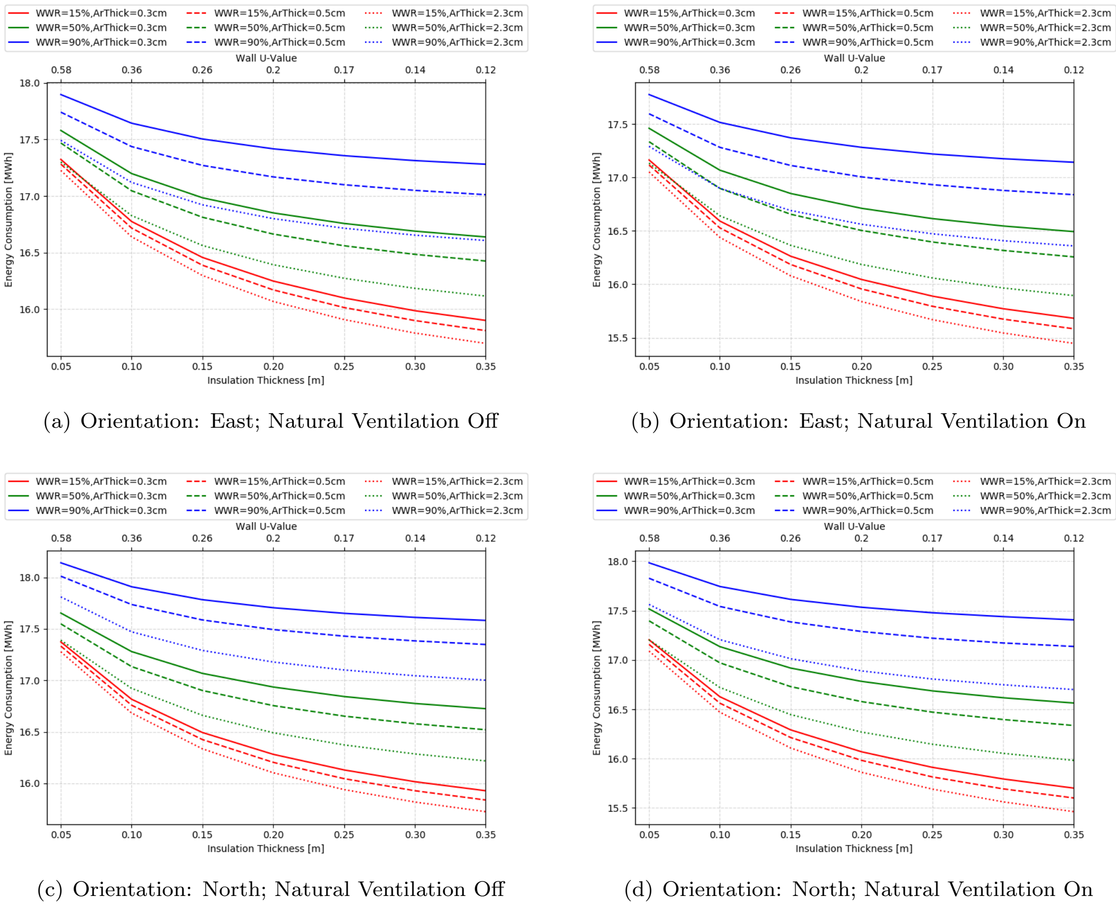
After having defined the building and the problems, in Section 4.1 the obtained results for the design parameters optimization are shown. In Section 4.2 an analysis on the prediction of the building energy demand is illustrated and, finally, in Section 4.3 the predictive model is investigated in terms of performances and prediction accuracy.

4.1 Parameters Optimization

In Section 4.1.1 the obtained results when the insulation thickness. the WWR and the Argon filled area are reported, whereas in Section 4.1.2 the ones referred to the different windows configurations are illustrated.

4.1.1 Insulation Thickness, WWR, Ar Filled Area

As shown in Figure 1(a) the analyzed office unit is symmetric, therefore orientation configurations could be limited to east and north, as the results for south and north or east and west are energetically identical.



(a) Orientation: East; Natural Ventilation Off

(b) Orientation: East; Natural Ventilation On

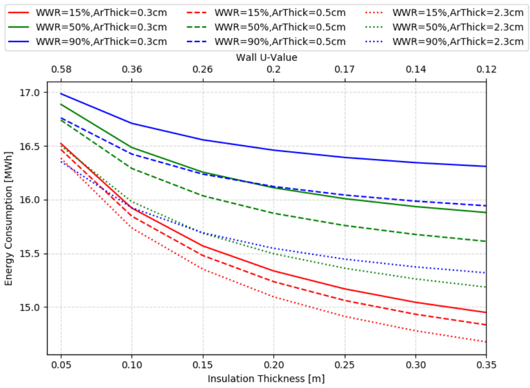
(c) Orientation: North; Natural Ventilation Off

(d) Orientation: North; Natural Ventilation On

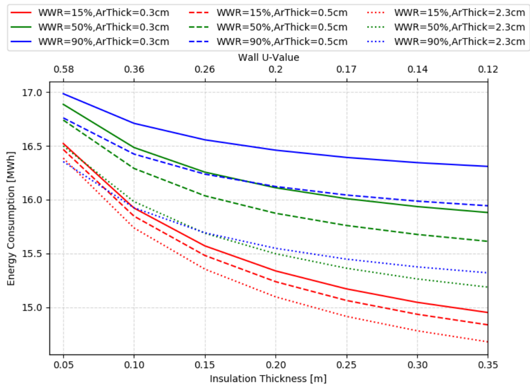
Figure 3: Annual evaluation of the building energy consumption with respect to WWR [15%, 50%, 90%], insulation thickness [5 cm - 35 cm] and Argon filled area [0.3 cm - 2.3 cm].

Figure 3 shows the annual simulation results with weather data referred to 2017. A higher insulation always leads to a lower energy consumption. However, the effectiveness of the insulation thickness is gradually diminishing. The observation of the results confirms the intuitive assumption that with a higher WWR the orientation of the building becomes more important. Causes for the effect must be sought in the solar heat gains and the energy consumption for lighting. When the insulation thickness is increased and the WWR is reduced, the effect of the orientation becomes less important. However the northern orientation of the office unit leads in general to a higher energy demand and simulations with a WWR of 90% are affected the most.

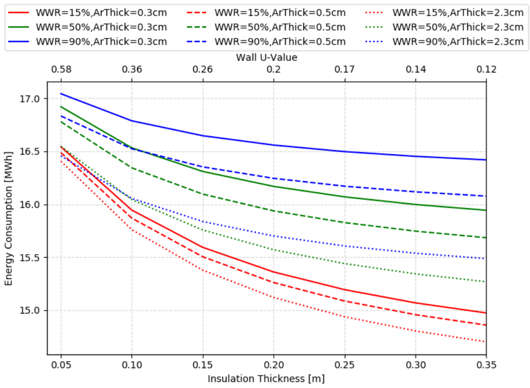
With a fixed WWR it can be observed that a higher Argon layer thickness behaves identically to the thickness of the insulation. Moreover a non-linear relationship between thickness and energy consumption is also apparent. In general, natural ventilation has an energy-saving effect.



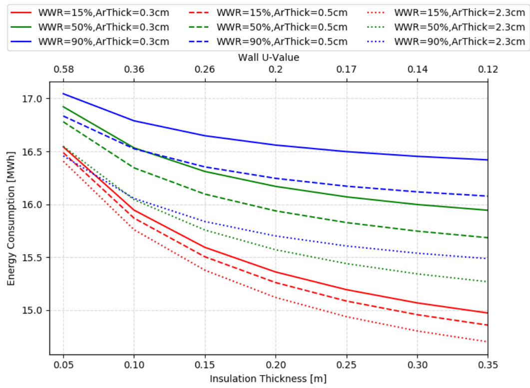
(a) Orientation: East; Natural Ventilation Off



(b) Orientation: East; Natural Ventilation On



(c) Orientation: North; Natural Ventilation Off



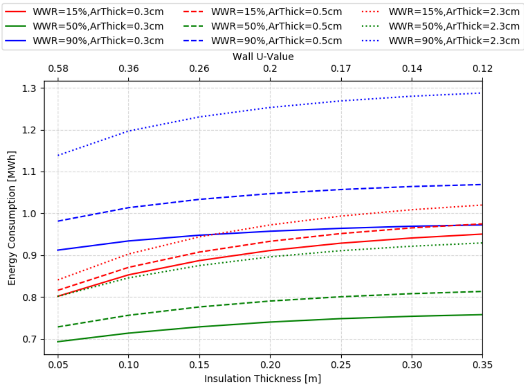
(d) Orientation: North; Natural Ventilation On

Figure 4: Wintertime evaluation of the building energy consumption with respect to WWR [15%, 50%, 90%], insulation thickness [5 cm - 35 cm] and Argon layer one [0.3 cm - 2.3 cm].

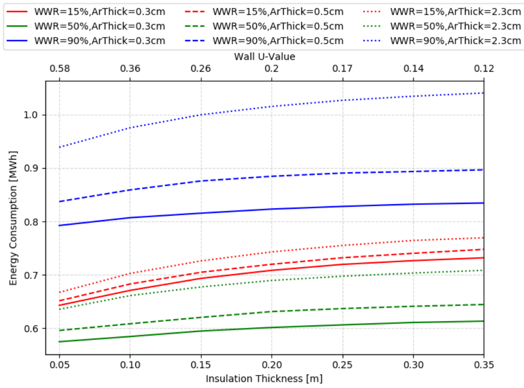
When looking at Figure 4, which shows the energy consumption of the building in winter time, it is possible to analyze the results in a differentiated way for the period in which no cooling of the building is necessary or possible and heating is required. In particular, the weighting of the respective period in the context of energy consumption can be seen and thus also the relative importance for energy and constructive decisions.

Energy consumption in the winter period accounts for approximately 90% of total consumption. Therefore, the plots of the winter period looks similar to the annual ones. Since natural ventilation is scheduled not to work in winter, its activation has no effect on the energy consumption, whereas, as seen before in Figure 3, a higher insulation always leads to a lower energy consumption. However, the effectiveness of the insulation thickness is diminishing.

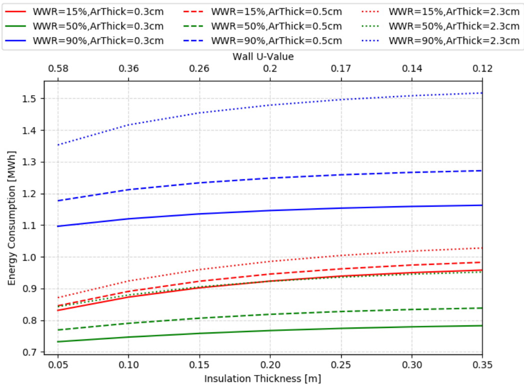
A northern orientation of the building leads to a slightly higher energy consumption. In principle, a lower WWR leads to lower energy consumption. This seems logical, as walls generally provide better insulation than windows. The graph shows that the efficiency of the insulation decreases with increasing thickness, especially in the configuration with a low WWR, this can be noticed. The intersections of the configurations in the graphs always indicate configurations which would lead to the same result from a purely energetic point of view.



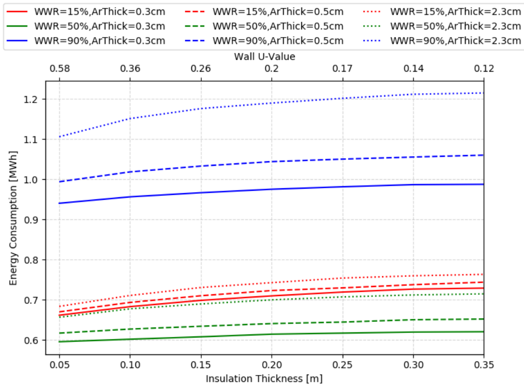
(a) Orientation: East; Natural Ventilation Off



(b) Orientation: East; Natural Ventilation On



(c) Orientation: North; Natural Ventilation Off



(d) Orientation: North; Natural Ventilation On

Figure 5: Summertime evaluation of the building energy consumption with respect to WWR [15%, 50%, 90%], insulation thickness [5 cm - 35 cm] and Argon layer one [0.3 cm - 2.3 cm].

The results obtained for the summer period (Figure 5) help to quantify possible overheating effects. As Moscow is geographically rather a cool area, it can be assumed that the summer period has no dominant effect on the optimal insulation thickness. This assumption has already been conditionally confirmed by the annual plots of Figure 3. By analyzing Figure 5 it is clear that the summer period accounts from 5% up to 12% for the overall energy consumption and when the natural ventilation is used, it is possible to achieve approximately a 20% of reduction.

As demonstrated in the correlation matrix of Figure 2, insulation thickness and energy consumption are slightly correlated and a similar behavior can be observed for the Argon layer thickness.

The highest energy consumption is achieved with a maximum insulation and Argon layer thickness and a maximum WWR. In this case the described configuration reminds of a greenhouse and a high consumption for cooling the surface is therefore logical. Comparable effects were measured in several studies, even more intense for buildings with double-skin facade [5].

Northern orientation leads to the highest energy consumption. It should be noted here that due to the symmetrical design of the office unit, one side of the window is in fact oriented to the north and therefore only receives a small amount of direct sunlight, but the other side is exposed to maximum solar radiation, so there is also a high cooling requirement here.

The best configuration is the one with both the lowest insulation and Argon layer thicknesses, but with the 50% WWR. The lowest performance of the 15% WWR one could be due to the increased artificial lighting consumption and the additional cooling required to balance its overheating.

4.1.2 Visible Transmittance

The dependence of the lighting consumption on the visible transmittance has been investigated with different configurations of WWR and orientation.

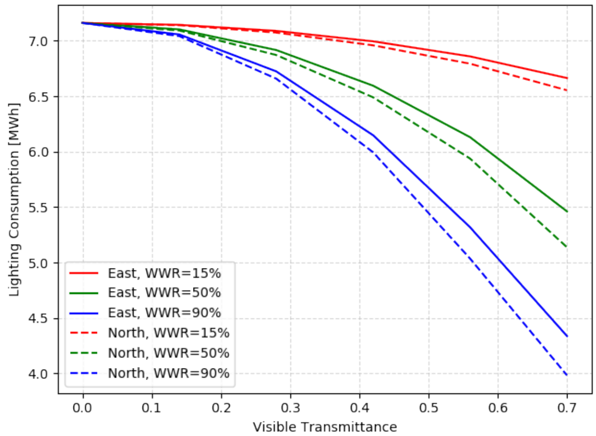


Figure 6: Lighting consumption with respect to different WWR configurations and orientations.

Figure 6 shows, as expected, a negative correlation between consumption and visible transmittance, which is stronger the higher the WWR is. The North orientation achieves better results than the East one, for the same reason described in the previous section. The improvement due to the orientation increases with both the WWR and the visible transmittance.

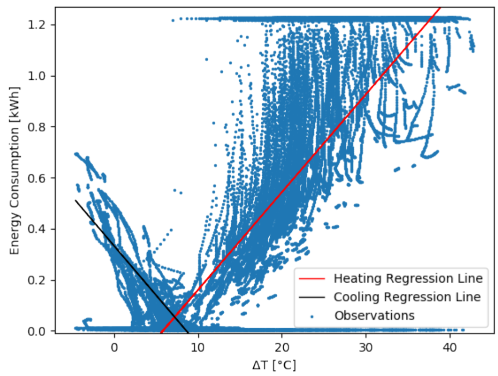
4.2 Energy Signature

After having performed the parameter optimization, a good and realistic compromise between the variables reported in Table 1 has been chosen. The presented configuration of the building represents only one possible exemplary combination of variables. For further research a consideration of different configurations for the determination of dependencies of the considered variables would have to be established and compared with theoretical values. Also with regard to the evaluation and classification of the heat loss coefficient, K_{tot}, which is represented by the slope of the regression, a further consideration would be interesting.

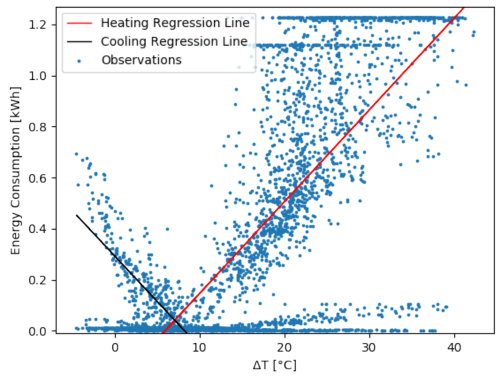
	Natural Ventilation	Orientaton	Insulation Thickness	Ar Filled Area	WWR
Value	On	East	0.25 m	0.005 m	15%
U-Value	-	-	0.17	2.85	-

Table 1: Best design choice after the optimization

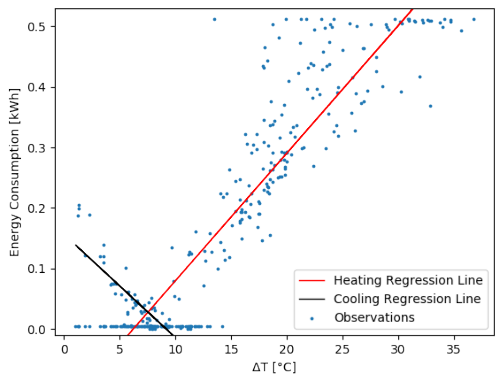
In order to evaluate the energetic profile of the building under analysis, the energy signature method is performed.



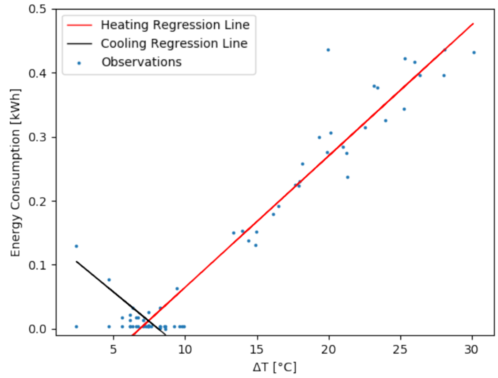
(a) Energy signature from observed values. 5 minutes resolution



(b) Energy signature from hourly values



(c) Energy signature from daily values



(d) Energy signature from weekly values

Figure 7: Energy signature obtained by different resamplings.

In order to carry out the regression separately for winter and summer, points from the determined data set without energy consumption for heating were excluded for the regression for the summer period and correspondingly points without energy consumption for cooling for the winter period. ΔT is, as described in Section 3.2, is defined as difference between internal and external temperature.

First of all the Figure 7(b) clearly confirms the findings about the dominating share of the winter period and therefore the heating consumption, that were observed in Section 4. For the deviations and fluctuations around the degrees of the regression, two primary disturbance factors are mentioned in the DIN ISO EN 15603:2008 Annex B. On the one hand, the fluctuation of the solar or internal heat gains, on the other hand the fluctuation of the specific heat transfer coefficients due to, for example, the effects of wind on permeable facade elements.

The heat loss coefficients, that were obtained by the application of the energy signature method are shown in Table 2. With regards to [2], the weekly value is considered to be the most meaningful.

Time-period	5 min	hourly	daily	weekly
K - Value [kWh/°C]	0.038	0.036	0.021	0.020

Table 2: Heat loss coefficients according to time resolution.

Finally, the intersection between the lines is due to the different HVAC setpoint values. The heating is set to provide 24 °C in Winter, whereas the cooling system is set to 26 °C. However the functioning of the two system cannot be overlapped thanks to their schedules. The cooling is operative from May to September (from 8:00 AM to 6:00 PM); the heating is active from October to April (from 8:00 AM to 6:00 PM).

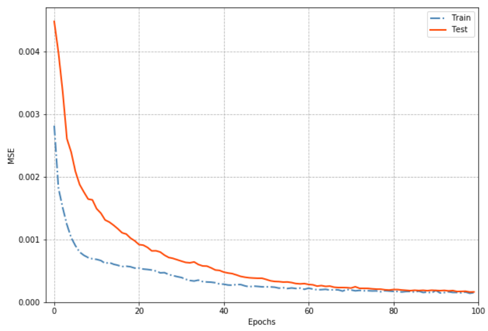
4.3 LSTM Models

LSTM models have been applied to the building designed according to Table 1.

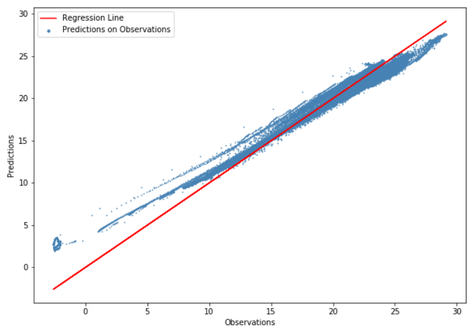
4.3.1 Internal Average Temperature Forecasting

The stack LSTM model has been trained for 100 epochs and different design choices have been tested. The ones described in Section 3.3.1 have proved the best with a Mean Absolute Percentage Error (MAPE) of 1.58%, a Mean Squared Error (MSE) of about 1.75e-04 referred to values belonging to the [0,1] range and a Mean Absolute Error (MAE) of 9.7e-3. These values are indicative of a quite high accuracy of the model.

The trend of the loss function for the training and test subsets shown in Figure 8(a) ensures that the model did not occur in overfitting.

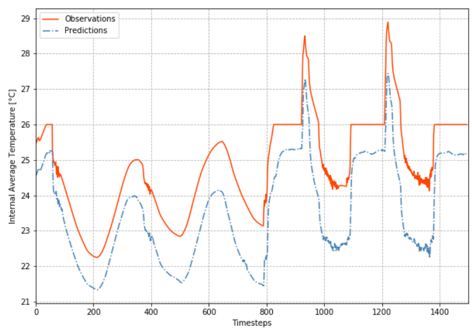


(a) Training and Test loss trends.

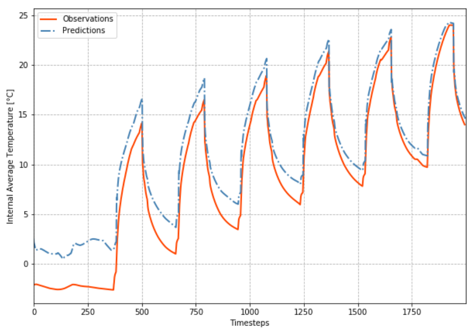


(b) Predictions and Observation comparison.

Figure 8: Performance evaluation of the LSTM model for the average internal temperature forecasting.



(a) Underestimation of observations greater than 20 °C



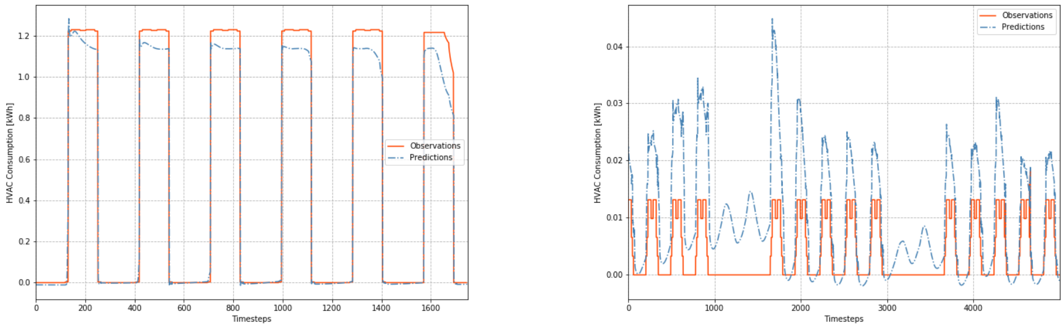
(b) Overestimation of observations less than 20 °C

Figure 9: Evaluation of predictions accuracy for the average internal temperature forecasting model.

Figure 8(b) shows a definitely not bad performance of the predictor, since most of the dots are near the line where the theoretical 100% accuracy is obtained. For observed values greater than 20 °C the model tends to underestimate the predictions. This can be noted in Figure 9(a), in which the general trend is lowered by approximately 2/4 °C than the real one.

Regarding the less dense dots of Figure 8(b) referred to values less than 20 °C, this is symptom of underestimation of the model, confirmed by the minimum and maximum peaks of Figure 9(a).

In light of this, it is possible to state that the model performances are quite accurate. The peak values are not perfectly detected, but, in general the 5 minutes trend of the average internal temperature of



(a) Underestimation of wintertime observations. (b) Overestimation of summertime observations.

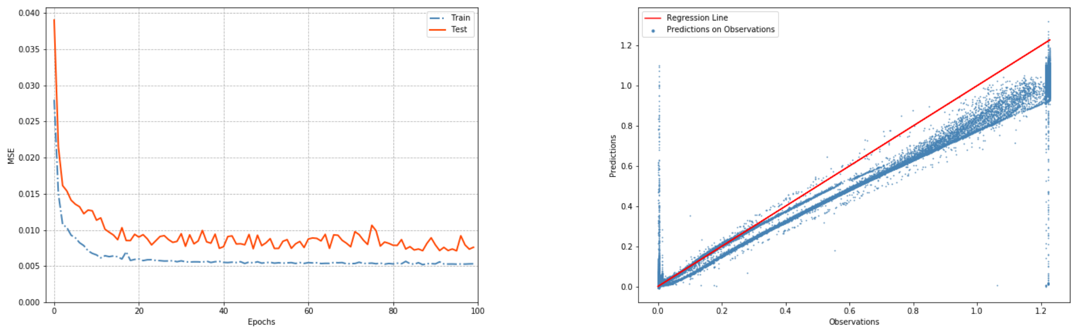
Figure 11: Evaluation of predictions accuracy for the HVAC power consumption forecasting model.

the office is well predicted. These results are positive in the context of the automated thermal control system development.

4.3.2 HVAC Power Consumption Forecasting

According to Section 3.3.2 the most of the data, which was the external environment one, have been discarded. Moreover additional binary information about the HVAC system schedule has been integrated to the available data related to the internal temperature.

The obtained performance was worse than the one of Section 3.3.1 with an MSE of 8.5e-3, a MAE of 0.035 and a Mean Absolute Percentage Error of 2.8e6%. The high value of the MAPE can been explained by considering that due to the system schedule (from 8:00 AM to 6:00 PM during the working days) the most of data is equal to 0. By considering that MAPE divides the absolute error by the actual data, it is reasonable that very high values are obtained. For the same reason of the MAPE, even the MSE records higher values than the one of Section 3.3.1, since the intermittent ON/OFF trend forced by the schedule makes the model learn a wide range $[0kWh, 1.5kWh]$ with a large amount of 0s.



(a) Training and Test loss trends. (b) Predictions and Observation comparison.

Figure 10: Performance evaluation of the LSTM model for the HVAC power consumption forecasting.

Figure 10(a) shows the trend of the loss function. If the training dataset leads to acceptable performances, the test one make the MSE (used as function to minimize) oscillate between 7e-3 and 1.2e-2 with resulting inaccurate predictions as shown in Figure 10(b). A part from observations close to 0 which are severely overestimated because of the steep trend when the system passes from ON to OFF and vice-versa, the model tends to underestimate all the observation. The magnitude of the underestimation increases when the observation increases too, by confirming the considerations about the MSE and MAPE values.

The trend of Figure 10(b) can be seen more accurately in Figure 11, where the Winter consumption of the heating system[2] shown in Figure 11(a) is lowered by values belonging to the $[1.1kWh,\ 0.8kWh]$ range. On the other hand, since the heating system is functioning from October to April, whereas the cooling one is operating from April to September, it is clear that the model tends to learn an overall high power consumption which leads to a severe overestimation of the low cooling system observations shown in Figure 11(b).

According to the obtained results and considerations, it is possible to state that differently from the average internal temperature model of Sections 3.3.1 and 4.3.1 such system cannot be treated as a reliable one in an automated power control system perspective.

5 Conclusions

After the performed analysis it is clear that the most of the building energy consumption is due to the heating one. This is reasonable by considering the cold location of the building under analysis. According to Section 4.1 the preliminary considerations about the energetic trends are confirmed, so the eastern orientation of the building together with the operative natural ventilation lead to the best performance in terms of consumption. However it is important to notice that the best design parameters have been chosen as one of the best compromises between all the considered variables. Indeed, if the insulation of the walls is increased over 0.25 m the energetic benefits are diminishing. The same considerations can be extended to the Argon filled area of the double glazed windows.

Regarding the windows configuration, all the obtained results are realistic and in line with the original assumptions, since by increasing the WWR the lighting consumption drastically decreases because of the larger amount of transmitted diffuse solar radiation, whereas the HVAC consumption increases because of the insulation worsening. Moreover, a good strategy to reduce the artificial light use is to make the visible transmittance grow, since more natural light is allowed.

The building energetic profile of Figure 7(d) shows an acceptable low heat loss coefficient $K = 0.021$ when the analysis is performed on a weekly basis, meaning that the chosen parameters can provide a sustainable development of the office.

Finally, the results of Section 4.3 show that if an LSTM model can be a right choice to develop an automated HVAC control system, since the average operating temperatures are well predicted, when its power consumption is taken into account, the forecasting becomes quite inaccurate. Thus a possible strategy can be choosing a grey box model such as the RC building model performing a new feature selection to provide more correlated variables.

[2]By considering the parameters optimization performed in Section 4.1 and by considering the usually cold location of Moscow, it is reasonable that the heating system is responsible of the most of the HVAC power consumption

A Deep Learning

Model evaluation and the choice of the optimizer are crucial parts of deep learning. The first helps to find the best model that represents the data and how well the chosen model will work in the future, the latter can improve or brake the model itself.

A.1 Performance Indicators

The performance indicators can be divided in two classes: the relative ones and the absolute ones. Two relative indicators are the

- Mean Squared Error (MSE). By considering $\mathbf{Y} \in \mathbb{R}^N$ as the vector of observed target variable, and $\hat{\mathbf{Y}} \in \mathbb{R}^N$ as the vector of the values predicted by the model, the MSE is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{Y}_i - \hat{\mathbf{Y}}_i)^2 \tag{4}$$

  so it measures the average of the squares of the errors. For this reason it is considered as a risk function, corresponding to the expected value of the squared error loss and so it is often taken as loss function in deep learning regression problems;

- Root Mean Squared Error (RMSE). It is the root of the MSE, defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathbf{Y}_i - \hat{\mathbf{Y}}_i)^2} \tag{5}$$

Being relative indicators, a threshold value to determine the goodness of the model is impossible to determined, however, the lower they are, the better the model is.

The absolute indicators are:

- Mean Absolute Error (MAE). It is a measure of difference between two variables. Graphically it can be defined as the average vertical or horizontal distance between each point and the identity line. By considering $\mathbf{Y} \in \mathbb{R}^N$ as the vector of observed target variable, and $\hat{\mathbf{Y}} \in \mathbb{R}^N$ as the vector of the values predicted by the model, the MAE is defined as:

$$MAE = \frac{\sum_{i=1}^{N}|\mathbf{Y}_i - \hat{\mathbf{Y}}_i|}{N} \tag{6}$$

- Mean Absolute Percentage Error (MAPE). It expresses the mean absolute error as a percentage by using the formula:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\mathbf{Y}_i - \hat{\mathbf{Y}}_i}{\mathbf{Y}_i}\right| \tag{7}$$

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