Machine Learning for Building Energy Prediction: A Case Study of an Office Building

Matias DOGLIANI[1], Nathan NORD[1], Ángeles DOBLAS[1], Ian CALIXTO[1], Sandra WILFLING[2], Qamar ALFALOUJI[2], Gerald SCHWEIGER[2].

1: FH Joanneum – University of Applied Sciences, Institut Energie-, Verkehrs- und Umweltmanagement, Werk-VI-Straße 46, 8605 Kapfenberg, Austria, {firstname}.{surname}@edu.fh-joanneum.at

2: Graz University of Technology, Institute of Software Technology, Inffeldgasse 16, 8010 Graz, Austria, {firstname}.{surname}@tugraz.at

Abstract: A pressing task for future energy systems is the design and operation of systems that integrate large shares of renewable energy. Buildings are responsible for 32% of total global final energy use and 19% of energy-related greenhouse gas emissions. To enable the transition to a sustainable energy system, buildings must evolve from their current static and inefficient performance to smart dynamic actors embedded in an overall smart energy system. To enable this, accurate forecasts of building energy use are needed. In this paper, we compare four different machine learning methods for predicting the energy usage of an office building in Graz, Austria. The used methods are linear regression, decision tree regression, support vector regression and multi-layer perceptron regression. Furthermore, we analyse how different lookback horizons influence the accuracy of the models. Results show that the decision tree regression outperforms the other models in terms of accuracy.

Keywords: *Building, Machine Learning, Energy Usage Prediction, Rolling window prediction*

1 Introduction

The main step to a sustainable future is the transition to renewable energies [1]. The challenge for systems with high shares of renewable energy is to match the available energy from variable renewable resources with the electricity demand in place, time and quantity. On the one hand, solar and wind energy must be used in conjunction with more stable energy sources such as hydropower or biomass. On the other hand, an overall intelligence must control and optimize the system [2]. In order to optimally control the systems, detailed forecasts of renewable energy generation and demand at different levels are crucial. Advances in Internet of Things technologies and Cyber-Physical Systems provide researchers and practitioners with large amounts of operational data on different scales of the energy system, leading to new opportunities for machine learning (ML) applications [3].

1.1 Related work

Buildings are responsible for 32% of total global final energy use and 19% of energy-related greenhouse gas emissions [4]. With an accurate forecast of energy usage from buildings , the supply of energy can be readily planned, making it easier to balance renewable energy supply from various sources. In energy usage prediction, ML models have been gaining increasing interest [3]. In contrast to conventional physical models, ML models are independent of system knowledge or parameters. The inherent structure of ML allows predictions of complex systems purely based on training data. [4]. Commonly used ML methods are linear regression [5] , decision tree regression [6], support vector machine (SVM) regression [7] and multi-layer perceptron (MLP) regression [8]. While linear regression and SVM are based on linear models, MLP models include non-linearity in their architecture. A completely different approach is used by decision tree regression, which is based on creating a set of decision criteria for each possible target value [9].

1.2 Main contribution

In this paper, energy consumption of a building at Graz University of Technology will be analyzed and predicted using 4 different machine learning methods: Linear Regression, Support Vector Regression (SVR), Decision Tree Regression (DTR) and Multi-Layer Perceptron Regression (MLPR). We analyse how different lookback horizons influence the accuracy of the models. The developments and the data are openly available (**https://github.com/matias-dogliani/energybuild**).

2 Method

We developed different machine learning models to create energy consumption forecasts. These models were trained on an data set obtained from energy usage measurements taken from a building at the Graz Universitiy of Technology. Additionally, weather data for the respective time span was acquired using the API from [10]. In each model, the same inputs were used: month, day, hour, holiday, temperature and week day. The output was energy consumption. In order to create the model, the following steps were taken: firstly, the data set was pre-processed, afterwards, the features for the model training were selected, and finally the model was trained and validated.

2.1 Data preprocessing

A machine learning model is only as good as the data it uses. Therefore, the data that the model uses must be cleaned and preprocessed, allowing the algorithm to easily recognize patterns it can later use to calculate the output. The first step in preprocessing data is to recognize and manage outliers. Historical data of hourly energy usage of a building was collected in the time span of 9 months. As shown in Figure 1, the distribution of this data was determined to be non-Gaussian.

Therefore, we could not use statistical methods to detect anomalies. Rather, a rule-based method was used. These rules are based on expert knowledge combined with visual analysis of the data. We defined outliers as negative values, zero values, and values that are obviously too high or too low for a given time period. The latter one was defined based on upper and lower bounds, which were set to 4 multiples of the median and 0.3 multiples of the median (see Figure 2). The outliers were replaced by linearly interpolated values.

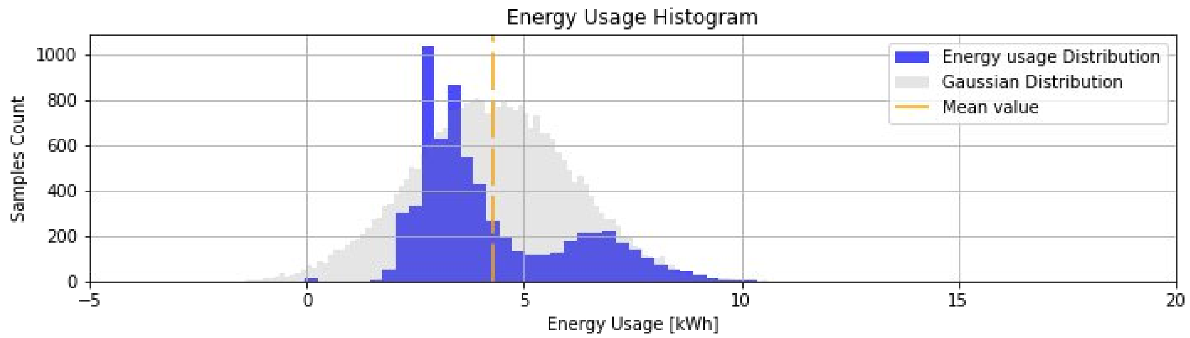


Figure 1: Energy Usage Histogram

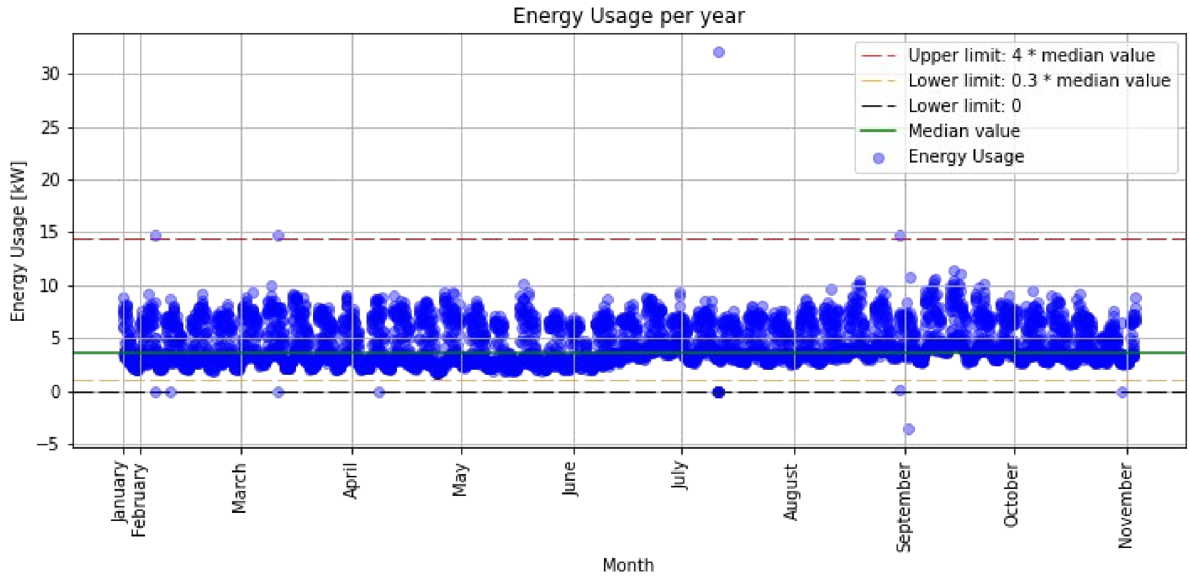


Figure 2: Energy Usage with upper and lower Limits

2.2 Features Construction and Selection

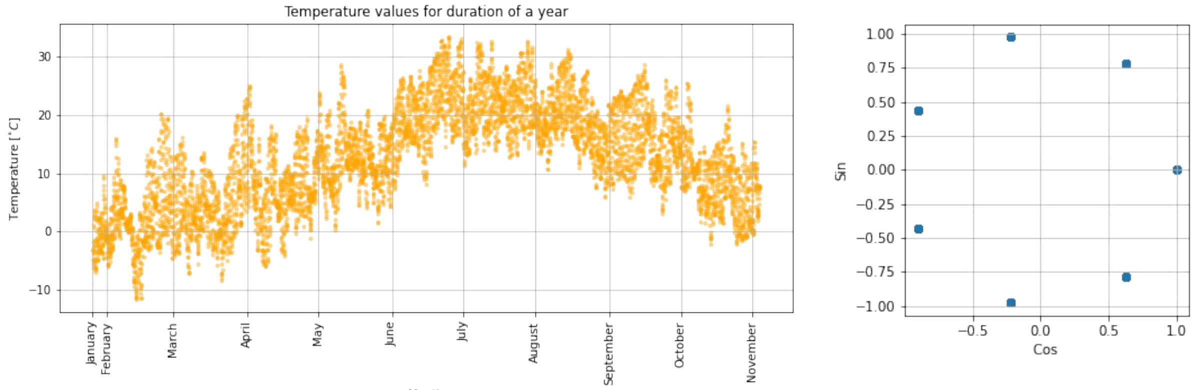
Feature selection is a crucial step in ML. Features act as the input variables in which the model can recognize patterns to ultimately predict the target. A more comprehensive feature selection process will result in a more accurate result. The features selected were basic factors contributing to energy use of a building; the features being temperature, weekday, holidays, month, day, and hour.

An important feature of energy usage in buildings is the temperature at any given hour. To obtain the temperature data for the given time, we used historical weather provided by [10]. The temperature values over one year are depicted in Figure 3a.

By visually analyzing the data, no outliers were observed, and hence there was no need to implement anomaly detection. All missing values were estimated using linear interpolation.

As the day of the week dictates whether an office building is used or not, defining week days was critical for the accuracy of the model. To represent the cyclical nature of the week days, an encoding method was used to have the same difference between consecutive days. First, each day (0-6) was represented with normalized values between 0 and 2π. Then, sin and cosine functions were evaluated for these values and assigned to each day of the week. These two values represent a unique combination that match the distance requirement and were used as input variables. The same distance between consecutive points (representing encoded days) is observed in Figure 3b, in which each combination of sin and cosine value is plotted.

Another important feature is holidays, as significantly fewer people are in the office building on these days. Therefore, a new input variable column was added, filled with 1 in each time stamps matching a holiday or 0 if not.



a) Temperature values over the duration of a year

b) Weekdays represented by cyclical function

Figure 3: Input features

2.2.1 Dynamic approach for time-series forecasting – Rolling window

To potentially improve the prediction accuracy, a rolling window approach was implemented. In contrast to conventional regression methods, rolling window regression includes not only the current value of the input features, but also previous input feature values depending on a lookback horizon [11]. Due to the fact that temperature highly affects the energy consumption, the "temperature" feature is chosen to be a "rolling window" feature with different number of lookback steps. This helps in increasing the number of features which is essential for some ML approaches. Every lookback step is defined as 1 hour. Figure 4 depicts a graphical description of the lookback time steps where a forecasting of the energy temperature at time t uses the temperature values according to the defined window size. We compared lookback horizons of 6 and 12.

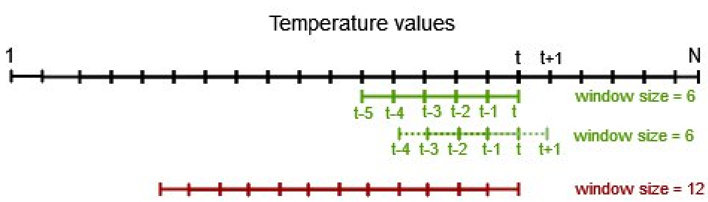


Figure 4: Overview of rolling windows with different sizes

2.3 Training and validation

The data set was separated into a training set consisting of 80% of the data, and a validation set consisting of 20% of the data. The training and validation set were selected based on random sampling of the input data. To assess and compare model performance we used three error metrics: the coefficient of determination (R^2), root-mean-square error RMSE, and mean-absolute error MAE.

3 Results

To evaluate the performance of the models, we first applied a hyperparameter tuning in the form of a grid search. We then evaluated the performance of static prediction and rolling window prediction.

3.1 Grid search

For each model, the optimal hyperparameter settings were determined through a grid search. Considering that each model follows different algorithms and hence has different set of parameters, different grid search settings were used for each model. The best configurations are shown in Table 1. Due to the high variance of the outputs range of the MLP, a k-fold cross validation with 10 splits was implemented, and the best split outputs are reported in the table.

Model	Parameters
Linear Regression	Default
Decision Tree Regression	criterion = mean-square-error (mse)
	minimum number of splits (min_num_of_split) = 60
Support Vector Regression	gamma = 0.01
Multi-Layer Perceptron	hidden_layer_sizes = (400,20)
	activation function = Tanh
	alpha = 0.001
	learning rate = constant value with the initial equals to 0.001

Table 1: Optimal grid search parameters

3.2 Rolling window temperature experiments

The rolling window approach was tested for lookback horizons of 0, 6, and 12 hours. A lookback horizon of 0 means that only the current values of the input features are considered. For each lookback, the four different models were trained and validated. The results of these experiments are shown in Table 2.

Model	Linear Regression			Decision Tree			SVR			MLP		
	0 Steps	6 Steps	12 Steps	0 Steps	6 Steps	12 Steps	0 Steps	6 Steps	12 Steps	0 Steps	6 Steps	12 Steps
R2	0.30	0.48	0.52	0.91	0.91	0.91	0.72	0.64	0.62	0.78	0.80	0.80
RMSE	1.51	1.32	1.25	0.55	0.56	0.55	0.96	1.10	1.12	0.83	0.80	0.73
MAE	1.19	1.05	1.00	0.36	0.38	0.37	0.68	0.76	0.73	0.58	0.55	0.57

Table 2: Experiment results for different lookback values

According to the three assessment metrics R^2, RMSE, and MAE, the DTR was determined as the best performing model. In addition, an effect of the features and lookback samples on implemented algorithm in the estimator can be observed from the results in Table 1. For instance, the performance of the linear models improves with more lookback samples. This result can be explained by the linear predictors trying to form a linear relation between the features, in which a higher number of features provides more information, but also requires more number of neurons and layers. On the other hand, Decision Trees, which randomly generate possible solutions to reach the optimal value, do not improve by using the added features. The SVR model showed the best performance without using any of the lookback steps, since it uses an internal regularization, therefore the performance ought to be good without applying any extensive feature selection, or more information which could lead to model over-fitting. For the final model selection, the lookback of 12 in combination with the grid search determined settings (Table 1) was determined to be the optimal choice.

3.3 Comparison of final results

Figure 5 shows the performance of each model using the optimal settings from the grid search (Table 1). The DTR, MLPR and linear regression models were selected with a lookback of 12, the SVR model was selected with a look back of 0. Figure 5 shows that the decision tree regression outperforms the other models in terms of accuracy.The results of linear regression and SVR show significantly lower correlation.

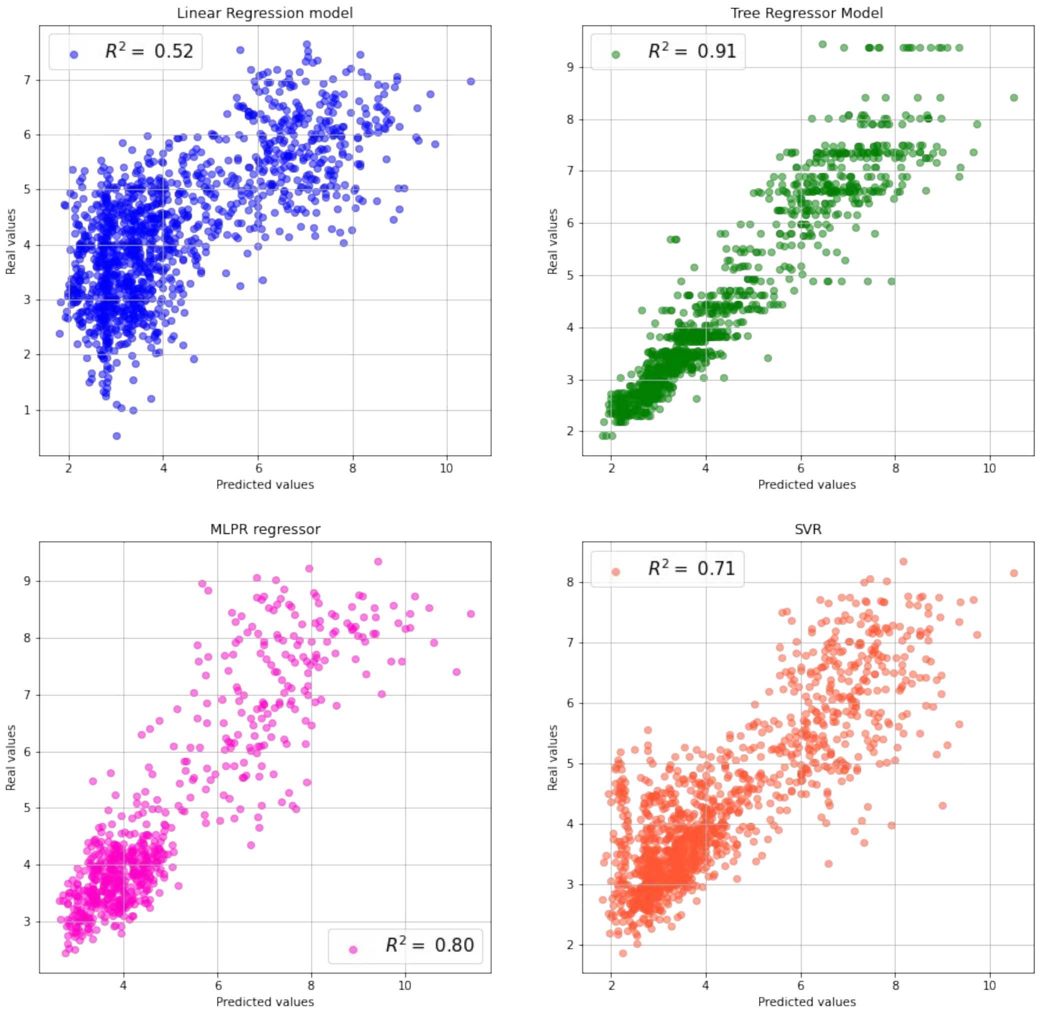


Figure 5: Comparison of real and predicted values.

The performance metrics of the four models are visualized in Figure 6. DTR models perform best across all metrics, followed by the MLP regressor, SVR, and linear regression.

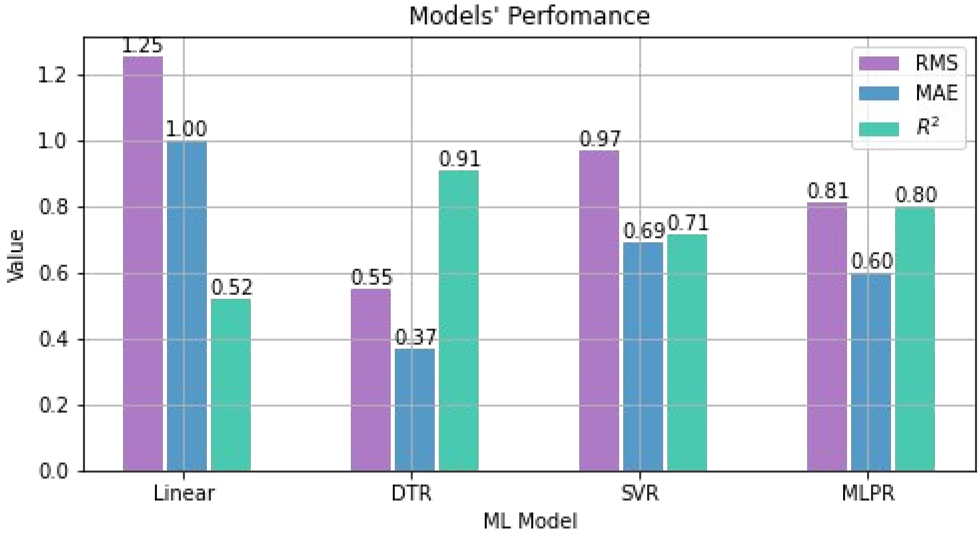


Figure 6: Model Performance Comparison

4 Conclusion

Energy usage predictions using physics-based models are complex, expensive, and require extensive computational power. Machine Learning is a promising alternative as it can overcome the limitations of physics-based approaches. In this paper, we compare four different machine learning methods for predicting the energy usage of an office building. Furthermore, since the energy demand is highly affected by the outdoor temperature, we analyze how different lookback horizons of the temperature influence the accuracy of the models. The results show that the performance of the linear regression and MLP regression increases with a higher lookback, due to the additional provided information which helps in forming a relation between the inputs and outputs and hence increases the prediction accuracy. On the contrary, the performance of the DTR and SVR slightly decreases with a higher lookback. Results show that the decision tree regression outperforms the other models in terms of accuracy. Further research could be devoted in applying the concept of dynamic features on the other inputs in order to analyze the feature importance and their contribution in the model performance, especially using the output of each time step as a new input for the next time step. In addition to use more models such as Neural Networks.

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