



# Machine Learning based Energy Consumption Prediction of Appliances in a Low Energy House

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**Abstract**—In reaction to the impacts of global warming, individuals are becoming increasingly conscious of their homes unchecked power usage, particularly the use of electrical energy for cooking, heating, refrigeration, dish-washing and drying. There is an increased concern about idle losses, expended by devices when not in use, which not only add to utility bills but also add to the waste of energy. Monitoring and controlling end-use electricity demand in residential buildings can have a significant impact on reducing peak demand and optimizing energy consumption that can be achieved in smart households with residential load control systems.

This study benchmarked eight Machine learning based algorithms: Linear, Ridge and LASSO regression; Support Vector Machine; Multilayer Perceptron; Nearest Neighbor regression; Extra-Trees and XG-Boost on a pre-collected “appliance energy” data-set. The specified algorithms were benchmarked on error metric of: training and testing set R-squared statistic; MAE; RMSE and also training time. Data-preprocessing and visualization was done to yield insight into data used. Firstly, un-tuned version of the eight algorithms were benchmarked, then model tuning via Grid-Search was carried for five algorithms and finally the effects of inclusion of certain features and varying parameters was tabulated and graphed. The least scores, on the specified error metrics, were obtained by the regression algorithms. The best scores were obtained by Extra-Trees and XG-Boost, which belong to ensemble algorithms of which Extra-Trees obtained best variance explanation (R-squared) scores of 98.94% on training set and 60.21% on testing set along with least scores on above specified error metrics.

**Keywords**— Machine Learning, Regression, Prediction.

## I. INTRODUCTION

Reduction of CO<sub>2</sub> emissions is the need of the hour as excessive energy usage has led to increase of ill effects of greenhouse gas and has impacted various sectors of economy in the world[1]. Among the various sectors, the residential block

remains a dominant consumer of electrical energy in each and every country and in need of special attention for the development of techniques to reduce energy consumption. In the U.S residential building consumes about 16-52% of all sectors combined and comes around a worldwide average of 30% [2]. In response to the effects of global warming, people are increasing becoming aware of the excessive energy consumption in their homes especially electrical energy use for cooking and heating[3]. They are now more conscience of the standby losses that appliances incur which not only increase utility bills but also contribute to energy wastage[4]. To help users in adopting renewable energy generation, implement demand side management, promote healthy energy consumption strategies and home automation infrastructure detailed models are need to capture the energy consumption habits of their home[5].

In general, the tentative estimate of complete energy usage in the housing industry is released by governments: compiling gross energy values presented by energy suppliers[6]. These estimates offer good indices of energy consumption in the incumbent sector but may be incorrect, since they do not cater for unreported energy or generation on-site

Techniques for modelling residential energy usage can be generally divided into two classifications: “top-down approach” and “bottom-up approach”. The top-down perspective treats the housing industry as an energy drain and individual uses does not differentiate energy usage because of personal end-use. The bottom-up method includes all models using input information below the level of the overall sector. Models can account for individual end-use power consumption; on the basis of the representative weight of the model sample, individual houses or groups of houses are then extrapolated to represent the region or nation

The approach taken in this study is that of a “Machine learning” model building approach. ML based energy consumption prediction methods have gained a lot popularity in recent years due to increase in computing power; especially increase in the processing power of graphic processing units (GPU), multi-core processors, open-source implementation of sophisticated algorithms and wide availability of data available

from various repositories that host data for ML model building purposes.

## II. RELATED WORK

Westergren et al.[7] Proposed a LR model which takes weather data as input and predicts electricity use of four homes located in Sweden. Three models were proposed for the prediction of electrical energy consumption per unit hour. The first two models were of the LR kind which took the mean of deviation of temperatures inside and outside the house. Al-Garni et al.[8] Developed a LR model to predict electricity consumption in Eastern Saudi Arabia by using environmental variables such the ambient temperature, humidity, solar irradiation. Model variables were selected using the step-wise regression technique. T.A Reddy et al.[9] Used synthetic data to develop a multiple regression and a Principle component analysis (PCA) based model to predict daily electricity consumption. Moletsane et al.[10] Implemented a LR model on real data collected over the period of two years from the sensors placed inside two houses. The electricity consumption data of a house was obtained every 30 minutes. The data was recorded using every wall socket plug in the house. Ambient temperature and outside weather conditions were used to develop the regression model. For home 1 an R-squared value of 0.67 was obtained which had not heating/cooling load control while for home 2 an R-squared value of 0.87 was obtained which had a better load control mechanism installed.

Kalogirou et al.[11] Used a multilayer recurrent neural network (RNN) with back-propagation for predicting the energy consumption of a passive solar house. Two cases were investigated: one with building walls fully insulated and one with partial insulation of building walls with thermal insulation and masonry. The effect of two seasons: summer and winter was also included in the experiment. The artificial neural network was trained on the simulated data using the variables listed above with the output being the building energy consumption in kWh. The model achieved an R-squared value of 0.9975 on the training data and an R-squared value of 0.9911 on the test data which signals accuracy of the model in explaining the variance in the building energy consumption of a building. Neto et al.[12] Implemented feed-forward neural network (FFNN) with 11 neurons and 4 hidden layers to predict the energy consumption of an administration building of a University campus in Sao Paulo and compared the performance of the algorithm with a detailed building energy simulation software (Energy-Plus). The input or feature variables were meteorological data: humidity, temperature, atmospheric pressure, solar radiation; the occupant behavior (air-conditioning use); effect of weekdays and weekends; lighting use in the building and the seasonal affects: summer, winter. The results showed that the detailed engineering approach to predicting building energy consumption that take building physical characteristics as input produced an error range of  $\pm 12\%$  for 80% of the testing data while the neural network model produced an average error of about 9% on the test set including the effects of weekends.

Gonzalez et al.[13] Used a multilayer perceptron with feed-back to predict hourly electricity consumption of a building. The dataset used was divided into two parts to simulate two distinct

building energy consumptions. The neural network was composed of one hidden layer, 25 neurons, and the tangent hyperbolic function was used as an activation function. The input features were environmental variables, building occupancy, time of day, hour of day, effect of public holidays. The predicted variable was total electricity consumed in an hour in the two building. The neural network was trained using a hybrid back-propagation method which had recursive feature. The trained neural network was able to achieve a coefficient of variation (CV) score of 1.4422, mean bias error (MBE) of 0.0332 and a mean absolute percentage error (MAPE) of 1.955. The authors used a training of 21 days to achieve the best results. The results showed that the training window was an important variable for increasing the algorithm's accuracy in forecasting electricity consumption

A Chae et al.[14] Implemented a neural network with Bayesian based regularization to predict energy usage of an office building. The data used consisted of 1000 sample point with 21 different types of measurements recorded at 15 minute intervals in (kWh). The variable used for the prediction were ambient conditions, weather variables, temperature, humid, time of the day, day of the week, operation cycle of the HVAC components especially chillers. The preliminary variable selection was performed using random forest (RF) algorithm. The algorithm was applied till 6 important variables were selected. A Bayesian regularized neural network was used to train on the reduced dataset. To select the optimal number of hidden layers and neurons the two were varied. The neurons were varied between 10 and 50 while number of hidden layer varied between 1 and 10. The best architecture had 6 hidden layers and 50 neurons with a sigmoidal activation. The trained network achieved an average of RMSE (RMSE) 10% and mean squared error (MSE) of 0.0099.

Biswas et al.[15] Applied feed-forward neural networks with two different kind optimization algorithms to train the network: the Levenberg-Marquardt (LM) and OWO-Newton to predict the energy consumption of an unoccupied house. Two cases were considered: one for predicting the overall energy consumption and the other for predicting the energy consumed by a heating pump. The model considered various weather parameters as input features: the dry bulb temperature, relative humidity and solar radiation. First an ANN was trained using the LM algorithm to predict the overall energy consumption of the unoccupied house. The data was collected during the summer from June 2013 to August 2013 with 60 sample points. 25% percent of the data was set aside for testing and rest for training. Using exploratory data analysis it was revealed that the overall energy consumed by the house was highly non-linear as compared to the energy consumption trend of heating pump. The ANN had one input layer, one hidden layer with 8 neurons and one output layer. The LM ANN was able to achieve an R-squared value 0.868 and the OWO-Newton ANN was achieved an R-squared value 0.871 with 1000 epochs. The same networks were used to predict energy consumption of heating

pump of the unoccupied house. The LM ANN predicated with an R-squared of 0.912 while the OWO-ANN achieved an R-squared of 0.886. From the results it was concluded that LM ANN performed had a slight edge over the OWO-Newton algorithm in terms of prediction accuracy

Dong et al.[16] Applied support vector regression to forecast the hourly energy consumption of four office buildings located in a tropical region in Singapore. The SVM used RBF as kernel and 4-fold CV was applied to find the Cost parameter (C) and epsilon error parameter ( $\epsilon$ ). A grid search was performed for the data of 4 buildings to estimate the value of C and  $\epsilon$ . The C varied between 2-5 and 25 and  $\epsilon$  varied from 0.001 to 0.1. The SVM with C = 2-5 and  $\epsilon$  = 2-2 was able to achieve an MSE = 0.14, %Error = -1.89, CV = 99%..

### III. METHODOLOGY

The approach taken in this study is that of a “Machine learning” model building approach. ML based energy consumption prediction methods have gained a lot popularity in recent years due to increase in computing power; especially increase in the processing power of graphic processing units (GPU), multi-core processors, open-source implementation of sophisticated algorithms and wide availability of data available from various repositories that host data for ML model building purposes. The seven steps are outlined below and are each explained in detail.

1. Data acquisition
2. Data Preparation or Pre-processing of data
3. Selecting algorithm
4. Training the algorithm
5. Testing the algorithm
6. Parameter tuning
7. Prediction

#### 1. Data acquisition

The data used for this study was downloaded from “UCI ML Repository”. The data-set consists of 19,735 sample points on 29 features. The data points comprised 10 minutes interval aggregated energy consumption data recorded by sensors placed in various rooms of a passive energy house. The data-set mostly consists of humidity and temperature conditions inside and outside house. The variable to be predicted is “appliance energy consumption”, represent by “appliances” column, whose units are in Watt-h.

#### 2. Data Preparation or Pre-processing of data

First, data is read using the “Pandas” library. The data-set is then split into training and testing set, in which, 75% is for training and 25% testing. After performing the split, the training data consisted of 14,801 sample points and 4,934 test sample points (Figure 1).

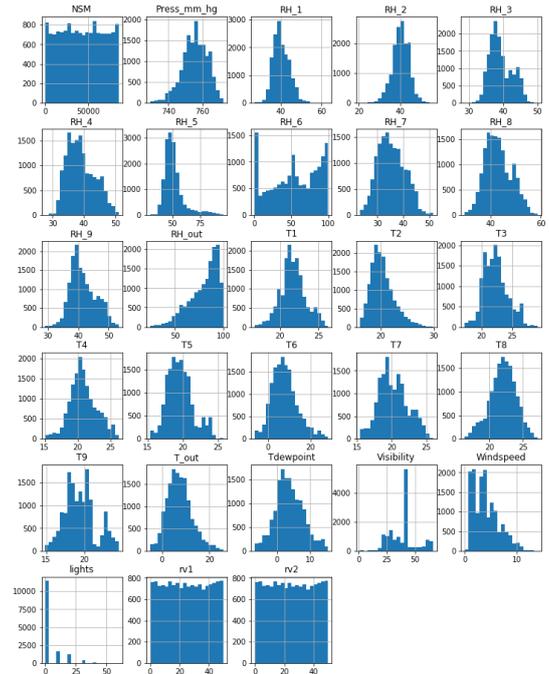


Figure 1. Distribution of predictors

To proceed with visualization of data, first the distribution of input features is plotted, the distribution of target variables and the correlation among them are also plotted, and finally some observations are made from visualization of data.

TABLE I. SUMMARY STATISTICS OF ENERGY USAGE

Count	14,801
Min value	10
Max value	1081
Mean	97.85
Standard error	102.93
25%	50
50%	60
75%	100

#### 3. Selecting algorithm

Selection of particular algorithm depends on numerous considerations, some of which are considered below:

**Problem type:** It is clear that algorithms were designed to solve specific instances of problems. It's important to know type of problem being dealt with and the type of algorithm used to solve that specific problem. It is vital to understand the nature of the problem and whether it yields itself to one of the following types of learning: Supervised, Unsupervised and Reinforcement learning.

**Training data size:** High bias and low variance classifiers (Naïve Bayes) have an edge over low bias and high variance classifiers (KNN) for a small training set, since the latter will start over-fitting. As high bias methods are not complex enough to provide accurate results, the low variance algorithms will start to show improved performance as the training set grows.

- Training time: Training time usually depends on the size of the dataset and the accuracy of output because algorithms have varying runtime.
- Parameter size: Parameters influence the behaviour of the algorithm, like tolerance for errors or number of iterations. Typically, in order to find a good mix, algorithms with a large number parameters require trial and error.
- Feature size: Compared to the amount of sample points, the amount of features in some datasets can be large. Often this situation has been observed in genetics and textual information. Some learning algorithms can be overwhelmed by the big amount of characteristics, making training time unfeasible. In this situation, certain algorithms such as SVM are especially suitable.
- Linearity assumption: Linear algorithms are good choice for first run of the data. This is the underlying assumption for many algorithms: LR, SVM, logistic regression, etc. it works well in some instances but may decrease the accuracy of the model in other situations.
- Accuracy: Approximation is sometimes sufficient, which can result in an enormous decrease in processing time. The desired accuracy is highly dependent on the ML problem. Approximation techniques are Noise immune and robust to over-fitting.

#### 4. Training the algorithm

The training process of an ML model includes providing sample data to learn from using an ML algorithm (learning algorithm). Training data should include the correct response, known as target attribute. Training data can be: collection of text, images, and that collected from individual processes by sampling. The learning algorithm discovers patterns in the sample data, mapping the target's input data features and yields an ML model capturing these patterns. The ML model is then employed to obtain predictions on news data for which the desired outcome is not known. Usually, 70% of the data is set aside of training.

#### 5. Algorithm Testing

To this end, a test harness is defined which means that a data set is created on which an algorithm is trained and tested against set performance measure. Testing the algorithm on an instance of a problem should be the objective of the test harness. The result of testing various algorithms will be an estimate of how a multitude of algorithms benchmark on the selected performance measure. Performance measurement is a means of assessing a solution to particular problem. Standard performance measurements will provide with a score that is relevant to domain of problem (e.g. classification accuracy). Using the entire transformed data set to train and test a specified algorithm is a more advanced strategy called CV which involves dividing the dataset into a number of instance sets (folds) of equal size. The model will then be implemented on all handles except one the developed model will be validated on the left out fold. This process is iteratively repeated for each fold and eventually performance measurements are averaged among all folds to assess the performance of the algorithm. 30 to 25% of data is used for testing.

#### 6. Parameter tuning

Hyper-parameters are external model settings variables whose values cannot be derived from data meaning in standard model training, they cannot be learned straight from the dataset. It is frequently specified prior to training by trial and error till best prediction performance measure is achieved by the algorithm. Grid Search is simply an exhaustive method of searching over a manually supplied subset of parameters in the hyper-parameter space. It has been the go to method for many researchers and been the conventional way of hyper-parameter tuning. The exhaustive search is tracked by a performance metric, usually training cross validation or test set evaluation score. It might need to manually set the boundaries or do a discretization of search space because search space of ML algorithm might contain real numbers or values which are unbounded.

#### 7. Prediction

After the model has been trained and cross validated the model is tested on 25% of data used for testing and the results are reported.

### IV. RESULTS

ML-algorithm benchmarking was done in "Jupyter notebook" which is a part of "Anaconda distribution" for Python. "Jupyter" provides an interactive environment for programming rather than a "compiled" approach. The libraries used for carrying out visualization of data were mainly "Matplotlib" and "seaborn"; for data analysis "Pandas" and for core-ML algorithms, the "Sci-kit learn" library was used which are all open-source and freely available. The simulation was carried out on a core-i5 7th gen processor with @ 16GB DDR5 memory.

#### Exploratory Data Analysis.

Temperature t1 through tout, are normally distributed. The interval values for inside house t1 to tout except t6 varies as 14.79°C to 29.65°C and outside house, t6, -6.04°C to 28.20°C. This range was obtained from "pandas' feature describe" function. Outside temp variability is more than inside temp (Table I). Humidity markers, both inside and outside house are mostly normally distributed and varies inside the house, for rh1 through rh9, between 20.63% to 63.56% except rh5 taking values 29.72% to 96.52% and rh6 which ranges 1% to 98.9%. Wind-speed, lights, visibility, rh6 and rhout have irregular distributions. Wind-speed exhibits positive skew while Visibility negative skew. Appliance exhibits positive skew with strong outliers as marked by high values of 1081. The mean of appliance column is 97.85 with standard deviation of 102.93. 75% of values lie below 100 which indicates lower energy use most time. The temp t1 through tout have positive correlations with appliances (**Error! Reference source not found.**). All indoor temp variables have strong positive correlation as compared to outside temps. A high correlation (> 0.94) exists between column t9 and t3, t5, t7, and t8 as shown plotted, t6 and tout also exhibit high correlation. The humidity markers have mild positive (< 0.6) correlations. Visibility, Tdewpoint, and Pressure\_mm\_hg have low (< 1) correlation values. Rv1 and rv2, the random variables have no effect. There are no variables that indicate Weekend days' consumption.

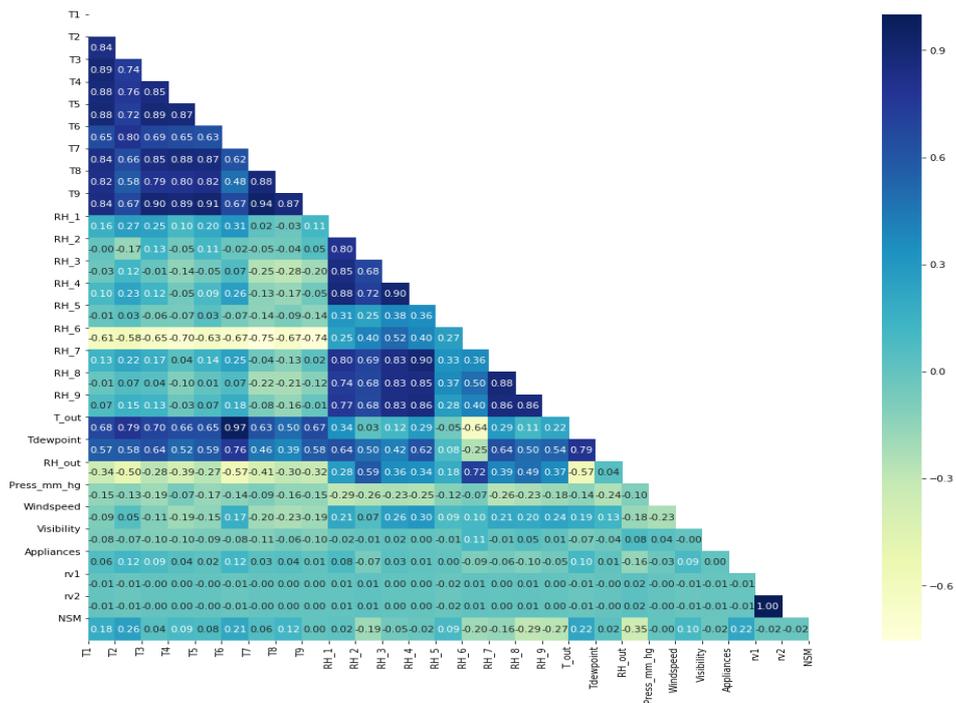


Figure 2. correlation among different predictors

### Data Normalization

Data pre-processing is done to normalize values between -1 and 1. To achieve this, the standard-scalar function is used which transforms the data-set to range specified. The target “appliance” is separated from the training set. This step is done to ensure no missing, corrupted or high values bias algorithm performance.

### Untuned models’ results

The un-optimized versions of ML-algorithm yielded the following performance results:

TABLE II. UNTUNED ALGORITHMS’ RESULTS

Name	Train R2	Test R2	Test Rmse	Mean absolute error	Train time
LASSO	0.0000	0.0000	1.000	0.5868	0.0050
RIDGE	0.1632	0.14522	0.9245	0.5522	0.0050
KNN	0.8410	0.4718	0.7267	0.3090	0.0471
SVR	0.2729	0.2403	0.8716	0.3610	6.5504
RF	0.91153	0.5073	0.7018	0.3397	1.7967
ET	1.0000	0.5436	0.6755	0.3149	0.6226
LR	0.1632	0.1452	0.9224	0.5229	0.0059
XGB	0.3603	0.2803	0.8483	0.4555	0.8302
MLP	0.4533	0.3576	0.8014	0.4545	4.5982

From the Table above (Table II), it can be seen that linear models: Linear, Ridge and LASSO regression have the least scores on RMSE, MAE and R-squared. Out of the regression models, LASSO was the poorest performer, indicating that

constrained based regression models should not be used on this data-set.

### Tuning via Grid Search

The KNN, MLP, SVR, XGB and DT algorithm wereselectedfor optimal parameter search. The optimal parameterGridSearch takes in a set of pre-specified set of values to gothrough in search of the best estimate. The parameter grid values for each of five ML-algorithms with 5-fold CV is given below:

- 1) KNN:
  - i) ‘No. neighbours’: { 2,4,6,8,10,15,20}
  - ii) ‘Leaf size’: { 15,20,25,30}
  - iii) ‘Metric’ = ‘Murkowski’
  - iv) ‘Weights’ = ‘uniform’
- 2) SVR:
  - i) ‘C’: { 1,5,10,15,20}
  - ii) ‘epsilon’: { 0.1,0.2,0.3,0.4,0.5,0.6,0.8}
  - iii) ‘Kernel’: ‘rbf’
- 3) MLP:
  - i) ‘Max iteration’: { 1000,5000,8000,12000,15000}
  - ii) ‘No. of hidden layers’: { 50,100,200,300,500}
  - iii) ‘Activation’=‘relu’
  - iv) ‘momentum’ = ‘Nesterov’
  - v) ‘learning rate’ = 0.001
  - vi) ‘momentum size’ = 0.9
- 4) XGB:

- i) 'No. of estimators': {1000,2000,4000,8000,12000}
- ii) 'min child weight': {1,2,3,5}
- iii) 'max depth': {5,10,15,20}
- iv) 'booster'='gbtree'

5) ET:

- i) 'max depth': {5,10,15,20}
- ii) 'No. of estimators': {1000,2000,4000,8000,12000}
- iii) 'max features': {auto,log2,sqrt}

*Tuned Algorithms Performance*

After grid searching for optimal parameters, the select algorithms were trained and tested (Figure 2) on the data.

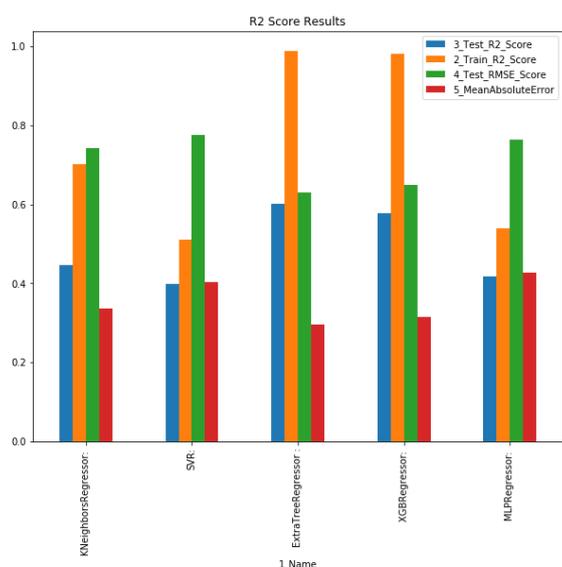


Figure 2. Tuned algorithms results

From tabulated error scores Table III, it is clear that the two best performing algorithms are XGB and ET.

TABLE III. TUNED ALGORITHMS' RESULTS

Name	Train R2	Test R2	Test Rmse	MAE	Train time
KNN	0.7027	0.4467	0.7438	0.3367	0.0508
SVR	0.5113	0.3987	0.7753	0.4033	5.4015
MLP	0.5402	0.4176	0.7631	0.4273	64.167
ET	0.9894	0.6021	0.6307	0.2953	629.3184
XGB	0.9820	0.55775	0.6500	0.3154	675.6424

**CONCUSLION**

One From data exploration, the results show that inside house temperature variable t1 through tout have more predicting power than outside temperature variable. Some temperature markers t3, t5, t7 and t8 had strong positive correlations with t9, so they were dropped. Humidity markers had mild correlations 0.3-0.6 with appliance variable while also exhibiting weak positive correlation 0.1-0.5 among itself. Lights variable was irregularly distributed with a lot of zero values. Target variable

'Appliance' exhibited strong positive skew indicating outliers while 75% of values (in Watt-h) fell below 100 Watt-h, indicating low energy use, usually.

Eight ML-algorithms Linear, Ridge, Lasso, KNN, SVR, MLP, XGB and ET regression were implemented. The worst performing algorithms belonged to regression family in which the least scores were obtained by Lasso: Train R2 =0; Test R2 =0; Test RMSE=1; MAE= 0.5868, indicating constrained regression models completely fail on this data-set. Out of the eight, five select ML-algorithms: KNN, SVR, MLP, XG-Boost and ET were chosen for model tuning. The algorithms were fit with best estimates of parameters returned by Grid-Search and the results were tabulated. Out of the five, two best scoring ML-algorithms belonged to ensemble family: XGB and ET, in which ET obtained best benchmarking scores of, Train R2 =0.9894; Test R2 =0.6021; Test RMSE=0.65; MAE=0.2953 and training time of 629 seconds, using 22 features. The effect of feature selection was observed which revealed that 'NSM', 'T3', 'lights', 'RH3' and 'RHout' were the highest ranked. Reducing the feature set deteriorated algorithm's performance. A same result was obtained by reducing variable 'max depth' while keeping the number of iteration constant. The training time increased linearly with increase in max depth of trees.

This research used a relatively small set of parameters for the Grid Search to go through. Mostly the "number of estimators", "max-depth of leaves", "max-features" and "size of cross-validation" were changed for the best performing algorithms over a restricted set due computational and time constraints. Besides, there are other parameters like "leaf-weight", "minimum fraction of leaf" and "minimum impurity split", etc. that needs an exhaustive Grid-Search which may be considered in future work. The Grid-Search over the MLP was very limited; only the "number of iteration" and "number of hidden layers" was varied. For a more accurate model "solver for back-propagation", increasing the depth of hidden layers and momentum size etc. could be looked at.

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