

Prediction of Heating Load and Cooling Load In HVAC System Using Machine Learning Techniques

Vinod Desai

*Assistant Professor
Department Of CSE*

Angadi Institute of Technology and Management, Belagavi

Sampada Jadhav

Department Of CSE

Angadi Institute of Technology and Management, Belagavi

Savita M Sanadi

Department Of CSE

Angadi Institute of Technology and Management, Belagavi

ABSTRACT

Recent research shows that 30%-40% of building energy consumption can be saved through optimized operation and management without changing the building structure. The major areas of energy consumption in buildings are heating, ventilation, and air conditioning. One of the way in which energy efficiency can be improved in residential, public, and commercial buildings is through improved design and construction techniques that reduce heating, cooling, ventilating loads. Some of the characteristics of buildings that greatly affect the Heating load and Cooling load requirements are considered in this paper. Experiments has been performed by building two models- (a) Three Ensemble algorithms- Random Forests, Gradient Boosting Machines, Extreme Gradient Boosting (b) Hybrid ensemble model- Random Forests, Gradient Boosting Machines, Extreme Gradient Boosting is built. Results show that Hybrid ensemble model outperform Ensemble techniques with an appreciable margin.

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I. INTRODUCTION

Several studies in the past years have shown that the utilization of energy in the most efficient manner is an urgent demand of the modern era, as energy is being used in each and every field. Globally buildings consume the largest percentage of energy, and HVAC system consumes most of the energy in a building. HVAC maintains desired temperature within a building by meeting Heating load and Cooling load requirements. Energy efficiency in heating, ventilating, and air-conditioning (HVAC) systems is a primary concern in process projects, since the energy consumption has the highest percentage in HVAC for all processes.

The use of energy is widespread and reached almost every known area, from Industries to means of transport, from offices to households. As you improve the energy efficiency of your home, you need less electricity and thus rely less on carbon-intensive power plants. This reduces your home's demand from the plant, which in turn benefits the environment by reducing their carbon dioxide emissions. Building energy consumption benchmarks are representative values for common building types against which a building's actual performance can be compared. The building sector encompasses a diverse set of end use activities, which have different energy use implications. In the modern world, no aspect of life can be thought of which doesn't consume energy.

Buildings consume about 40% of the total energy consumed in the world. HVAC systems are responsible for the regulation of heat, airflow, ventilation, and air conditioning of an entire building. Heating and ventilation are of utmost importance in buildings. Heating Ventilation and Air Conditioning (HVAC) system function to maintain the comfort and safety of building occupants. HVAC systems have the potential to use upwards of 40% of the total electricity consumed in any building, as heating and especially cooling are generally run by electric power.

Further studies show that within buildings, HVAC (Heating, Ventilation and Air conditioning) system is the largest energy consumer accounting for 40-50% consumption. It is responsible for meeting the Heating

load and Cooling load of a building. These two are related to the thermal load of the building. When the building is cold, the thermal load is converted into Heating load and when the building is hot, thermal load is converted into Cooling load. The Heating load and Cooling load of a building directly affect its energy performance.

This paper focusses on several characteristics of buildings, analyses them and uses them for predicting the Heating load and Cooling load by building two models- (a) Three Ensemble algorithms- Random Forests, Gradient Boosting Machines, Extreme Gradient Boosting (b) Hybrid ensemble model- Random Forests, Gradient Boosting Machines, Extreme Gradient Boosting is built.

II. MACHINE LEARNING

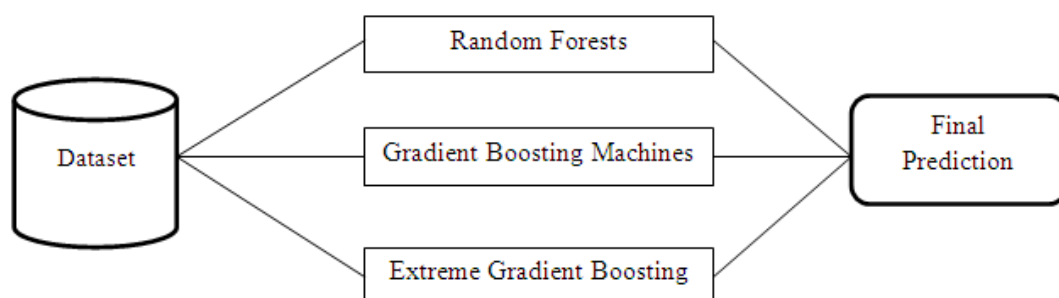
A. Ensemble Techniques

The basic fundamental of Ensemble techniques is to integrate the results of individual Machine Learning models, such that the prediction results exhibit improvement in terms of accuracy and robustness. Bagging and Boosting are two popular ensemble methods. The Ensemble techniques used in this paper are explained as follows:

- **Random Forests:** It is a tree-based ensemble technique that can be applied for both Classification as well as Regression. Some of the features which make Random Forests appealing are: Prediction efficiency, suitability for highly multi-dimensional problems, missing values handling, outlier removal etc.
- **Gradient Boosting Machines:** GBM is also an ensemble learning technique, whose underlying structure is Decision Tree. In GBM additive regression models are created by iteratively fitting a simple base to currently updated pseudo residuals by calculating least squares at every continuous iteration.
- **Extreme Gradient Boosting:** XGBoost is also a tree-based ensemble technique. Apart from performance and speed as its key features, this technique has an added feature of Scalability. Several optimizations have been performed on the basic algorithm to ensure the scalability of the model.

B. Hybrid Ensemble Techniques

In this task, the three different types of machine learning models are used as weak learners to build a hybrid ensemble learning model. These models are – Random Forests, Gradient Boosting Machines and Extreme Gradient Boosting. The term hybrid is used here because, in other ensemble models, a homogeneous collection of weak learners is used but, in this task, a heterogeneous collection of weak learners is used.



III. LITERATURE SURVEY

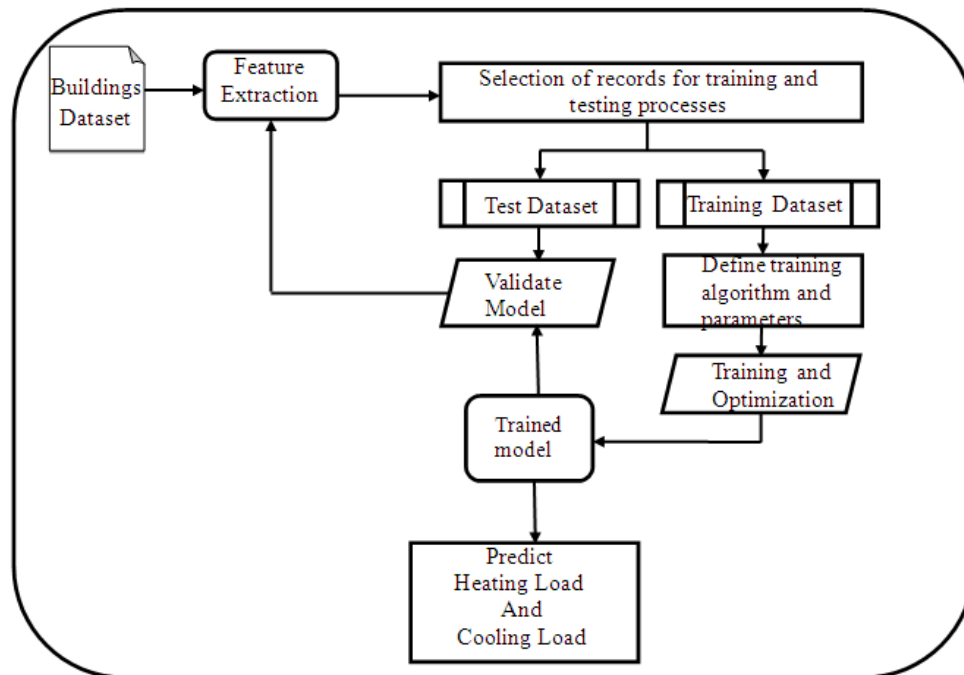
This section will review the different studies done so far to predict heating load and cooling load in buildings.

- A model developed for predicting of energy efficiency in building using three Machine Learning algorithms- Multiple Linear Regression, K Nearest Neighbors, Support Vector Regression and three Ensemble algorithms- Random Forests, Gradient Boosting Machines, Extreme Gradient Boosting and results show that Ensemble techniques outperform Machine Learning techniques with an appreciable margin.
- A ML framework developed to analyze the effect of different building parameters on Heating load and Cooling load using Iteratively Regressive Least Squares, Random Forests algorithms and results of Random Forests were better at revealing relationships between input and output variables.
- A model developed for HVAC energy optimization using MLP ensemble and result shows that energy savings were more when Internal Air Quality was taken into consideration.
- Model developed for predicting energy usage by appliances in residential building using MLR, SVM, RF, GBM algorithms and GBM outperformed other models; atmospheric pressure is an important predictor.
- Developed a new model which linearly combined the five ML models for better accuracy using ARIMA, RBFNN, MLP, SVM, FLANN and the model developed was better in terms of feasibility and performance

- Another model developed by using ML techniques applied to predict accurate Air quality index using DT, Naïve Bayes, SVM, RF, LR, stacking ensemble, Voting ensemble and the Ensemble techniques outperformed others.

IV. METHODOLOGY

This section will explain the methodology used in this research work.



A. Data Collection

The dataset used in this research is a standard dataset that has been collected from the UCI repository. This dataset is related to Energy Efficiency in Buildings and consists of eight different characteristics of buildings which act as input variables and Heating load and Cooling load of buildings as two output variables.

B. Data Analysis and Pre-processing

Data pre-processing is a process that consists of checking the dataset for missing values and filling them with appropriate values, detecting and removing any outliers, converting it into a particular form suitable for applying algorithm, attribute selection etc. The dataset used in this research has been specifically created by a Civil Engineer for performing energy analysis in different kinds of buildings, so much pre-processing was not required. Pearson Correlation Coefficient was calculated to derive the strength of the relationship among several variables of the dataset. This coefficient facilitates the derivation of optimal filters for reducing noise. A zero value for the Pearson Correlation Coefficient means the variables are not correlated i.e., they are independent. A value closer to 1 indicates a high correlation among variables. The obtained Correlation Coefficient values are represented in matrix form.

C. Data Partitioning

Dataset was partitioned according to 70% - 30% rule into two subsets: Training dataset and Testing dataset. For partitioning, Random Sampling without Replacement was applied which resulted in 70% Training data and 30% Test data.

D. Model Construction

The model was constructed by applying three Ensemble techniques namely, Random Forests, Gradient Boosting Machines, and Extreme Gradient Boosting and Hybrid Ensemble model. The models were applied on the Training dataset and validated using the Testing dataset.

E. Model Evaluation

The evaluation of the results obtained after applying models was done using five well-known performance metrics namely Root Mean Square Error, Mean Square Error, Mean Absolute Error, R Squared and Accuracy.

V. RESULTS

All the experiments of the research were performed using Python. Three Ensemble techniques namely, RF, GBM, and XGBoost and Hybrid Ensemble techniques have been experimented on the collected dataset. The hybrid ensemble learning model has outperformed all the individual ensemble learning model.

A. Results of Ensemble ML model

The results obtained after applying all three above mentioned Ensemble Machine Learning algorithms on the dataset is 99.7% and 96.7% of accuracy for Y1 i.e., heating load and Y2 i.e., cooling Load for Random Forests algorithm, 99.7% and 97.4% of accuracy for Y1 i.e., heating load and Y2 i.e., cooling Load for Gradient Boosting Machines 99.7% and 97.3% of accuracy for Y1 i.e., heating load and Y2 i.e., Cooling Load for Extreme Gradient Boosting.

B. Results of Hybrid Ensemble ML model

The results obtained after applying all three above mentioned Ensemble Machine Learning algorithms on the dataset is 99.75% and 99.08% of accuracy for Y1 i.e., heating load and Y2 i.e., cooling load respectively.

VI. CONCLUSION

The issue of energy consumption at a fast pace and in large amounts demands solutions in this area, which can help in efficient energy use. Buildings being the largest energy consumer need more focus from researchers. The HVAC system consumes a large percentage of building's total energy. HVAC needs energy for operation so that it can meet the Heating load and Cooling load requirements of the building. Heating and Cooling loads are greatly affected by various attributes of a building. This research implements certain Ensemble techniques and Hybrid model to predict the Heating load and Cooling load of a building. The results of experiments prove the Hybrid model perform better than that of Ensemble techniques.

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