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# Predicting the power of Combined Cycle Power Plant

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## ABSTRACT

***With the rising share of renewables in the energy mix, there is a need for alternative flexible power capacity to mitigate its intermittency. The emerging role of the aggregator is important in untapping the potential of new flexibility sources. An aggregator bundles the flexibility of distributed generation and demand response, and offers the collective resources to wholesale electricity markets. This technical aggregation is referred to as a Virtual Power Plant (VPP). The main aim of this paper is to work towards a model to estimate flexibility characteristics of aggregates of DR (demand response) and DG (distributed generation) to better provide smart grid services from those aggregates in existing and future wholesale markets. This knowledge is the missing connection to ensure capabilities of real-time response into energy markets with a fixed time control loop. Traditionally this has been done using detailed information on device makeup of a virtual power plant (VPP), i.e with detailed knowledge of flexible device state and their performance capabilities. This low level detailed knowledge requirement presents barriers such as performance and security of private information. Therefore, this paper will investigate the applicability of machine learning techniques using only currently available market information to black box estimate aggregate flexibility characteristics, specifically capacity available during run-time and longevity, the amount of time a power deviation can be maintained.***

***Keywords****-Predicting Power of CCPP, Machine Learning*

## 1. INTRODUCTION

Single-cycle gas turbine power plants generate electricity by using natural gas and compressed air. Air is drawn from the surroundings, compressed, and fed into the combustion chamber of the gas turbine. Here, natural gas is injected which mixes with the compressed air and ignited. The combustion produces a high-pressure, hot gas stream that flows through the turbine causing it to spin (at tremendous speeds). Consequently, this spins a generator which is connected to the turbine to produce electricity. For single-cycle gas turbines, much of the energy is wasted as hot exhaust achieving an energy conversion efficiency of 35% at best. Combined cycle power plants exploit this inefficiency by capturing the waste heat using a heat recovery steam generator (HRSG), to produce even more power. Combined cycle power plants are power generation plants that use both gas and steam turbines together to generate electricity. The waste heat generated from the gas turbine is used to produce steam which is fed to a steam turbine to generate even more electricity. This increases the power produced (up to 50% more) for the same amount of fuel, as well as increases the plant's efficiency to about 60%. The Output power of the Combined Cycle Power Plant (CCPP) is dependent on a few parameters which are atmospheric pressure, exhaust steam pressure, ambient temperature, and relative humidity. Being able to predict the full load electrical power output is important for theefficient and economic operation of the power plant. In this article, we will be using machine learning to develop a predictive model to predict the full load output power of a CCPP. individuals in Mauritius who buy new cars are also very apprehensive about the resale value of their cars after certain number of years when they will possibly sell it in the used cars market.

## 2. REQUIREMENT ANALYSIS

**Hardware requirements** Operating system- Windows 7,8,10 Processor-dual core GHz (i5 or i7 series Intel processor or equivalent AMD) RAM- 4,8 GB

**Software Requirements: Python, JUPYTER Notebook,MS Excel Chrome**

## 3. LITERATURE SURVEY

Aggregated residential demand response flexibility characteristics have been investigated previously in a number of ways. Quantifying formulas were developed to estimate the ramp power longevity and capacity of aggregated cluster of thermal buffers based on detailed information from low level devices available such as the state of charge (SOC) [1]. Further, a bottom- up approach to quantifying flexibility using detailed lower-level information has been used to accurately offer aggregate small demand response [2]. Also, grey box techniques for flexibility assessments where some lower-level information, such as SOC, have been used to estimate the aggregate flexibility capacity.

 

## 4. BUILDING MACHINE LEARNING MODEL

### Machine Learning

Machine learning (ML) is the study of computer algorithms that improve automatically through experience and by the use ofdata. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

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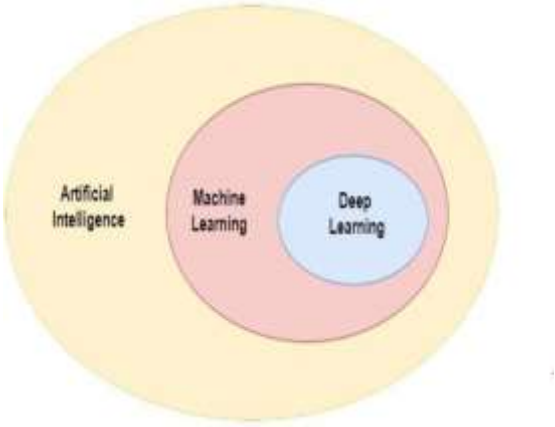



Figure 1.1

There are 3 types of Machine Learning which are based on the way the algorithms are created. They are:

**1.Supervised Learning 2.Unsupervised Learning 3.Reinforcement Learning**

**Supervised Learning:** Supervised learning algorithms build a mathematical model of a set of data that contains both the inputs and the desired outputs. The data is known as training data, and consists of a set of training examples. Each training example has one or more inputs and the desired output, also known as a supervisory signal. In the mathematical model, each training example is represented by an array or vector, sometimes called a feature vector, and the training data is represented by a matrix. Through iterative optimization of an objective function, supervised learning algorithms learn a function that can be used to predict the output associated with new inputs. An optimal function will allow the algorithm to correctly determine the output for inputs that were not a part of the training data. An algorithm that improves the accuracy of its outputs or predictions over time is said to have learned to perform that task.

Types of supervised learning algorithms include active learning, classification and regression. Classification algorithms are used when the outputs are restricted to a limited set of values, and regression algorithms are used when the outputs may have any numerical value within a range. As an example, for a classification algorithm that filters emails, the input would be an incoming email, and the output would be the name of the folder in which to file the email.

Similarity learning is an area of supervised machine learning closely related to regression and classification, but the goal is to learn from examples using a similarity function that measures how similar or related two objects are. It has applications in ranking, recommendation systems, visual identity tracking, face verification, and speaker verification.

This is similar to a teacher-student scenario. There is a teacher who guides the student to learn from books and other materials. The student is then tested and if correct, the student passes. Else, the teacher tunes the student and makes the student learn from the mistakes that he or she had made in the past. That is the basic principle of Supervised Learning.

**Unsupervised Learning:** Unsupervised learning algorithms take a set of data that contains only inputs, and find structure in the data, like grouping or clustering of data points. The algorithms, therefore, learn from test data that has not been labeled, classified or categorized. Instead of responding to feedback, unsupervisedlearning algorithms identify commonalities in the data and react based on the presence or absence of such commonalities in each new piece of data. A central application of unsupervised learning is in the field of density estimation in statistics, such as finding the probability density function. Though unsupervised learning encompasses other domains involving summarizing and explaining datafeatures.

Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that observations within the same cluster are similar according to one or more predesignated criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make different assumptions on the structure of the data, often defined by some similarity metric and evaluated, for example, by internal compactness, or the similarity between members of the same cluster, and separation, the difference between clusters. Other methods are based on estimated density and graph connectivity.

The data collected here has no labels and you are unsure about the outputs. So you model your algorithm such that it can understand patterns from the data and output the required answer. You do notinterfere when the algorithm learns.

Unsupervised Learning, as discussed earlier, can be thought of as self-learning where the algorithm can find previously unknown patterns in datasets that do not have any sort of labels. It helps in modelling probability density functions, finding anomalies in the data, and much more. To give you a simple example, think of a student who has textbooks and all the required material to study but has no teacher to guide. Ultimately, the student will have to learn.

## 5. BUILDING MACHINE LEARNING MODEL

### Model Development

1.Import the Libraries2.Import the Dataset 3.Clean the Dataset 4.Process the Dataset 5.Perform EDA 6.Split the Dataset 7.Build Model 8.Model Evaluation

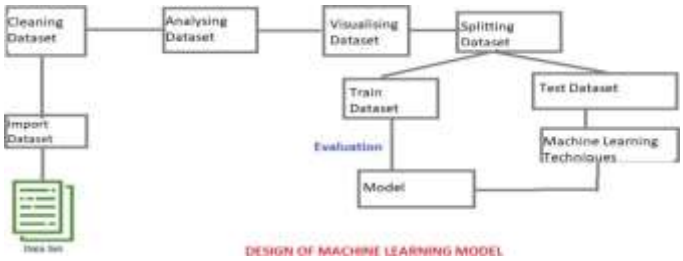



**Figure 1.2**

**Build Model**

**Algorithm used: GRADIENT BOOSTING**

**What is Boosting**?

Boosting is a technique to combine weak learners and convert them into strong ones with the help of Machine Learning algorithms. It uses ensemble learning to boost the accuracy of a model. Ensemble learning is a technique to improve the accuracy of Machine Learning models.

There are two types of ensemble learning:

**1. Sequential Ensemble Learning**:

It is a boosting technique where the outputs from individual weak learners associate sequentially during the training phase. The performance of the model is boosted by assigning higher weights to the samples that are
incorrectly classified.

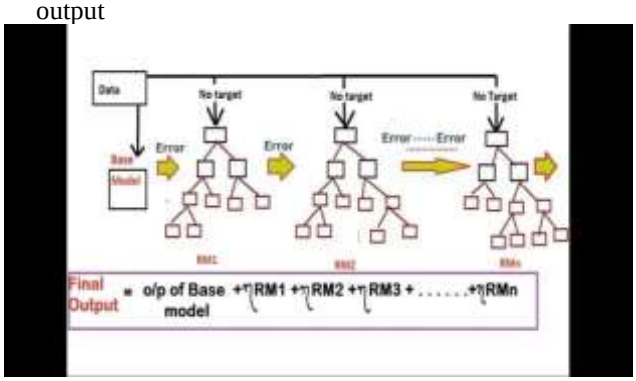
**2. Parallel Ensemble Learning:**

It is a bagging technique where the outputs from the weak learners are generated parallelly. It reduces errors by averaging the outputs from all weak learners. The random forest algorithm is an example of parallel ensemble learning.

**Mechanism of Boosting Algorithms:** Boosting is creating a generic algorithm by considering the prediction of the majority of weak learners. It helps in increasing the prediction powerof the Machine Learning model. This is done by training a series of weak models.

Below are the steps that show the mechanism of the boosting algorithm:

- Reading data
- Assigning weights to observations
- Identification of misinterpretation (false prediction)
- Assigning the false prediction, along with a higher weightage, to the next learner
- Finally, iterating Step 2 until we get the correctly classified output




**Gradient Boosting:**

In Machine Learning, we use gradient boosting to solve classification and regression problems. It is a sequential ensemble learning technique where the performance of the model improves over iterations. This method creates the model in a stage-wise fashion. It infers the model by enabling the optimization of an absolute differentiable loss function. As we add each weaklearner, a new model is created that gives a more precise estimation of the response variable.

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. When a decision tree is the weak learner, the resulting algorithm is called gradient boosted trees, which usually outperforms random forest It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

The gradient boosting algorithm requires the below components to function:

**Loss function:** To reduce errors in prediction, we need to optimize the loss function. Unlike in AdaBoost, the incorrect result is not given a higherweightage in gradient boosting. It tries to reduce theloss function by averaging the outputs from weak learners.

**Weak learner:** In gradient boosting, we requireweak learners to make predictions. To get real values as output, we use regression trees. To get the most suitable split point, we createtrees in a greedymanner, due to this the model overfits the dataset.

**Additive model:** In gradient boosting, we try toreduce the loss by adding decision trees. Also, wecan minimize the error rate by cutting down theparameters. So, in this case, we design the model in such a way that the addition of a tree does not change the existing tree.

Finally, we update the weights to minimize the error that is being calculated.

**Model Evaluation:**

Model Evaluation is an integral part of the model development process. It helps to find the best model that represents our data and how well the chosen model will work in the future. Evaluating model performance with the data used for training is not acceptable in data science because it can easily generate overoptimistic and overfitted models. There are two methods of evaluating models in data science, Hold-Out and Cross-Validation. To avoid overfitting, both methods use a test set (not seen by the model) to evaluate model performance.

When selecting machine learning models, it's critical to have evaluation metrics to quantify the model performance. In this post, we'll focus on the more common supervised learning problems. There are multiple commonly used metrics for both classification and regression tasks. So it's also important to get an overview of them to choose theright

**Mean Squared Error:**

Mean Squared Error (MSE), the most common measure for regression prediction performance, is the average of the squared residuals (the difference between the actual value and the predicted value).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Actual output — Predicted output

Mean — Squares of the errors

Assume we have n observations Y1, Y2 ….. Yn, the MSE formula is below:
As you can see, the smaller the MSE, the better the predictorfits the data.

**Mean Absolute Error:**
Besides squared error, we can also compute the average of the absolute value of residuals. Thismetric is called Mean Absolute Error (MAE):
mean absolute error formula metrics

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

MAE is easier to interpret and more robust to outliers compared to MSE.

## 5. RESULT

**Prediction and Model Evaluation:**
Now that our model is trained. It has to be tested on data. As we have earlier split the data for the testing of our model, that data is used to test the model.
Data is tested and predictions of the subsequent test data are made. Predictions are saved in predict.csv file.

## 6. CONCLUSION

This model is based on the machine learning algorithms and we were trying to predict the output power of a combined power plant based on the dataset provided at Kaggle. To predict this dataset, we used machine Boosting technique i.e Gradient Boosting. The prediction of the model is further compared with the test dataset created by picking random values from the original dataset and the evaluation of the prediction is further evaluated using different methods. After a complete evaluation of the predictive model, we can conclude that the accuracy of this model is very good, and Gradient Boosting is one of the best algorithm for regression problems. This technique is highly accurate and fast in prediction irrespective of thesize of the dataset.

In the summary, At the beginning of the report, we set out to develop a predictive model for full-load output power (PE) based on the dataset provided. We explored the dataset to find out if we had missing values or other problems, then predicted the output power of based on four dependent variables. We were able to discover that using a complete set of parameters or features on the Gradient Boosting Regression algorithm yielded the best results. We obtained Mean squared error of 42.178 and mean absolute error of 4.81.

## 7. REFERENCES

[1] A. L. Polyzakis, C. Koroneos, and G. Xydis, “Optimumgas turbine cycle for combined cycle power plant”, Energy Convers. Manag., vol. 49, no. 4, pp. 551-563, 2008.
[2] E. A. Elfaki and A. H. Ahmed , ”Prediction of Electrical Output Power of Combined Cycle Power Plant Using Regression ANN Model” ,J. Power Energy Eng., vol. 06, no. 12, pp. 17-38, 2018.
[3] “UCI Machine Learning Repository”: Combined Cycle Power Plant Data Set.”.
[4] H. Kaya, P. Tufekci, and S. F. Gurgen, “Local and Global Learning Methods for Predicting Power of a Combined Gas & Steam Turbine,” Int. Conf. Emerg. Trends Comput. Electron. Eng. (ICETCEE 2012), pp. 13-18, 2012.
[5] M. Azzeh “Fuzzy Model Tree for early effort estimation”,in Proceedings – 2013 12th International Conference on Machine Learning and Applications, ICMLA 2013, 2013, vol.2, pp. 117-121.
[6] M. Azzeh and S. Banitaan, “Comparative analysis of soft computing techniques for predicting software effort based usecase points”, IET Software, vol. 12, no. 1.pp. 19-29,2018.
[7] M. Azzeh, S. Banitaan, and F. Almasalha, “Pareto efficient multi objective optimization for local tuning of analogy-basedestimation”, Neural Comput. Appl., vol. 27, no. 8, pp. 2241- 2265, 2016.
[8] M. Hosni, A. Idri, and A. Arban, “On the value of parameter tuning in heterogeneous ensembles effort estimation”, Soft Comput., vol. 22, no. 8, pp. 5977-6010,2018.
[9] S. H. Brown, “Multiple Linear Regression Analysis: AMatrix Approach with MATLAB”, Alabama J. Math., no. Spring/Fall, pp. 1-3, 2009.
[10] I. Shahin and S. Hamsa, “Emotion Recognition Using Hybrid Gaussian Mixture Model and Deep Neural Network”, IEEE Access, vol. 7, pp. 26777-26787, 2019.