Predicting Household power consumption: Using Gradient Boosting and Deep Quantile Regression Model

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Abstract. The rapid development of technology, cities, and the introduction of IoT has caused high fluctuations in energy consumption. Therefore, efficient energy management and forecasting energy consumption for buildings are important in decision-making for effective energy-saving and keeping the world a better place. Over the years researchers have tried to propose machine learning approaches to forecast and monitor abnormal electricity consumption, however, there is still a need for more new approaches to forecasting energy consumption correctly and precisely. This paper attempts to address the global issue of efficient electricity management through a data science approach. The paper proposes a quantile learning approach for predicting household electricity consumption. We propose a deep quantile regression model and a gradient boosting model to forecast power consumption. In addition, we propose an approach to detect abnormal patterns in energy consumption data using estimated consumption intervals. We tested our approach on a publicly available univariate time series dataset collected from a house located in Sceaux.

1. Introduction
Since the 1970’s global energy production keeps on increasing, world gross electricity generation was 3.9% higher in the year 2018 than in 2017 [1]. More than 50% of world electricity is generated from combustion fuels such as oil, coal, biomass, etc.[1]. European Commission’s Joint Research Centre data on electricity consumption for the year 2019 shows a 0.9% increase in CO₂ emission from energy combustion [2]. Growing global energy consumption creates a threat to the environment in the form of global warming and creates the need to shift our energy production from fossil fuel to renewable sources of energy. While we are focusing on finding alternate sources of energy to meet our needs, it is important to address that energy efficiency remains the biggest challenge. According to federal data approx two-third of the power generated by the US goes to waste [3]. Hence apart from finding alternative energy sources, we need to focus on global energy efficiency to address environmental issues worldwide.

Household energy consumption is one of the major sources of CO₂ emission therefore requires efficiency measures. Although estimation and prediction of house hold the energy to take efficiency measures is challenging due to human behavior involved which leads to uncertain consumption patterns. The advent of new technology like smart meter provides the possibility to retrieve data on consumption daily as well as an hourly basis in households. Such data could be used for forecasting future demand and can help in electricity demand management in a locality,
Recently Artificial neural networks (ANN) are being popularly used for classification and clustering, pattern recognition [4, 5, 6] as well as forecasting in many fields. One of the strengths of an Artificial neural network in comparison to traditional machine learning linear models is that it can model linear as well as non-linear relationships and can easily infer those relationships directly from its input data. At the present age, it is evident that ANNs are the best choice for universal numerical function approximation due to their self-learning and non-linearity modeling capacity.

In this paper, we address the issue of electricity consumption efficiency through forecasting energy consumption in households and abnormal consumption patterns. Firstly, we propose a deep quantile regression model architecture based on an artificial neural network (ANN) and a Gradient boosting model to forecast household consumption. Secondly, we propose an anomaly detection approach based on quantile learning to predict if an electricity meter reading is abnormal or not. Thirdly, we conduct experiments to select a suitable machine learning algorithm for household energy forecasting and abnormal pattern recognition. Finally, we propose an approach for labeling household energy consumption dataset for anomaly detection, classification tasks.

The structure of this paper is as follows: Section II outlines the related work on deep quantile learning, household energy consumption forecasting, and anomaly detection. In Section III, the proposed model details are presented, while Section IV presents the implementation details and obtained results followed by discussions. The paper is concluded in Section V with possible future directions.

2. Related Works

The increase in mobile and smart appliances and meters in households has provided researchers access to consumption data and have provided them with the opportunity to develop several prediction models for efficiency, utility, cost-minimization, etc [7, 8, 9, 10, 11]. A lot of literature is available on predicting household electricity consumption utilizing several machine learning models. Feng [12] forecasts energy consumption of China using grey model GM(1,1), the paper develops 3 models each for total energy, coal energy, and clean energy consumption and claims that the models are appropriate to simulate and to forecast the original data sequences of the energy consumption characterized by grey type. Duy Ha [13] has its focus on demand-side load management for residential areas. The proposed model works on the anticipation layer and allocates energy to households based on the predicted events. Paper proposes meta heuristic Tabu Search for solving household energy management problem (HEMP).

Fayaz [14] carried proposes a model for predicting consumption in buildings using Feed Forward Back Propagation Neural Network Several papers use an artificial neural network as well for example Lee [15] examines the variation in energy consumption as a function of user activities within the same building and proposes an artificial neural network to predict user-based energy consumption. The study is carried out on Korean citizens and classify users into six user characteristics, namely gender, age, occupation, income, level of education, and occupancy period for consumption prediction and identify the difference in energy usage according to six user characteristics. Another very close work is presented in Balachander [16], the paper proposes the Estimation of power requestin an individual house with five unique models dependent on ARIMA, ANN, RBF, SVM, and ANFIS.

Ekonomou [17] describes the ANN-based method for Greek energy consumption. Sozen [18] proposes 2 models for Turkish energy consumption and shows that the ANN approach can be used to predict the ED based on sectoral energy consumption. Deng [19] proposes a Deep Quantile Regression model for load forecasting of a residential area the model is being tested on 20 randomly selected residential data the model achieves the best results in the AQS, AACE matrix.
Indeed, more refined prediction models are demanded [20, 21, 22, 23, 24], taking into account also the specifics metrics of the associated software components [25, 26, 27, 28, 29, 30, 31, 32] and the software process in use [33, 34, 35, 36, 37, 38].

3. The Proposed Model
This section presents our proposed model pipeline. The proposed pipeline is shown in Fig. 1. It consists of four main stages: A) Data Preprocessing & Feature Engineering, B) gradient boosting model, C) deep learning model, and C) anomaly detection and energy consumption estimation. The following sections outline the details of each stage.

![Diagram of the proposed model pipeline]

Figure 1. The proposed model pipeline.

3.1. Data Preprocessing and Feature Engineering
Data processing is one of the crucial parts of machine learning. It curates and prepares the data for further processing. The data processing technique heavily depends on the raw data and the machine learning model to be employed for further data analysis. For the deep quantile model, we standardized the input data. However, for the gradient boosting model we did not standardize the input data since standardization does not affect the ensemble learning process. The data standardization re-scales numerical attributes to unit variance and zero mean. For missing values, we filled by the average of the respective attribute column.

For feature selection and feature engineering, we summed up all sub-metering values for each sample to create a total consumption attribute. From the timestamp attribute, we extracted six more attributes which are the day of the month, day of the week, hour, interval, month, and season. The final dataset to train and test the prediction models consisted of the attributes generated from the timestamp and sub-metering attributes.

3.2. Gradient Boosting Models
Gradient boosting models (GBM) is one of the most powerful and popular machine learning techniques. It is an upgrade of the traditional ensemble learning algorithms such as Adaptive boosting (AdaBoost) [39]. Boosted trees algorithms are based on sequentially growing a tree (decision tree) by extending the main tree at every step. Each tree added to the main tree is grown using information from previously grown trees to improve performance. Gradient Boosting Models (also called Gradient Boosting Machines) training solves a numerical...
optimization problem where the objective is to minimize the classification or regression error of the model using an SGD like approach [40]. Friedman [41] generalized the GBM framework to regression problems and multiple loss functions by adopting the important statistical concepts employed in AdaBoost. His GBM framework still stands as a base of the state-of-the-art machine learning modern implementations.

3.3. Deep Quantile Regression Model

The deep quantile regression model is a deep learning model mostly applied in the exploration of uncertainty in estimates. Deep learning (DL) is a subfield of machine learning which have proved to be more robust compared to ML traditional methods such as statistical methods [42, 43]. The cornerstones of deep learning models robustness are mainly the capability to deal with the huge amount of data (i.e Big data) and the ability to capture nonlinear relationships in data. To leverage the advantages offered by DL models, we utilize a deep quantile regression model to estimate energy consumption.

The deep quantile regression model fits as a good choice for household consumption estimation because in such cases one needs to know how confident the prediction model is when it produces an estimation so that decisions can be made adequately. Deep quantile regression purely focuses on inferring quantiles which can be intuitively considered as an estimation of intervals. The learning process of the deep quantile regression model is driven by the loss function defined by the following equation:

\[
\mathcal{L}(y, f|\alpha) = \frac{1}{N} \sum_{n=1}^{N} \mathcal{L}(y_i - f(x_i)|\alpha)
\] (1)

Where the loss for an individual data point is defined as follows:

\[
\mathcal{L}(\xi_i|\alpha) = \begin{cases} 
\alpha \xi_i & \text{if } \xi_i \geq 0 \\
(\alpha - 1) \xi_i & \text{if } \xi_i < 0 
\end{cases}
\] (2)

And:

\[
\xi_i = y_i - f(x_i)
\] (3)

The value of \(\alpha\) is the required quantile which is between 0 and 1. Function \(f(x)\) represents the predicted quantile and \(y\) is the observed value for the corresponding input data point \(x\). To minimize the loss and successfully infer the target quantile, the model is trained in a traditional neural network training manner whereby optimization strategies such as stochastic gradient descent (SGD) approach is used to minimize the loss.

In our approach, we propose a deep learning model comprised of three quantile models whereby each quantile model estimates a specific quantile value. The three deep quantile models have distinct \(\alpha\) value. The number of layers in each neural network is the same for each deep quantile learning model. The backpropagation algorithm through the gradient descent method was used as the optimal, simple, and efficient algorithm.

4. Evaluation and Results

This section presents details about the dataset used in experiments, considered performance metrics, results followed by a discussion to affirm the applicability in a real-world setting.
4.1. Datasets Description
To evaluate the validity of our proposed approach we performed experiments on a publicly available univariate time series dataset collected from a house located in Sceaux. It contains 2,075,259 data-points captured over 47 months. The dataset has 4% of rows with missing values and we deal with this situation by imputation with average. Further information about the collection and publicity of the data can be found at [44]. To create labels for each data point in the dataset we calculated the corresponding 90th and 5th based on the day of the week and hour. We later assigned the abnormality status of each based on its position in the interquartile range (IQR). If the consumption value at a given time lies between the specified quartiles, then it’s classified as normal otherwise anomaly. This approach of anomaly labeling follows the same pattern of anomaly detection using the three-sigma rule [45].

4.2. Performance Metric
To evaluate the effectiveness of our proposed approach we used five standard performance metrics. The performance measures are divided according to the machine learning task solved. The performance measures concerning the machine learning task are as follows:

**Classification** : precision, recall, F1-score and accuracy

**Regression** : mean squared error (MSE)

The classification performance metrics are derived from the values of the confusion matrix and computed as:

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (4)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (5)
\]

\[
F1 - score = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (7)
\]

Where, TP is the number of true positives, TN is the number of true negative, FP is the number of false positives and FN is the number of false negatives.

MSE which is basically data sample dependent, is the mean of the squares of the errors. It is computed as:

\[
\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 \quad (8)
\]

Where \( N \) is the total number of data points, \( Y \) are observed values and \( \hat{Y} \) are predicted or estimated values.

4.3. Experiments and Discussion
The deep quantiles regression models were implemented using an open-source neural network library Keras in python environment [46]. On the other hand, the gradient boosting quantile regression models were implemented using a python library called sklearn (version 0.21.2) [47]. Each model was trained on an Intel Core i5 CPU with 8GB RAM. The training data contained data points collected between the year 2006 to 2009 while the testing data was data for the year 2010. The optimal hyperparameters are described in Table 1 & 2.
Table 1. The optimal hyperparameters of gradient boosting regression model

| Parameter          | upper ($\alpha = 0.9$) | median ($\alpha = 0.5$) | lower ($\alpha = 0.1$) |
|--------------------|-------------------------|--------------------------|------------------------|
| number of estimators | 700                     | 700                      | 700                    |
| maximum depth      | 5                       | 5                        | 5                      |
| learning rate      | 0.1                     | 0.1                      | 0.1                    |
| criterion          | friedman mse             | friedman mse             | friedman mse           |
| Loss function      | quantile                | quantile                | quantile              |

Table 2. The optimal hyperparameters of Deep quantile regression model

| Parameter      | upper ($\alpha = 0.9$) | median ($\alpha = 0.5$) | lower ($\alpha = 0.1$) |
|----------------|-------------------------|--------------------------|------------------------|
| Ephocs         | 2000                    | 2000                     | 2000                   |
| Optimizer      | adadelta                | adadelta                 | adadelta              |
| Loss           | quantile                | quantile                 | quantile              |
| Activation     | relu                    | relu                     | relu                   |
| Learning rate  | 0.1                     | 0.1                      | 0.1                    |
| EarlyStopping  | True                    | True                     | True                  |
| Batch size     | 32                      | 32                       | 32                    |
| Number of layers | 3                       | 3                        | 3                     |

Table 3. Confusion matrices for anomaly classification

|               | Deep Quantile Model | GBM |
|---------------|---------------------|-----|
| True Positive | 48                  | 50  |
| False Positive| 148                 | 117 |
| True Negative | 6914                | 6945|
| False Negative| 809                 | 807 |

The confusion matrix for the anomaly classification is reported in Table 3. Both anomaly detection models had 0.1 and 0.9 as 1st and 3rd quantile set. Resulting performance on test sets (i.e., Accuracy, Precision, Recall and F1-scores) for each model is illustrated in Table 4.

5. Conclusion
In this paper, we proposed a deep quantile regression model and gradient boosting model for household energy consumption forecasting and abnormal patterns detection. We performed experiments to select an ideal model for forecasting and abnormal behavior recognition. The experiments were performed on a publicly available univariate time series dataset collected from a house located in Sceaux. We compared the GBM against the deep quantile regression model
Table 4. Performance measures for anomaly classification

| Metric     | GBM    | Deep Quantile Model |
|------------|--------|---------------------|
| Accuracy   | 0.88   | 0.88                |
| Precision  | 0.96   | 0.96                |
| Recall     | 0.88   | 0.88                |
| F1-score   | 0.92   | 0.91                |

Table 5. Performance GBM and Deep quantile model on consumption estimation

| Parameter | GBM    | Deep Quantile Model |
|-----------|--------|---------------------|
| MSE       | 49.411 | 96.474              |

in the regression and classification task where we noticed that GBM is best for the regression task while the deep quantile model gives the best results in the anomaly detection task. In the near future, we plan to investigate the effect of the quantile values on the accuracy of detecting abnormal patterns in energy consumption data. We would like also to promote a wide diffusion of the data and of the algorithms in use, which is the best way to promote the growth of this research area [48, 49, 50, 51, 52, 53, 54, 55, 56, 57]

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