Predicting increased electricity consumption during severe weather events using Artificial Intelligence

Vasu G. Patel
Civil & Environmental
Engineering Department
Stanford University
vgpatel1@stanford.edu

Ipshita Dey
Earth System
Sciences
Stanford University
ipshi91@stanford.edu

Uzma Shaikh
Electrical
Engineering Department
Stanford University
uzma0214@stanford.edu

Abstract

The unprecedented levels of climatic changes has led to increased unpredictability of the users' electricity consumption, causing Energy Management Systems (EMS) to make an unplanned shutdowns of electricity grids. Accurate energy/electricity consumption prediction is an essential component in ensuring reliability of the grid and providing steady electricity output during severe weather events. *Machine learning (ML)* and *Deep Learning (DL)* methods is recognized as one of the suited approach for understanding co-relations between weather conditions and electricity consumption. However, there has not been the avalanche of the usage of ML methods for accurately predicting increased electricity consumption using weather as an input data. Our project focuses on using the ML, DL methods to predict the increased electricity consumption from the baseline consumption during extreme weather conditions.

1 Introduction

Severe weather events cause deleterious effects on communities, and natural ecosystems. These extreme conditions lead to hundreds of deaths, loss of habitats, injuries and damage to infrastructure of the place leading to huge economic losses every year. The damage caused can occur during or immediately after the hazard and leaves a long lasting impact on the country. Every year the government proposes to spend millions of dollars to reduce the impact and help people survive. Human activity is causing rapid changes in the environment leading to global warming which is accelerating the occurrence and causes of such extreme weather events. The frequency of such events is a global concern. Electricity is one of the most important sources of energy that can help overcome challenges and support critical operations to save lives during tough times. It can help hospitals, various control stations and emergency services offices to monitor situations and operate effectively saving lives reducing the loss to the economy. During such events power failure is common as these events damage the infrastructure. We are trying to model the effect of severe weather events on electricity consumption. A reliable forecasting technique is essential for accurate investment planning of energy production/generation distribution. Our main goal is to predict the amount of electricity that is required during such events and help develop electricity grid infrastructure well in advance. We have taken electricity weather data of California state from July 2015 - Nov 2021 and applied Synthetic Minority Oversampling Technique (SMOTE) for data augmentation. We used machine learning models like Linear Regression, Lasso, Linear Discriminant Analysis, Logistic Regression with L2, SVM and Deep Neural Network using dropout regularization. Hyper-parameter tuning was carried out to come up with hyper parameters to best fit the model. Using the best model we are able to predict the range of electricity demand during the extreme weather events with 95% accuracy.

2 Related work

Several studies have been conducted to predict energy demand previously. In the past, statistical techniques were used mainly to predict energy demand. Munz et *al*. predicted a time series of irregular patterns using K-means clustering [7]. Kandananond et *al.* used different forecasting methods - auto regressive integrated moving average (ARIMA), Artificial Neural Network (ANN) and multiple linear regression (MLR) - to predict energy consumption [8]. However, due to the irregular patterns of energy demand, statistical techniques have limited performance performance and many model of prediction using machine learning methods have been investigated. Dong et *al.* predicted the demand of building energy using SVM with consumption and weather information [9]. Ekici et *al.* predicted the building energy needs with properties of buildings without weather conditions [10]. In this project, we provide the increased electricity demand during extreme weather conditions. We use monthly electricity consumption data and various weather features as an inputs to train our deep neural networks.

3 Datasets Used

In this study, we have used daily weather summaries obtained from National Oceanic and Atmospheric Administration [1] from 1200 stations in California during Jul 2015 - Nov 2021. This dataset consists of 45 different weather parameters which are described in the Appendix. For the same period, total electricity demand in units of Megawatts-Hour [MWh] obtained from US Energy Information Administration [2] is also available. This includes residential, commercial as well as industrial consumption.

3.1 Weather data pre-processing and feature selection

For each day, the weather parameters are averaged over all stations to give a single instance. The days with any missing/nan features have been removed from the dataset resulting in total 2158 examples. Feature dropout method was implemented for various models to evaluate the impact of individual features on the model performance. The results of this experiment are shown in Table 5 of Appendix A.

3.2 Electricity data pre-processing

The daily total electricity demand (in MWh) is a real valued number ranging from 534,646-1,160,559 MWh. In order to compute the excess demand during warmer months of the year, the baseline is computed by taking the net average of demand and thereafter subtracted from the demand values. This quantity will be referred to as Δ where:

$$\Delta = Daily\ Demand - Baseline$$

$$\Delta_N = \frac{\Delta - \mu_\Delta}{\sigma_\Delta}$$

Δ_N is the normalized Δ_N and is only used for linear regression model where μ_Δ and σ_Δ are the mean and standard deviation as computed for entire electricity dataset from July 2015 to Nov 2021. We choose data normalization using this method to make our model robust for its applicability to other locations, duration (any given year) and variability in electricity consumption values. For classification algorithms, the Δ values are binned into 5 classes as shown in Table 1.

Table 1: Class their corresponding Lower & Upper Demand

Class	Lower Demand (MWh)	Upper Demand (MWh)
0	534,646	659,828.6
1	659,828.6	785,011.2
2	785,011.2	910,193.8
3	910,193.8	1,035,376.4
4	1,035,376.4	1,160,559

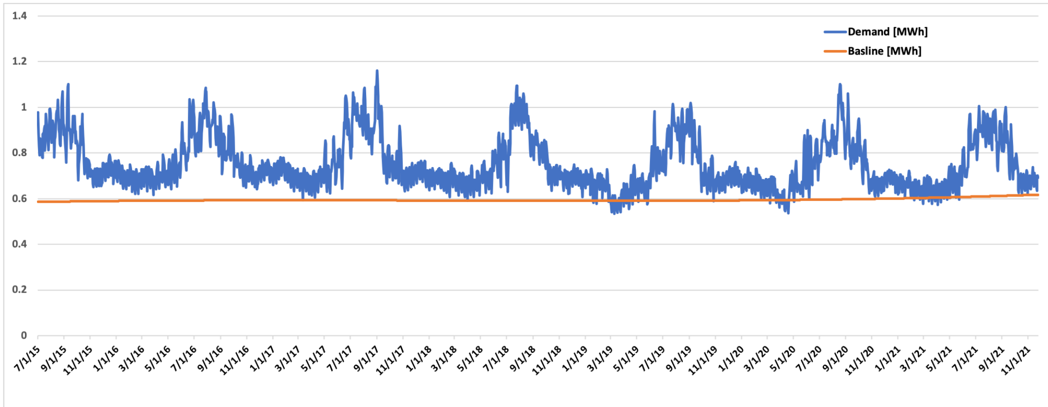
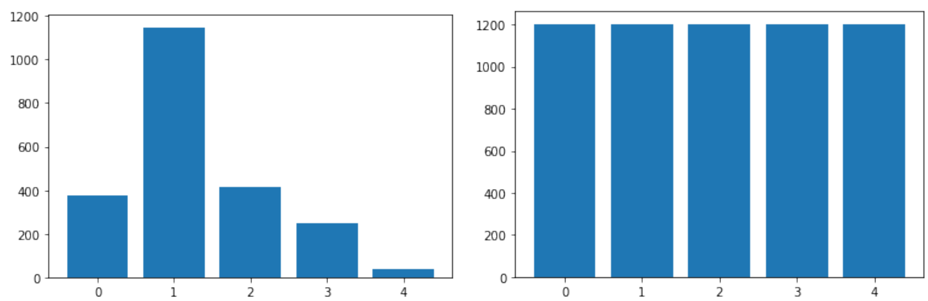


Figure 1: Daily electricity demand and baseline during Jul, 2015 - Nov, 2021

3.3 Data Augmentation using SMOTE

The distribution of the original datasets are skewed heavily towards the lower classes as depicted in Figure 2a. This dataset had unequal distribution of electricity consumption classes Fig. 2. Data augmentation is implemented using SMOTE to generate uniformly distributed classes Fig. 2(b). Using this technique it generates equal distribution of data points for each classes and the dataset increased from 2158 to 6015. Implementing SMOTE helped has a positive effect in improving model performance (accuracy) and reducing the over-fitting (i.e. improved generalization).



(a) (b)

Figure 2: Data distribution for each class (a) without and (b) with SMOTE implementation

4 Methods and Experiments

A total of nine models (1 regression and 8 classification) were implemented using the augmented dataset. Three different implementations of Logistic regression with "l2" regularization using (a) "liblinear" solver with "one-vs-rest (OVR)" classification [LOGREG-1] (b) "newton-cg" solver with "multinomial" classification [LOGREG-2] and (c) "newton-cg" solver with "OVR" classification [LOGREG-3]. Both solvers use the Categorical Cross-Entropy loss as their objective function. The "liblinear" solver uses a coordinate descent algorithm. However, it cannot learn a true multi-class model; instead, the optimization problem is decomposed in a "one-vs-rest" fashion so separate binary classifiers are trained for all classes. Additionally, four implementations of Support Vector Classifiers (SVC) with (a) linear kernel (b) RBF kernel (c) polynomial (deg=3) kernel and (d) sigmoid kernel were also implemented to improve upon the scores.

4.1 Deep Neural Network Model Architecture

We implement Deep Neural Network (DNN) on pre-processed data points using five class classification. Our base starting DNN model consisted of ten hidden layers with varying units in each

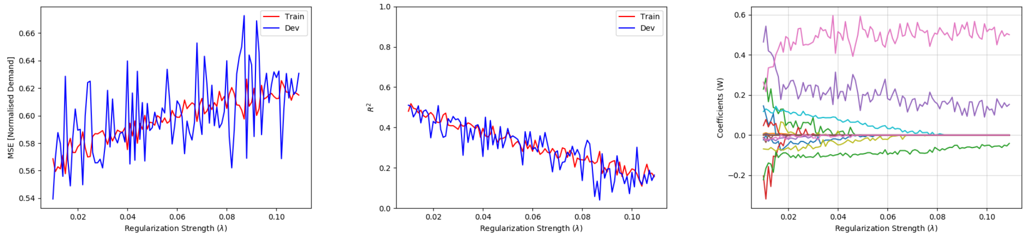


Figure 3: Lasso Regularization

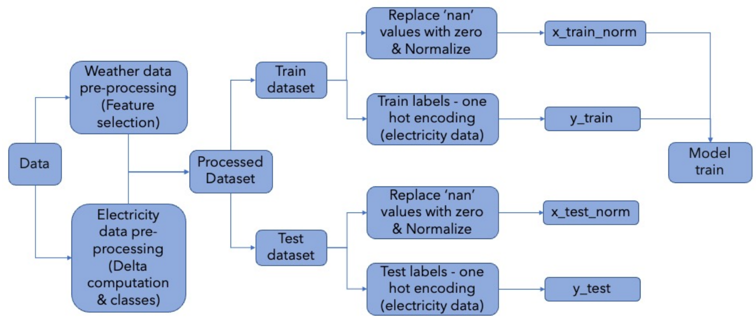


Figure 4: Data pre-processing & Model pipeline

layer. Hyper-parameter tuning was carried out on learning rate, number of layers, number of units, activation function, regularization, epochs and choice of optimizer function. After carrying out hyper parameter tuning, we find the optimum learning rate to be 0.0008, number of hidden layer to be six, ReLu activation function for all hidden layers, adams optmizer and dropout regularization worked out to better than L1 and L2 regularization.

5 Results and Discussion

(a) **Linear Regression**: The normalized training datasets with Δ_N as the output were trained using linear regression with "l1" regularization ($\lambda = 0.01$). The normalized mean squared error (MSE) obtained on training and test datasets was found to be 0.56 and 0.55 respectively. The coefficient of determinations (R^2) were 0.52 and 0.51. Lasso regularization ("l1") was implemented on the same dataset using different regularization strengths ranging from 0.01-0.1 [Figure 1]. As a result, approximately 22 features were selected to be removed that had values of coefficient less than 0.05. However, the removal of those 22 features did not improve either MSE or R^2.

As mentioned previously, the input (with target (Δ) are binned and augmented using SMOTE to be applied to the classification algorithms as follows:

(b) **Logistic Regression**: The hyper-parameters for LOGREG 1-3, namely the regularization strengths, error tolerance and maximum number of iterations are tuned using cross-validation to maximize the class-balanced/weighted F1-scores and accuracy. The best parameters set found on each of the LOGREG models resulted in scores tabulated in Table 2. LOGREG-3 was found to perform better than the other two with average accuracy of 79%.

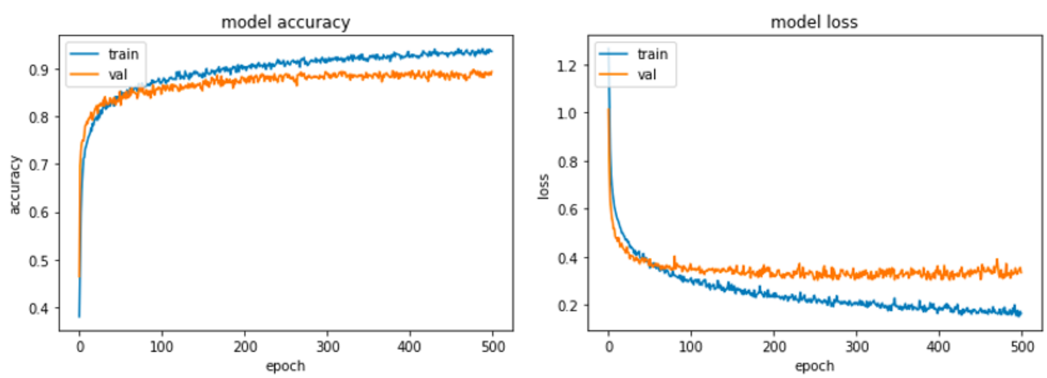
Next, we implemented LOGREG-3 with the best tuned hyper-parameters after dropping one of the 15 features that were weaned out by Lasso-regression in the previous section. The results of the dropout-experiments are presented in Table 3. Two features viz. "SN32" and "SX35" when dropped had the least impact on the scores, hence these features are dropped from the rest of the implementations.

(c) **Support Vector Classifier**: The SVC implementation with radial basis (RBF) kernel viz. SVC-4 was found to outperform other SVC implementations for training datasets with a balanced accuracy and average F1-score of 0.94 and 0.94 respectively. Additionally, the hyper-parameters namely regularization strenth (C) and γ were optimized to achieve best scores and were found to be 10 and 0.7 respectively. The significant jump in accuracies using RBF indicates that the decision boundary that separates the classes are not linear.

(d) **Deep Neural Network**: After carrying out hyper-parameter tuning on Deep Neural Network (viz. DNN), best model architecture consists of six hidden layers each having ReLu activation and dropout regularization (p=0.2), 128 units in 1st layer, followed by 64 units in 2nd to 5th layer and 32 units in 6th hidden layer. Input layer consist of 32 input features and final output has SoftMax activation with 5 class. Our DNN, achieves training accuracy (95%)and validation accuracy (90%) as shown in Fig.5(a). The loss for DNN during training & validation is decreasing with epochs and reducing gap which shows little variance Fig.5(b). In addition to accuracy, we computed F-1 score and testing accuracy which is as shown in Table2

Table 2: Class Balanced F-1 Score and accuracy for classification models

Model Name	**F-1 Score**	**Accuracy**
LOGREG-1	0.85	0.72
LOGREG-2	0.788	0.79
LOGREG-3	0.708	0.71
LDA	0.XX	0.71
SVC-1	0.734	0.73
SVC-2	0.73	0.73
SVC-3	0.57	0.57
SVC-4	0.942	0.94
DNN	0.86	0.86



(a) (b)

Figure 5: Accuracy and loss for Deep Neural Network implementation

Table 3: Precision, Recall and F-1 Score for Deep Neural Network

Class	Precision	Recall	F1-score
0	0.81	0.79	0.80
1	0.70	0.70	0.70
2	0.88	0.87	0.87
3	0.91	0.96	0.93
4	1.00	1.00	1.00
–	–	–	–
Accuracy			0.86
Macro average	0.86	0.86	0.86
Weighted average	0.86	0.86	0.86

6 Conclusion and Future Work

After trying various machine learning models, we find that SVC with RBF and has comparable accuracy as Deep Neural Network. SMOTE implementation (data augmentation technique) is helpful in reducing over-fitting and increase accuracy of our model. For future, we are considering increasing our dataset and implementing Recurrent Neural Network (using PyTorch lightning) for predicting electricity consumption using time series data. We plan to achieve 95% accuracy with increased dataset rather than applying data augmentation.

7 Contributions

Ipshita obtained the weather dataset and implemented the algorithms for collocating and pre-processing of weather input and electricity output dataset along with implementations of Logistic Regression and Support Vector classification with hyper-parameter optimizations and feature dropout experiments. Report writing.
Vasu obtained electricity dataset, implemented algorithm for pre-processing and collating electricity data. Implemented SMOTE data augmentation method for increasing the dataset. Developed Deep Neural Network model architecture using Keras and carried out hyper-parameter tuning. Report writing.
Uzma researched into the various literature related to the topic and obtained the sources for the electricity dataset. Implemented linear regression, Lasso and Linear Discriminant Analysis and report writing.

8 Acknowledgments

Amoh, CS 230 project partner, researched into the various literature related to the topic and obtained the sources for the electricity and weather dataset. He also curated the weather data, developed the data pre-processing to feeding into the DNN network and helped developed the DNN architecture.

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Appendix A

Table 1: Features- abbreviation and Description

SR No.	Abbreviations	Description
1	AWND	Average wind speed
2	DAPR	Number of days included in the multiday precipitation total (MDPR)
3	DASF	Number of days included in the multiday snow fall total (MDSF)
4	EVAP	Evaporation of water from evaporation pan
5	MDPR	Multiday precipitation total (use with DAPR and DWPR, if available)
6	MDSF	Multiday snowfall total
7	MNPN	Daily minimum temperature of water in an evaporation pan
8	MXPN	Daily maximum temperature of water in an evaporation pan
9	PGTM	Peak gust time
10	PRCP	Precipitation
11	PSUN	Daily percent of possible sunshine for the period
12	SN33	Maximum soil temperature with bare ground cover at 20 cm depth
13	SN32	Minimum soil temperature with bare ground cover at 10 cm depth
14	SN35	Maximum soil temperature with bare ground cover at 100 cm depth
15	SNOW	Snowfall
16	SNWD	Snow depth
17	SX32	Minimum soil temperature with bare ground cover at 10 cm depth
18	SX33	Minimum soil temperature with bare ground cover at 20 cm depth
19	TAVG	Average Temperature.
20	TMAX	Maximum temperature
21	TMIN	Minimum tempreature
22	TOBS	Temperature at the time of observation
23	TSUN	Total sunshine for the period
24	WDF2	Direction of fastest 2-minute wind
25	WDF5	Direction of fastest 5-second wind
26	WDFG	Direction of peak wind gust
27	WDMV	Total wind movement
28	WESD	Water equivalent of snow on the ground
29	WESF	Water equivalent of snowfall
30	WSF2	Direction of fastest 2-minute wind
31	WSF5	Direction of fastest 2-minute wind
32	WSFG	Peak gust wind speed
33	WSFI	Highest instantaneous wind speed
34	WT01	Fog, ice fog, or freezing fog (may include heavy fog)
35	WT02	Heavy fog or heaving freezing fog (not always distinguished from fog)
36	WT03	Thunder
37	WT04	Ice pellets, sleet, snow pellets, or small hail"
38	WT05	Hail (may include small hail)
39	WT06	Glaze or rime
39	WT07	Dust, volcanic ash, blowing dust, blowing sand, or blowing obstruction
40	WT08	Smoke or haze
41	WT09	Blowing or drifting snow
42	WT10	Tornado, waterspout, or funnel cloud
43	WT11	High or damaging winds
44	SN32	Minimum soil temperature with bare ground cover at 10 cm depth
45	SX35	Maximum soil temperature with bare ground cover at 100 cm depth

Table 2:Results from Feature Dropout in LOGREG-2

SR No.	Feature Dropped	Label-1 F1-score	Label-2 F1-score	Label-3 F1-score	Label-4 F1-score	Label-5 F1-score	Avg. Accuracy
1	AWND	0.71	0.57	0.77	0.79	0.92	0.75
2	EVAP	0.69	0.58	0.78	0.82	0.94	0.76
3	MXPN	0.69	0.62	0.79	0.75	0.91	0.75
4	PGTM	0.69	0.55	0.77	0.78	0.94	0.74
5	PRCP	0.70	0.64	0.77	0.79	0.93	0.76
6	SN32	0.72	0.63	0.80	0.83	0.96	0.79
7	SN33	0.70	0.63	0.76	0.78	0.95	0.76
8	SN35	0.68	0.58	0.75	0.74	0.91	0.73
9	SNWD	0.71	0.57	0.74	0.79	0.94	0.75
10	SX32	0.73	0.64	0.79	0.78	0.92	0.78
11	SX33	0.72	0.60	0.76	0.80	0.95	0.77
12	SX35	0.73	0.67	0.80	0.81	0.95	0.7
13	TMAX	0.71	0.61	0.80	0.78	0.92	0.77
14	TOBS	0.73	0.60	0.73	0.78	0.92	0.75
15	WDF5	0.69	0.61	0.75	0.77	0.93	0.75