

Building Flexibility using Deep Learning

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Abstract—In the power system, power data analysis, such as electricity consumption predictions, have always been used as a basis for adjusting electricity prices, substation regulation, total load prediction, and peak avoidance management. In order to create intelligent green cities, we have to increasingly explore the flexibility potential of commercial buildings with the increasing output of renewable energy sources (RES) and the increasing number of electric vehicles (EV). It is noteworthy, however, that when a variety of activities are analyzed such as cooling, heating, fans, lights, and equipment, the volume of consumption data is significantly higher than it was previously. We present here a way to identify the flexibility of commercial buildings from very large datasets using a big data processing framework. This paper uses deep learning algorithm LSTM (Long-Short Term Memory) to predict the future electricity usage.

Index Terms— Artificial Intelligence, Demand Response, LSTM, Electricity, Load Flexibility, Commercial Buildings.

I. INTRODUCTION

Modern economies depend on electricity for almost every activity in the modern era. It is the pivotal element in supporting technologically advanced industrialization. The demand and use of electric energy has increased across the globe over the past few decades, yet the generating, transmitting, and disseminating processes remain complex and expensive. Thus, optimal grid management is crucial to the reduction of energy costs and the increase of electric power production to meet the growing demand for electric energy.

The proper management of a grid therefore requires proper load demand planning, an adequate maintenance schedule for generation, transmission and distribution lines, and an efficient distribution of loads through the supply lines. To maximise efficiency in the planning process, it is imperative that accurate load forecasting is undertaken in the power generation industries. Electrical Energy Demand (EED) forecasting has been enhanced by applying a variety of computational and statistical techniques.

Energy prediction is necessary in the first step of creating a management plan for an energy management system (EMS) as global energy demand grows. In traditional energy prediction models, prediction performance is the focus, however an efficient system must take into account a variety of factors in predicting energy demand. This paper proposes a method for predicting energy demand in various situations using a deep learning model based on an auto encoder. Model of energy demand estimation consists of a projector that defines an appropriate state

for a given situation, and a predictor that predicts energy demand from the defined state. With 60-minute demand to date, the proposed model predicts consumption for 15, 30, 45, and 60 minutes. Using the household electric power consumption data for five years, this model not only outperforms the conventional models with a mean square error of 0.384, it also enhances the ability to explain predictions by visually illustrating the state with LSTM algorithm. While the proposed model does not require supervised representation learning, we found that it does predict the state of the energy demand well.

II. LITERATURE SURVEY

[1] Profound cooperation of the interest side into the energy the board and exchanging adventures and proficient blending of adaptable burdens (FLs), prosumers and sustainable power sources (RESs) into the energy framework are significant objectives in arranging the future shrewd network. All things considered, RESs have various advantages over the ordinary energy age sources since they are the spotless energy providers with very little activity and upkeep (O&M) cost and zero emanation cost. Additionally, RESs are accessible all over, simple to introduce, require more modest space, non complex designs, and contain fewer parts.

[2] The interest in making individual energy creation framework by environmentally friendly power sources is expanding step by step after the worldwide mindfulness with respect to issues of non-environmentally friendly power sources and benefits of renewables have been scattered. The world has been encountering an absence of accessibility of non-renewable energy sources since the 1970s which brought about an expanded cost of power. The inaccessibility of petroleum derivatives and the unsafe impacts of ozone harming substance (GHG) outflows caused individuals to understand that nothing is more advantageous than making own power creation utilizing Renewable Energy Systems (RES). Yet, the irregularity of RES blocks the chance of superseding the petroleum derivative based power frameworks. Energy Storage Systems (ESS), notwithstanding, have turned into an inescapable piece of RES as they offer the best answer for stay away from this discontinuity issue. This blend of ESSs with RESs is regularly considered as Hybrid Renewable Energy System (HRES). Because of the difficulties related with RES and ESS frameworks, momentum research works are for the most part centered around the improvement of a mechanization framework that can naturally deal with the utility in view of the accessibility of flow and future energy. To make it more astute and more gainful, Building Automation Systems (BAS) have been presented.

[3] Present day structures are served by many implanted Technical Building Systems (TBSs) required for their activity, both for solace and wellbeing. A significant number of these frameworks are very energy requesting, hence, these days, legitimate administration is vital for energy saving, as referenced in the fifth Assessment Report, WG III. IPCC. In the assessment of the energy execution of a structure the frameworks that should be thought of, as indicated by European guidelines are: warming, ventilation, and cooling (HVAC), homegrown heated water (DHW), worked in lighting (L). Other primary energy clients in structures are implicit helper frameworks (for example lifts, observation, and so forth), apparatuses and cooking that together record for 38% of energy end-use. It is notable that energy reserve funds can be accomplished by means of Building Automation Control Systems (BACSs), as featured.

[4] Electrical examples at the structure level are perceived to have an exceptionally non-straight and non-fixed person. In the one hand, the increment in changeability is given by the new age abilities of the structures, just as the most customary perceived elements to affecting it like cost, meteorological conditions, etc. Then again, a more dynamic commitment of end-client interest, along with arising brilliant network advancements and applications are relied upon to show up in not so distant future and to add much greater inconstancy in the electrical patterns. Aiming to give adaptability and effectiveness in the entire energy framework, in this paper, we examine how the most recent man-made reasoning strategies can be utilized to investigate and separate the valuable information from exceptionally factor electrical patters. Especially, utilizing an observing stage in light of start to finish particular sensor arrangement with high testing rate we proposed a coordinated information driven model for building energy forecast and adaptability.

[5] Lattice scale energy stockpiling frameworks are progressively being sent to give matrix administrators the adaptability expected to keep up with this equilibrium. Energy stockpiling additionally bestows strength and vigor to the network framework. The Energy Management System (EMS) is answerable for ideal and safe activity of the energy stockpiling frameworks. The power change framework (PCS) is answerable for the lattice electrical point of interaction and overseeing power streams. The PCS gets orders from the EMS, and points of interaction to a gadget the board framework (DMS).

[6] It is a kind of disseminated control methodology that utilizes market components to connect with self-intrigued responsive burdens to accomplish power balance in the electrical power lattice. Propose a transactive control approach of business building Heating, Ventilation, and Air Conditioning (HVAC) frameworks for request reaction. First depict the framework models, and distinguish their model boundaries utilizing information gathered from Systems Engineering Building (SEB). Next present a transactive control market structure for business building HVAC frameworks, and portray its representative offering and market clearing system.

III. PROPOSED WORK

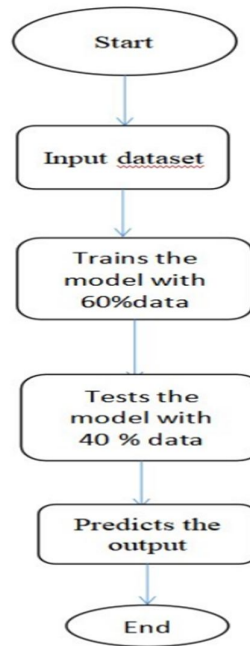


Fig. 1. Flowchart of proposed work

The above figure shows the flow process of the proposed system. In our proposed system, we first take the dataset and input the dataset to the model. Then it preprocesses the data by removing all the null values and removing the unused columns from the dataset. Then we train the LSTM model by giving the 60 percent of data to the model. Then we can get the model trained by adjusting the weights. We test the model with the remaining 40 percent data to get the highest accuracy. By using this model we can predict the electricity consumed for the next year.

A. Technologies used

- LSTM is an artificial recurrent neural network(RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can process not only single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connected handwriting recognition, speech recognition and anomaly detection in network traffic or IDSs. An RNN using LSTM units can be trained in a supervised fashion, on a set of training sequences, using an optimization algorithm, like gradient descent, combined with backpropagation through time to compute the gradients needed during the optimization process, in order to change each weight of the LSTM network in proportion to the derivative of the error (at the output layer of the LSTM network) with respect to corresponding weight.
- Profound learning is an AI method that encourages PCs to do what works out easily for people: learn as a visual cue. Profound learning is a critical innovation behind driverless vehicles, empowering them to perceive a stop sign, or to recognize a passerby from a light post. It is the way to voice control in customer gadgets like telephones, tablets, TVs, and sans hands speakers. Profound learning is standing

out enough to be noticed recently and understandably. It's accomplishing results that were impractical previously. In profound learning, a PC model figures out how to perform arrangement undertakings straightforwardly from pictures, text, or sound. Profound learning models can accomplish cutting edge precision, 3 in some cases surpassing human-level execution.

B. Libraries used

- NumPy can be utilized to play out a wide assortment of numerical procedure on clusters. It adds strong information constructions to Python that ensure proficient estimations with clusters and grids and it supplies a tremendous library of significant level numerical capacities that work on these exhibits and networks.
- PyTorch is a numerical library that permits you to perform proficient calculation and programmed separation on diagram based models. Accomplishing this straightforwardly is testing, albeit fortunately, the cutting edge PyTorch API gives classes and colloquialisms that permit you to effectively foster a set-up of profound learning models.
- SciPy, a logical library for Python is an open source, BSD-authorized library for math, science and designing. The SciPy library relies upon NumPy, which gives advantageous and quick N-layered exhibit control. The fundamental justification for building the SciPy library is that, it should work with NumPy exhibits. It gives numerous easy to understand and effective mathematical practices like schedules for mathematical mix and advancement. This is an initial instructional exercise, which covers the basics of SciPy and depicts how to manage its different modules.
- TensorFlow is a start to finish open-source AI stage with an attention on profound neural organizations. Profound learning is a subtype of AI that investigations enormous measures of unstructured information. Since it works with organized information, profound gaining is not quite the same as expected machine learning. TensorFlow gives an assorted and complete arrangement of libraries, apparatuses, and local area assets. It permits designers to make and send cutting edge AI controlled applications. One of the most engaging parts of TensorFlow is that it utilizes Python to make a pleasant front-end API for creating applications that disagreement elite execution, advanced C++.
- OpenCV is an enormous open-source library for PC vision, AI, and picture handling. OpenCV upholds a wide assortment of programming dialects like Python, C++, Java, and so on It can deal with pictures and recordings to recognize items, faces, or even the penmanship of a human. At the point when it is coordinated with different libraries, for example, Numpy which is a profoundly upgraded library for mathematical tasks, then, at that point, the quantity of weapons expansions in your Arsenal i.e whatever activities one can do in Numpy can be joined with OpenCV
- Matplotlib is an astonishing representation library in Python for 2D plots of clusters. Matplotlib is a multi-stage information representation library based on NumPy clusters and intended to work with the more extensive SciPy stack.

C. Dataset Description

Time	Global_active_power	Global_reactive_power	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
12/17/2006 17:00	4.22080889	0.229	234.643889	38.1	0	0.52777778
12/17/2006 18:00	3.8122	0.08033333	234.362087	25.8	0	0.75666667
12/17/2006 19:00	3.40233333	0.08233333	233.2325	14.70333333	0	1.43333333
12/17/2006 20:00	3.00566667	0.0751	234.2715	13.56666667	0	0
12/17/2006 21:00	2.05666667	0.07666667	237.128887	13.04666667	0	0.51666667
12/17/2006 22:00	2.00333333	0.06266667	238.76	9.53333333	0	0.53333333
12/17/2006 23:00	2.0036	0.07143333	240.629667	8.89666667	0	0.08333333
12/17/2006 0:00	1.80706667	0.10433333	240.802333	8.22666667	0	0.46666667
12/17/2006 1:00	3.3494	0.13803333	240.488333	14.24666667	0	25.23333333
12/17/2006 2:00	1.58706667	0.07823333	245.838667	6.87	0	0.56666667
12/17/2006 3:00	0.6622	0.07953333	244.5135	7.20666667	0	0.76666667
12/17/2006 4:00	2.21706667	0.09386667	243.8535	9.30333333	0	0.56666667
12/17/2006 5:00	1.90733333	0.08023333	243.770887	8.76666667	0	0.56666667
12/17/2006 6:00	1.3533	0.08483333	244.1435	6.53	0	0.71666667
12/17/2006 7:00	1.63033333	0.0986	243.848667	6.88033333	0	0.56666667
12/17/2006 8:00	1.89056667	0.11856667	243.3135	8.05	0	0.75
12/17/2006 9:00	2.00566667	0.07923333	238.847333	10.033333	0	7.16666667
12/17/2006 10:00	3.6389	0.1946	235.441	15.533333	8.88333333	22.35
12/17/2006 11:00	1.471	0.1057	240.528667	26.803333	9.46	5.05666667
12/17/2006 12:00	1.91506667	0.29403333	237.788667	8.15666667	0	0.53333333
12/17/2006 13:00	1.60706667	0.17353333	238.102667	6.92033333	0	8.05
12/17/2006 14:00	2.00233333	0.2574	244.096667	8.6	0	0.53333333
12/17/2006 15:00	2.9354	0.0886	240.488333	12.426667	6.96666667	6.2
12/17/2006 16:00	3.30033333	0.09133333	236.783333	14.76666667	8.58333333	0.06666667
12/17/2006 17:00	3.40766667	0.16633333	234.228333	14.55	0	0.46666667
12/17/2006 18:00	3.8972	0.15066667	234.172333	25.75	0	16.88333333
12/17/2006 19:00	2.9084	0.26516667	233.159667	12.556667	0	0.51666667
12/17/2006 20:00	3.3623	0.1715	236.4265	14.766667	0	1.51666667
12/17/2006 21:00	3.04076667	0.26766667	239.124267	12.758667	0	1.2

Fig 2. Dataset

The dataset consists of various columns which contain the electricity consumed per hour. It contains the time column and also submetering column in which electricity consumed is noted and one column global active power is present, it is the total amount of electricity consumed per hour in the whole building. We can take only

one column global active power column and remove all the columns. After removing we need to analyze the dataset and then preprocess. After that training and prediction of electricity.

D. Data Preprocessing

This stage is a significant one and it includes organizing information into suitable configurations and types. As recently referenced, when playing out an investigation, we might experience organized, semi organized and unstructured information. Information preprocessing is done through standardization and accumulation strategies. This change interaction guarantees information is effectively coherent by the applied handling calculations.

In this interaction it eliminates every one of the invalid qualities and furthermore eliminates the superfluous sections. Eliminating of invalid qualities is finished by supplanting the invalid worth with the proper worth mean or middle or zero. Likewise it standardizes the data. It changes over the information into a reach.

```

lstm - Notepad
File Edit Format View Help

def preprocess_df(df, shuffle=False):
    sequential_data = []
    prev_days = deque(maxlen = SEQ_LEN)
    # this is a list that will CONTAIN the sequences
    # These will be our actual sequences.
    # They are made with deque, which keeps the maximum length
    # by popping out older values as new ones come in
    for i in df.values:
        prev_days.append([n for n in i[:-1]])
        # iterate over the values
        # store all but the label
        if len(prev_days) == SEQ_LEN:
            sequential_data.append(np.array(prev_days, i[-1]))
            # make sure we have 30 sequences!
            # append those bad boys!

    if(shuffle == True):
        random.shuffle(sequential_data)
        # shuffle for good measure.

    x = []
    y = []

    for seq, target in sequential_data:
        # going over our new sequential data
        # X is the sequences (features)
        # y is the targets/labels
        x.append(seq)
        y.append(target)

    return np.array(x), np.array(y) # return X and y...and make X a numpy array!

def train_length(length, batch_size):

```

Fig. 3. Python code for data preprocess

E. Training and testing the model

We train LSTM with 21 hidden units. A lower number of units is utilized so it is doubtful that LSTM would impeccably retain the succession. We utilize the Mean Square Error misfortune work. The learning rate is set to 0.001 and it rots each 5 ages. We train the model with 100 successions for every bunch for 15 ages.

The future boundary is set to 6, and that implies that the model results where it accepts it will be in the following 6 time bars . This should make the value change noticeable a couple of time bars before it occurs. We have prepared the lstm model with the 60% of information , by changing the loads of the nodes. Then it tests the model with the excess 40% of information and observes the exactness of the model. If it has most elevated precision then it predicts the power or, more than likely it changes the loads to get the most elevated exactness and to foresee impeccably.

IV. RESULT ANALYSIS

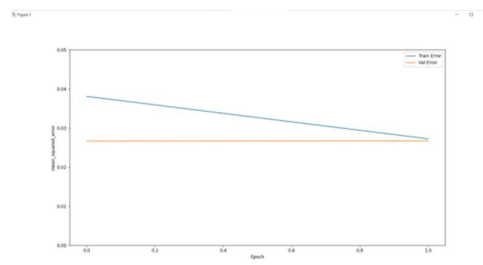


Fig 4. Training vs validation error

It shows graphically the difference between the training error and the validation error.

In the plot above, we can observe that predicted values closely match the actual values, which seems great at first sight. But the future parameter was set to 6, which means that the yellow line should react before a spike occurs instead of covering it.

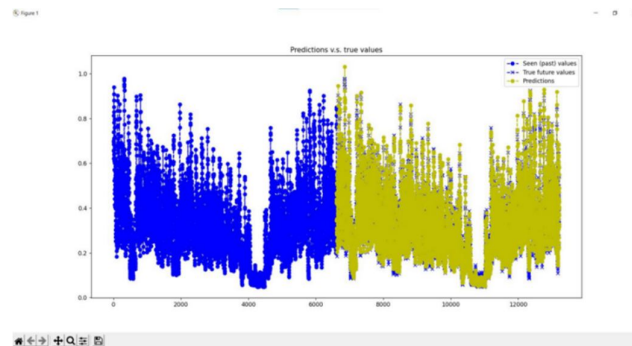


Fig. 6. Predicted electricity

V. CONCLUSION

The business structures produce an exceptionally enormous volume of information that requires large information innovations to evaluate the adaptability of the power utilization and gauge likely investment funds. In this way, we propose a profound learning procedure which predicts the power consumed via preparing a neural organization model utilizing a long momentary memory calculation. It requires the one year hourly power consumed information and trains the information and afterward predicts the electricity. The precision of the calculation is additionally almost close to 100%.

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