Energy Consumption Forecasting

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Abstract- *Electricity consumption has increased gradually during the past few decades. This increase is causing burden to the electricity distributors. Therefore, predicting electricity consumption will provide an opportunityto the electricity distributor. Predicting electricity consumption requires many parameters. This study uses two approaches with one using a Recurrent Neural Network (RNN) and another one using a Long Short Term Memory (LSTM) network, which considers the previous electricity consumption, weather and holidays data to predict the future electricity consumption. This study uses the publicly available London smart meter dataset of electricity usage, weather conditions data and Holidays data of UK. To assess the applicability of the RNN and the LSTM network to predict the electricity consumption, they are used to predict the accurate electricity consumption.*

Keywords- Electricity Consumption,RNN, LSTM.

I. INTRODUCTION

For economical budget designing and profit analysis on investments, load prognostication of electricity load for a amount of 1 year or additional is a very important tool for utility firms. These utility firms use the load forecasts to make your mind up the development of recent power plants, extension of transmission lines and verify the fuel sources of generation facilities. The accuracy of prognostication considerably affects the money performance of participants in electricity market.Moreover, Energy Service suppliers sign forward contracts on a yearly basis to maximise their profits and cut back the risks on investments. This needs energy service suppliers to predict year-ahead load so as to create associate degree educated call and end their strategy. If the electricity load forecast is overestimated, it will lead to higher investments than needed whereas the client load demand would be difficult to fulfill with a real understatement. With a monthly or annual roughness, the restricted range of observations cannot capture the options and dependencies of the parameters poignant electrical masses and so cause inaccurate predictions. Because the fashionable sensible grids supply high-resolution hourly knowledge of electricity load, prediction of hourly load demand on a protracted term basis may be advantageous for an additional correct forecast. Long Term load prediction refers to predicting electricity load demand in an exceedingly explicit space for durations pertaining longer than a year. Most of the work on load prognostication has been centered on short-run load prognostication wherever the forecast amount does not exceed quite period. varied applied math and deep learning based mostly models are projected for short-run load prognostication together with regression,Feed forward neural network, neuro-fuzzy models and support vector machines. However, terribly restricted work has been projected for forecast of electrical load demand of quite a year. Vlahovic et al. projected a mathematical model supported regression for prognostication future load demands back within the Nineteen Eighties. A model supported gray theory has conjointly been recommended for correct predictions. Different models projected were supported statistic models like ARIMA, symbolic logic and hybrid neural model. A spatial load prognostication technique has been projected for future prognostication and is employed by varied utility firms. However, majority of the mentioned works utilize annual resolution of either peak energy demand or total energy consumption to forecast load for amount of 1 to 10 years. Attributed to the little range of observations, these forecasts are inadequate for creating associate degree educated call of designing and investments for the utility firms. Here i exploit a Long-Short-Term-Memory based mostly continual Neural Network (LSTM-RNN) model for prognostication electricity demand for amount of 5-years.A self-adaptive face detection algorithm supported colouring for images with complex background. First histogram colour model is made and then skin colour segmentation is implemented employing histogram back projection.

II. PROBLEM DEFINITION

Electricity as a product has terribly totally different characteristics compared to a cloth product. for example, electricity energy can't be kept because it ought to be generated as shortly as it is demanded. Any industrial power company has many strategic objectives. one amongst these objectives is to produce finish users (market demands) with safe and stable electricity. Therefore, electrical Load prediction could be a vital method within the designing of electricity trade and also the operation of electrical power systems. correct forecasts lead to substantial savings in operation and maintenance prices, accumulated responsibility of power provide and delivery system, and correct selections for future development. Electricity demand is assessed by accumulating the consumption periodically; it is almost thought of for hourly, daily, weekly, monthly, and yearly periods. The Existing system uses electricity data on day basis and the proposed system uses electricity data on hour basis and also considers the external factors like weather and holidays data in order to forecast accurately.

. DESIGN METHODOLOGY

A.Architecture

In this phase of system design, we will be defining the architecture, modules, interfaces and the data for the system to satisfy specified requirements. System design can be seen as the application of systems theory for the proposed project or product development. All the datasets are read individually and merged. Then the dataset is further classified to training and testing for fitting the LSTM algorithm to form the model. The final results shows the predicted electricity consumption and compare actual values with predicted values.

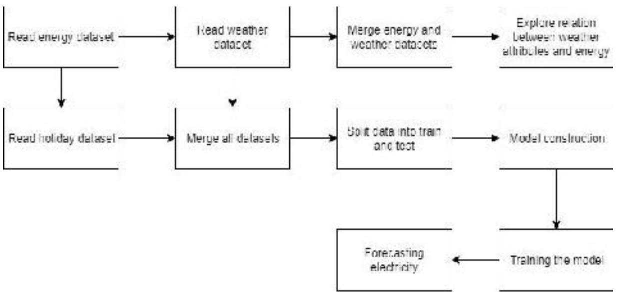


Figure 1: Workflow of model

The above Figure 1 shows and explains the work flow of the energy consumption prediction model where initially the data is collected and analyzed to gain useful insights from it.

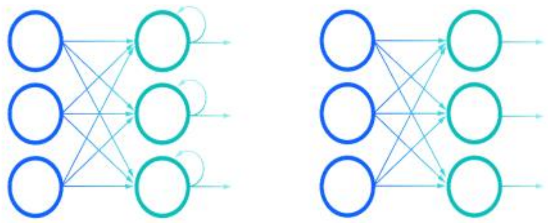
B. Dataset

To accurately forecast the electricity prediction there is need of electricity consumption dataset .here this model uses electricity load consumption of London on hour basis which in turn helps to forecast exact consumption. The external factors like weather and holidays also effect the electricity consumption .therefore adding the external factors like weather data on hour basis and holidays data helps in resulting accurate electricity consumption.

C. Modules

Recurrent Neural Network

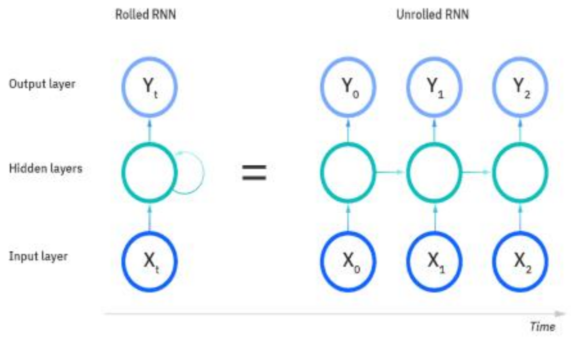
A recurrent neural network (RNN) is a type of artificial neural network which uses sequential data or time series data. These deep learning algorithms are commonly used for ordinal or temporal problems, such as language translation, natural language processing (nlp), speech recognition, and image captioning; they are incorporated into popular applications such as Siri, voice search, and Google Translate. Like feedforward and convolutional neural networks (CNNs), recurrent neural networks utilize training data to learn. They are distinguished by their “memory” as they take information from prior inputs to influence the current input and output. While traditional deep neural networks assume that inputs and outputs are independent of each other, the output of recurrent neural networks depend on the prior elements within the sequence. While future events would also be helpful in determining the output of a given sequence, unidirectional recurrent neural networks cannot account for these events in their predictions.



Comparison of Recurrent Neural Networks (on the left) and Feedforward Neural Networks (on the right)

Let’s take an idiom, such as “feeling under the weather”, which is commonly used when someone is ill, to aid us in the explanation of RNNs. In order for the idiom to make sense, it needs to be expressed in that specific order. As a result, recurrent networks need to account for the position of each word in the idiom and they use that information to predict the next word in the sequence.

Looking at the visual below, the “rolled” visual of the RNN represents the whole neural network, or rather the entire predicted phrase, like “feeling under the weather.” The “unrolled” visual represents the individual layers, or time steps, of the neural network. Each layer maps to a single word in that phrase, such as “weather”. Prior inputs, such as “feeling” and “under”, would be represented as a hidden state in the third timestep to predict the output in the sequence, “the”.



.Another distinguishing characteristic of recurrent networks is that they share parameters across each layer of the network. While feedforward networks have different weights across each node, recurrent neural networks share the same weight parameter within each layer of the network. That said, these weights are still adjusted in the through the processes of backpropagation and gradient descent to facilitate reinforcement learning.

Recurrent neural networks leverage backpropagation through time (BPTT) algorithm to determine the gradients, which is slightly different from traditional backpropagation as it is specific to sequence data. The principles of BPTT are the same as traditional backpropagation, where the model trains itself by calculating errors from its output layer to its input layer. These calculations allow us to adjust and fit the parameters of the model appropriately. BPTT differs from the traditional approach in that BPTT sums errors at each time step whereas feedforward networks do not need to sum errors as they do not share parameters across each layer.

Through this process, RNNs tend to run into two problems, known as exploding gradients and vanishing gradients. These issues are defined by the size of the gradient, which is the slope of the loss function along the error curve. When the gradient is too small, it continues to become smaller, updating the weight parameters until they become insignificant—i.e. 0. When that occurs, the algorithm is no longer learning. Exploding gradients occur when the gradient is too large, creating an unstable model. In this case, the model weights will grow too large, and they will eventually be represented as NaN. One solution to these issues is to reduce the number of hidden layers within the neural network, eliminating some of the complexity in the RNN model.[7]

Long Short Term Memory

In 1997, LSTM was proposed by Hoch Reiter and Schmidhuber as a more efficient RNN architecture. In a Recurrent neural network, the algorithm fails to converge to the optimum minima attributed to the problem of vanishing gradients. This was the primary motivation behind the development of LSTM which successfully incorporates long term dependencies and hence improves the overall accuracy of the model .

Contrary to an RNN model, the hidden layers of LSTM have a complex structure. In particular, each hidden layer in an LSTM is introduced to the concept of memory cells. Assuming each memory cell to be denoted by *cj*, these memory cells encompass a central linear unit having a static self- connection. *cj* receives inputs from input gate *inj*, output gate *outj* and *net (cj)*. We have

y (outj(t)) = *f* {outj(net(outj(t)))} (2)

y (inj(t)) = *f* {inj(net(inj(t)))} (3)

net (outj(t)) = Σ wout uyu(t – 1) (4)

net (inj(t)) = Σ win uyu(t – 1) (5)

net (cj(t)) = Σ wc uyu(t – 1) (6)

where *y(t)* is the activation at time *t* of *inj* or *outj*, *u* may represent the input units, memory cells, gate units or hidden units. At any time *t*, the output of *cj* is computed as

ycj(t) = youtj(t)   (sc (t)) (7)

Here scj(0) = 0 and for t>0,

sc (t) = sc (t − 1) + yinj(t)g(net (cj(t)))(8)

In (7), *h()* function scales memory cell outputs and in (8), *g()* is a differential function that squashes *net(cj(t))* . For long term load forecasting, long term dependencies between the samples of training data need to be taken into account.[9]

D. Methodology

(LSTM) based method which is processed by an historical energy consumption data listed in hourly basis. In the first step of our work we integrate data pre-processing and follow data reorganization mechanism. In second step, we design our LSTM network and the reorganized data is fed to the proposed network to learn the input sequence pattern effectively. Lastly, we compare the actual and predicted data series obtained through our proposed network and evaluates the prediction through error metrics. Our simulation results show that the proposed LSTM algorithm effectively improve the prediction accuracy of energy consumption. The model is implemented on real time electricity data provided by the UK,Weather conditions of UK and holidays of UK. The predictions have hourly frequency and hence are highly beneficial for use by the utility companies. The hourlypredictions provide a more accurate description of load demand in the forthcoming years and maximum load demand can also be computed on a monthly basis using the data obtained. For performing time series predictions, Recurrent Neural Networks (RNNs) are one of the most widely used models . However, they suffer from an inherent problem of vanishing gradient descent. To overcome this problem and additionally formulate long term dependencies between training samples, LSTM-RNN is used which significantly increases the precision of the proposed model . The model presented in the paper is found to be competently accurate with an overall Mean Absolute Error.

IV. RESULTS

After loading the energy consumption, weather and holidays datasets the relationship between weather parameters and energy comsumption.

1) Temperature

The Figure 3 shows that energy and temperature have an inverse relationship-we can see the peaks in one appearing with troughs in the other. This confirms the business intuition that during low temperature, it is likely that the energy consumption through heaters etc. increases.

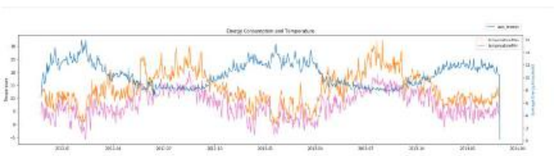


Figure 3 : Energy w.r.t Temperature

2) Humidity

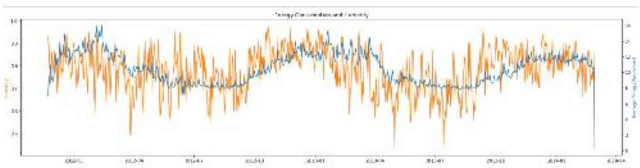


Figure 4: Energy w.r.t Humidity

The above Figure 4 shows Humidity and the average consumption of energy seems to have the same trend.

3) Dew Point

The Figure 5 shows that Dew Point- is a function of humidity and temperature therefore it displays similar relation to energy consumption.

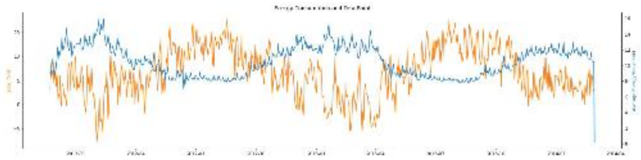


Figure 5: Energy w.r.t DewPoint

4) Cloud Cover

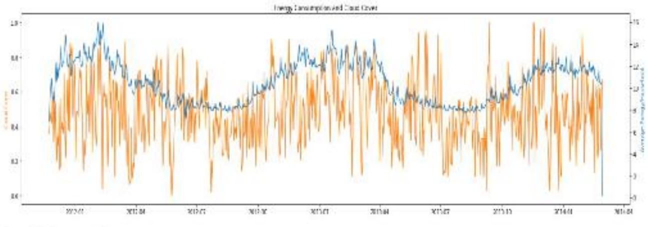


Figure 6:Energy w.r.t cloud Cover

The Figure 6 shows that cloud cover value seems to be following the same pattern as the energy consumption.

5) Visibility

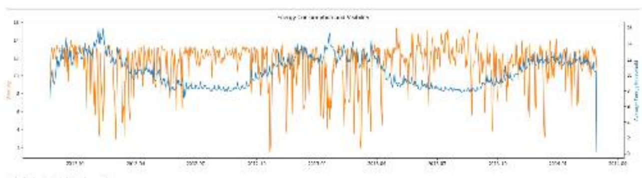


Figure 7: Energy w.r.t Visibility

The above Figure 7shows that the visibility factor does not seem to affect energy consumption at all- since visibility is most likely an outdoors factor, it is unlikely that it's increase or decrease affects energy consumption within a household**.**

6) Wind Speed

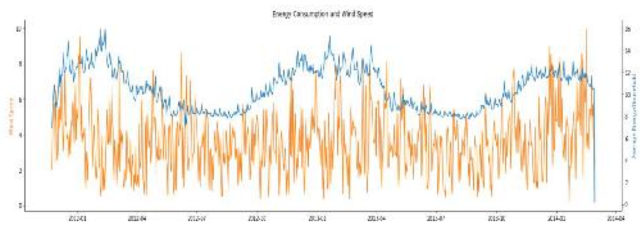


Figure 8 : Energy w.r.t Wind Speed

The above Figure 8 shows that wind speed seems to be an outdoors factor which does not affect in the energy consumption as such.

7) UV Index

The Figure 9 shows that the UV index has an inverse relationship with energy consumption.

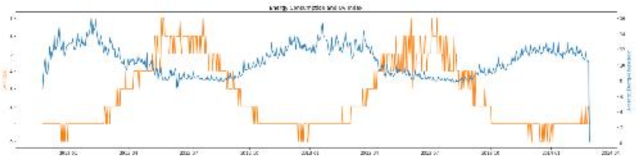


Figure 9 :Energy w.r.t UV Index

After exploring the relation between each parameter of weather with energy consumption RMSE values will be predicted by LSTM (Long Short Term Memory) .

```
act = [i[9] for i in inv_y]
pred = [i[9] for i in inv_yhat]

# calculate RMSE
import math
rmse = math.sqrt(mean_squared_error(act, pred))
print('Test RMSE: %.3f' % rmse)
```

```
Test RMSE: 0.000
```

Figure 10: RMSE rom LSTM

The above Figure10 shows the RMSE (Root Mean SquareError) value obtained using LSTM model.

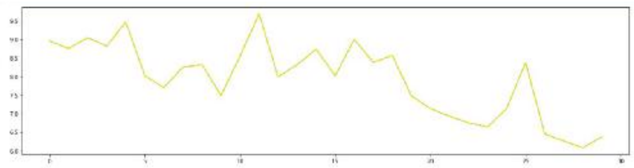


Figure 11: Actual and Predicted values

The above Figure 11shows the actual and predicted values that are obtained using LSTM.

V. CONCLUSION

In this paper LSTM-RNN model for long-term load forecasting with hourly resolution is used . Recurrent Neural Network model is extremely suitable for time series electricity data and LSTM establishes long term dependencies in the data in order to increase the precision of long term electricity load forecasts. Model has been implemented on real time data of the available London smart meter dataset of electricity usage, weather conditions data and Holidays data of UK ISO. Long term load forecast with an hourly resolution can be used by energy service providers to plan investments with minimum risks and set up of new generation facilities. The high resolution of data helps in improving the accuracy as well as allows the companies to make a more informed decision and devise an effective strategy for investments. The model is found to be highly accurate with a Root Mean Square Error (RMSE) value of 0.000 which indeed helps to predict energy

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