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Original Article

Smart Electricity Demand Forcasting by Using Improved LSTM Algorithm

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Abstract: *Demand forcasting, which concerns the estimation of future electricity demand, is needed for the operation and management of power systems. Effective Electricity demand forecasting can relieve the conflict between power supply and demand. Furthermore, effective load forecasting can improve the efficiency of power stations and ensure the safety of the grid. It is suggested that a reduction of a few percentage points in prediction accuracy would have significant cost impact on companies operating in highly competitive power markets. In our project we are going to forecast the electricity demand by using a Deep learning algorithm which is called as Improved Long Short Term Memory. By using Improved LSTM we can able to get accurate Future predicted output.*

Keywords: *Long Short Term Memory, Forcasting, Power Supply, Demand, Effective Load Forcasting.*

I. INTRODUCTION

A. Qualitative method

Otherwise known as the judgmental method, qualitative forecasting offers subjective results, as it is comprised of personal judgments by experts or forecasters. Forecasts are often biased because they are based on the expert's knowledge, intuition, and experience, and rarely on data, making the process non-mathematical.

One example is when a person forecasts the outcome of a finals game in the NBA, which, of course, is based more on personal motivation and interest. The weakness of such a method is that it can be inaccurate.

a) Forcasting:

Forecasting refers to the practice of predicting what will happen in the future by taking into consideration events in the past and present. Basically, it is a decision-making tool that helps businesses cope with the impact of the future's uncertainty by examining historical data and trends. It is a planning tool that enables businesses to chart their next moves and create budgets that will hopefully cover whatever uncertainties may occur.

b) Forecasting Methods:

Businesses choose between two basic methods when they want to predict what can possibly happen in the future, namely, qualitative and quantitative methods.

B. Quantitative Method

The quantitative method of forcasting is a mathematical process,making it consistent and objective.it steers a way from basing the result on opnion and intuition,instead utilizing large amounts of data and figures that are interpreted.

a) Electricity Demand Forcasting:

Effective planning of a power system requires the forecast of several key variables. Whether planning for network or generation assets, variables such as the customer count, energy consumption and annual summer or winter maximum demand are necessary for identifying future requirements in the next decade. While maximum demand is especially important in capacity planning, other variables such as the customer count and energy consumption, are required for economic evaluation and financial planning.

C. Features s of Forecasting

Here are some of the features of making a forcast.

(a) Involves future events

Forecasts are created to predict the future, making them important for planning.forcasts are based on opinions, intuition, guesses, as well as on facts, figures, and other relevant data. All of the factors that go into creating a forecast reflect to some extent what happened with the business in the past and what is considered likely to occur in the future.

D. The Process of Forecasting

Forecasters need to follow a careful process in order to yield accurate results. Here are some steps in the process:

A. Estimate the future operations of the business.

Based on the investigation conducted during the first step, the second part of forecasting involves estimating the future conditions of the industry where the business operates and projecting and analyzing how the company will fare.

B. Regulate the forecast

This involves looking at different forecasts in the past and comparing them with the actual things that happened with the business. The differences in previous results and current forecasts are analyzed, and the reasons for the deviations are considered.

II. LITERATURE SURVEY

[1] Yun Li, Member, IEEE and Ben Jones,"The Use of Extreme Value Theory for Forecasting Long-Term Substation Maximum Electricity Demand" Volume: 35, 2020

The major contribution of this paper is proposing a new methodology for forecasting substation annual maximum demand as a function of other forecast variables using extreme value theory. For a given substation, the times of daily load exceedances above a given high threshold To account for the influence of the customer count, average demand, and PV capacity, we have employed a PP model whose location and scale parameters that depend on the trends in these factors.future work is to implement this project with the accuracy of over 95%.

[2] David Obst , Joseph de Vilmarest , and YannigGoude, "Adaptive Methods for Short-Term Electricity Load Forecasting During COVID-19 Lockdown in France" Volume: 36, 2021.

In this paper we introduce two methods to adapt generalized additive models, alleviating the aforementioned issue. Using Kalman filters and fine-tuning allows adapting quickly to new electricity consumption patterns without requiring exogenous information. The proposed methods are applied to forecast the electricity demand during the French lockdown period, where they demonstrate their ability to significantly reduce prediction errors compared to traditional models. Finally, expert aggregation is used to leverage the specificities of each predictions and enhance results even further.

III. SYSTEM IMPLEMENTATION

A. Existing System

In the existing system they used support vector regressing algorithm for demand forcasting, it is suitable for short term forecasting only.The stability of output of SVR algorithm is also very low. It is suitable for linear prediction only. And hence its predicted values are very much different from the actual values.

B. Proposed System

In the proposed system we use a Deep learning model which is called as Long Short Term Memory which is suitable for long term forecasting. By using LSTM, we predict the future 2 month electricity demand values with high accuracy.

C. Data Collection

We collected the electricity demand dataset from kaggle website.The dataset covers 2016 days between 1 January 2015 and 6 October 2020.

Date: Datetime, the date of the recording
Demand: Float, a total daily electricity demand in MWh
RRP: Float, a recommended retail price in AUD$ / MWh
Demand_POS_RRP: Float, a total daily demand at positive RRP in MWh
RRP_Positive: Float, an averaged positive RRP, weighted by the corresponding intraday demand in AUD$ / MWh

Demand_NEG_RRP: Float, a total daily demand at negative RRP in MWh
RRP_Negative: Float, an average negative RRP, weighted by the corresponding intraday demand in AUD$ / MWh
Frac_at_NEG_RRP: Float, a fraction of the day when the demand was traded at negative RRP
Min_Temperature: Float, minimum temperature during the day in Celsius
Max_Temperature: Float, maximum temperature during the day in Celsius
Solar_Exposure: Float, total daily sunlight energy in MJ/m^2
Rainfall: Float, daily rainfall in mm
School_Day: Boolean, if students were at school on that day.

D. Data Pre-Processing

At first the dataset is fetched by using pandas library and then we save the datas inside a pandas dataframe, At first this dataset consists of lots of null values, then we replace all the null values into 0, because our Deep learning model cannot able to process null values.

E. Proposed System Architecture

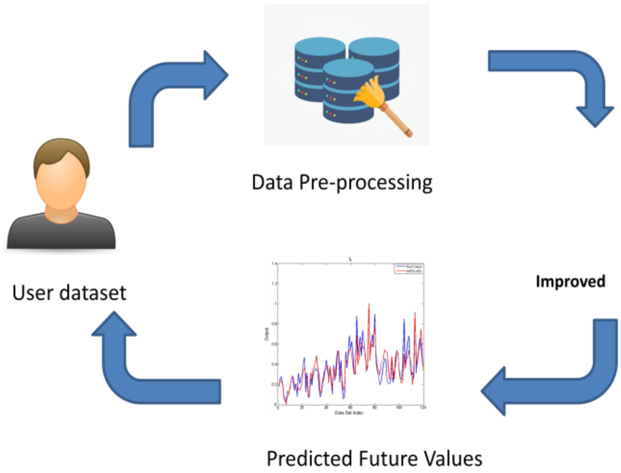


Figure 1: Proposed System Work Flow

IV. LONG SHORT TERM MEMORY (LSTM)

A. Long short-term memory (LSTM)

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 future prediction,unsegmented,connected hand writing recognition, speech recognition and anomaly detection in network traffic RNNs, hidden Markov models and other sequence learning methods in numerous applications.

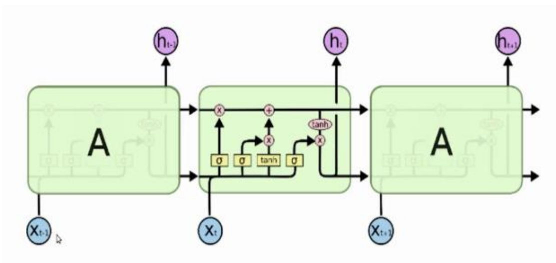


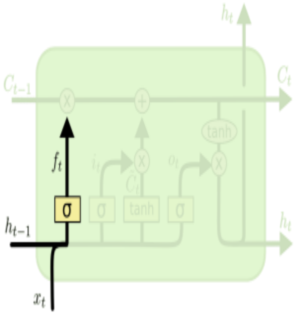
Figure 2: LSTM Structure

B. Steps in LSTM

a) STEP-1

The first step in our LSTM is to decide what information we're going to throw away from the cell state. This decision is made by a sigmoid layer called the "forget gate layer." It looks at ht−1ht−1 and xtxt, and outputs a number between 00 and 11 for each number in the cell state Ct−1Ct−1. A 11 represents "completely keep this" while a 00 represents "completely get rid of this."

Let's go back to our example of a language model trying to predict the next word based on all the previous ones. In such a problem, the cell state might include the gender of the present subject, so that the correct pronouns can be used. When we see a new subject, we want to forget the gender of the old subject.

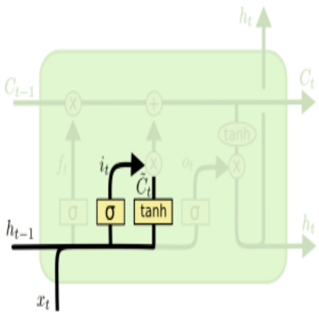


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Figure 3: Steps 1 in LSTM

b) STEP-2

The next step is to decide what new information we're going to store in the cell state. This has two parts. First, a sigmoid layer called the "input gate layer" decides which values we'll update. Next, a tanh layer creates a vector of new candidate values, C~tC~t, that could be added to the state. In the next step, we'll combine these two to create an update to the state. In the example of our language model, we'd want to add the gender of the new subject to the cell state, to replace the old one we're forgetting.



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Figure 4: Step 2 in LSTM

C. Python applications

One of the most famous platforms where Python is extensively used is YouTube. The other places where you will find Python being extensively used are the special effects in Hollywood movies, drug evolution and discovery, traffic control systems, ERP systems, cloud hosting, e-commerce platform, CRM systems, and whatever field you can think

a) Versions

At the time of writing this book, two main versions of the Python programming language were available in the market, which are Python 2.x and Python 3.x. The stable release as of writing the book were Python 2.7.13 and Pyth

b) Python programming examples

Hello world program:

```
print('Hello, world!')
```

Program to calculate the factorial of a positive integer:

```
n = int(input('Type a number, then its factorial will be printed: '))
if n < 0:
raiseValueError('You must enter a positive number')
fact = 1
i = 2
whilei<= n:
fact = fact * i
i += 1
print(fact)
```

V. EXPERIMENTAL AND DATASET ANALYSIS

Electricity demand prediction is implemented using Python IDE 3.7.6. in this project datasets are collected from the kaggle
(a datascience website).

1	date	demand	RRP	demand_	RRP_posit	demand_	RRP_nega	frac_at_ne	min_temp	max_temp	solar_exp	rainfall	school_da	holiday
2	01-01-2015	99635.03	25.6337	97319.24	26.41595	2315.79	-7.24	0.020833	13.3	26.9	23.6	0	N	Y
3	02-01-2015	129606	33.13899	121082	38.83766	8523.995	-47.8098	0.0625	15.4	38.8	26.8	0	N	N
4	03-01-2015	142300.5	34.56485	142300.5	34.56485	0	0	0	20	38.2	26.5	0	N	N
5	04-01-2015	104330.7	25.00556	104330.7	25.00556	0	0	0	16.3	21.4	25.2	4.2	N	N
6	05-01-2015	118132.2	26.72418	118132.2	26.72418	0	0	0	15	22	30.7	0	N	N
7	06-01-2015	130672.5	31.28231	130672.5	31.28231	0	0	0	17.7	26	31.6	0	N	N
8	07-01-2015	153514.8	48.31231	149498.7	49.63971	4016.105	-1.1	0.020833	18.9	37.4	20.7	0	N	N
9	08-01-2015	142015.7	49.11728	142015.7	49.11728	0	0	0	23.1	28.2	13.5	19.4	N	N
10	09-01-2015	121801.2	34.49068	121801.2	34.49068	0	0	0	16.5	18	3.1	1.2	N	N
11	10-01-2015	103043.7	20.22982	103043.7	20.22982	0	0	0	13.6	21.7	5.6	5.2	N	N
12	11-01-2015	99865.76	18.23477	99865.76	18.23477	0	0	0	15.6	27.5	29.9	0	N	N
13	12-01-2015	131261.1	33.69481	131261.1	33.69481	0	0	0	16.1	31.3	31.6	0	N	N
14	13-01-2015	126527.4	27.53786	126527.4	27.53786	0	0	0	20.2	25.6	4.2	0	N	N
15	14-01-2015	119741.6	29.01852	119741.6	29.01852	0	0	0	18.3	22.7	15.2	15.8	N	N
16	15-01-2015	118411.2	30.93654	118411.2	30.93654	0	0	0	15.8	20	14.6	0	N	N
17	16-01-2015	116690.8	23.01519	116690.8	23.01519	0	0	0	13.1	27.3	30.3	0	N	N
18	17-01-2015	99371.31	18.99493	99371.31	18.99493	0	0	0	15.9	25	27.5	0	N	N
19	18-01-2015	97728.75	17.00868	95473.97	20.91179	2254.785	-148.26	0.020833	15.3	19.5	23.4	0	N	N
20	19-01-2015	116883.1	26.92788	116883.1	26.92788	0	0	0	13.5	23.6	29	0	N	N
21	20-01-2015	128968.1	23.07807	128968.1	23.07807	0	0	0	13	30.4	19.6	0	N	N
22	21-01-2015	148702.5	34.44342	148702.5	34.44342	0	0	0	19.7	33.1	25.8	0	N	N
23	22-01-2015	153232.1	35.23076	153232.1	35.23076	0	0	0	18.7	35.8	23.1	0	N	N

Figure 6: Dataset Collected from the Kaggle

A. Input Dataset

The above figure 7 shown the input data set in table format 12 coloumns and over 10000 rows.The following figure 4.2 describes the dataset.

```
63/63 [==============================] - 9s 139ms/step - loss: 0.0203
Epoch 17/50
63/63 [==============================] - 9s 138ms/step - loss: 0.0200
Epoch 18/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0199
Epoch 19/50
63/63 [==============================] - 9s 140ms/step - loss: 0.0201
Epoch 20/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0201
Epoch 21/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0197
Epoch 22/50
63/63 [==============================] - 9s 140ms/step - loss: 0.0201
Epoch 23/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0202
Epoch 24/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0198
Epoch 25/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0196
Epoch 26/50
63/63 [==============================] - 9s 141ms/step - loss: 0.0196
Epoch 27/50
63/63 [==============================] - 9s 140ms/step - loss: 0.0196
Epoch 28/50
63/63 [==============================] - 9s 139ms/step - loss: 0.0200
Epoch 29/50
63/63 [==============================] - 9s 141ms/step - loss: 0.0199
```

Figure 7: Input Dataset

B. LSTM Trained Model

After the completion of training the trained knowledge is stored as a file, which is in the format of h5. The following figure 8 showed the electricity demand prediction validation result.

	Electricity Demand
0	121711.3
1	121426.2
2	119327.5
3	112961.9
4	103653.8
5	102209.4
6	114006.1
7	117318.7
8	117748.2
9	116489.3
10	111426.8
11	103211
12	101499.1
13	112585.8
14	116180.7
15	116266.1
16	114469.8
17	108907.6
18	100008
19	98864.04
20	109769.3
21	112845.1
22	114039.9
23	114418.1

Figure 8: Electricity Demand Predicted Result

C. Predicted Result for Future 2 Months

The above figure 4.6 represents the future predicted electricity demand values for 2 months.

VI. CONCLUSION

In our project we used Long Short Term Memory for predicting future electricity demand data's. It is a one of the deep earning technique which can able to train and predict nonlinear data's for long term prediction also. We used electricity demand data's which holds over 6 year data's for training purpose, it is a nonlinear dataset. After training we predict future 2 months of electricity demand values by using LSTM. The predicted results by LSTM is accurate and stable, its patterns are also matched with the existing dataset patterns. And hence our model is perfectly trained and it can able to predict future values with high stability

VII. FUTURE WORK

In the future, we are decided to make the electricity demand prediction by using hybrid lstm and Arima model.ARIMA, stands for 'Auto Regressive Integrated Moving Average' is actually a class of models that 'explains' a given time series based on its own past values, that is, its own lags and the lagged forecast errors.

Hybrid LSTM with arima model will enhance the system performance. This hybrid technique will provide good accuracy and stability for future prediction and also we are decided to gather and increase the dataset so that the machine can able to get more training knowledge.

Output:

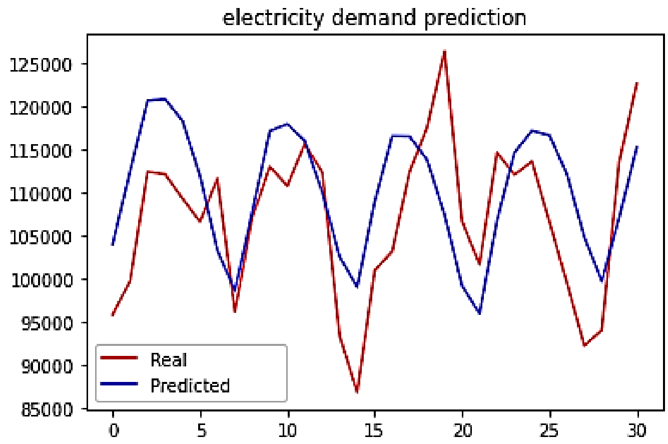


Figure 9: Output of the Electricity Demand Prediction

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