# A RNN-LSTM Based Framework for Real-Time Load Management in Smart Grid

*Project report submitted*
*in partial fulfillment of the requirement for the degree of*

**Bachelor of Technology**

By

**ABDUL RAHMAN (18BEC001)**
**AJMAL A (18BEC003)**
**ARYAN KUMAR (18BEC004)**
**B K LIKHITH KUMAR (18BEC005)**

Dharwad
ज्ञानेन विकासः

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY

DHARWAD

# CERTIFICATE

It is certified that the work contained in the project report titled “A RNN-LSTM Based Framework for Real-Time Load Management in Smart Grid” by “Abdul Rahman (Roll No:18BEC001)”, “Ajmal A (Roll No:18BEC003)”, “Aryan Kumar (Roll No:18BEC004)” and “B K Likhith Kumar (18BEC004)”has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

**Dr Prakash Pawar**<br>
**Department of Electronics and Communication Engineering**<br>
May, 2022

# Declaration

We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Abdul Rahman
18BEC004

Ajmal A
18BEC003

Aryan Kumar
18BEC004

B K Likhith Kumar
18BEC005

# Approval Sheet

This project report entitled A RNN-LSTM Based Framework for Real-Time Load Management in Smart Grid by Abdul Rahman, Ajmal A, Aryan Kumar and B K Likhith Kumar is approved for the degree of Bachelor of Technology in Electronics and Communication Engineering.

**Supervisor**

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___________________________

**Head of Department**

___________________________

**Examiners**

___________________________

___________________________

Date :_____________
Place:_____________

**A Project Report on**

# *A RNN-LSTM Based Framework for Real-Time Load Management in Smart Grid*

# INDEX

# INTRODUCTION

With the rapid growth of energy needs from different sectors around the world, there is a lot of pressure on the power grid to maintain balance between demand as well as supply. In this context, the intelligent grid (SG) may play an important role as it provides a two-dimensional flow of power between resources and end users. Unlike a normal power grid, it has Advanced switching sensors and sensors (for example, sensors and actuators) for measuring load and high shaving. In SG systems, various smart devices and electronic devices are placed in smart buildings regularly to produce related data in the use of force, seating patterns, or the movement of end users. By using effective data processing as well as data analysis process, this data can be analyzed for extraction of important energy patterns that can be used to respond to demand management, load prediction, and high shaving. But, one of them The biggest challenges for SG plans is having an integrated approach pre-processing and analyzing data on small amounts of errors and high accuracy. To address the challenges mentioned above, an integrated system based on in-depth and repetitive reading neural networks (RNN) proposed in this paper. Data collected in smart houses is first processed and decomposed using high-order singular value decomposition (HOSVD) as well and then a short-term memory model (LSTM) used on it. As the data collected from SG is data based on timeline as well The LSTM-based retrospective model provides the minimum root square measure (RMSE) and values mean absolute percentage error (MAPE). Compared to alternative ways reportable within the literature. A case study of 112 smart homes with hourly data considers the evaluation of the proposed system where the capacity patterns are predicted at least by RMSE and MAPE. Results clearly show that the proposed system is the best performance compared to other existing programs.

We need to obtain high reliability over existing power system.So we use a term called smart grid. we need to roughly obtain the hourly load requests from the users and also we should calculate per unit cost of energy so we use Augrid model. Augrid Means Au means forecast and grid means Smart grid. It is an LSTM based model (Long Short Term Memory) and LSTM takes particular information with the help of recurrent neural networks(RNN). Augrid gives an idea to suppliers about the weather so that they can use in particular time rather than being insecure and by using smart grid we can exchange information and energy based on our requirement so it leads to reduction in per unit cost. It's mandatory to develop dynamic pricing so that we can cross check the how far the predictions are correct from the actual requests and set per unit cost correctly.But in power distribution system the main grid which distributes energy to prosumer in unidirectional way.We have one disadvantage is that prosumer can't interact with main grid in pratical.So what prosumer can do is get request from the microgrid using cloud enabled energy distribution which is one of the important feature in Smart grid.Generally microgrid is used to produce variable amount of energy and renewable resources such as wind and biomass at every hour of the day.If microgrid fails to produce energy the user must go through a certain period of delay. But we have another solution to get help from the main grid but the problem is it incurs high costs from the users.

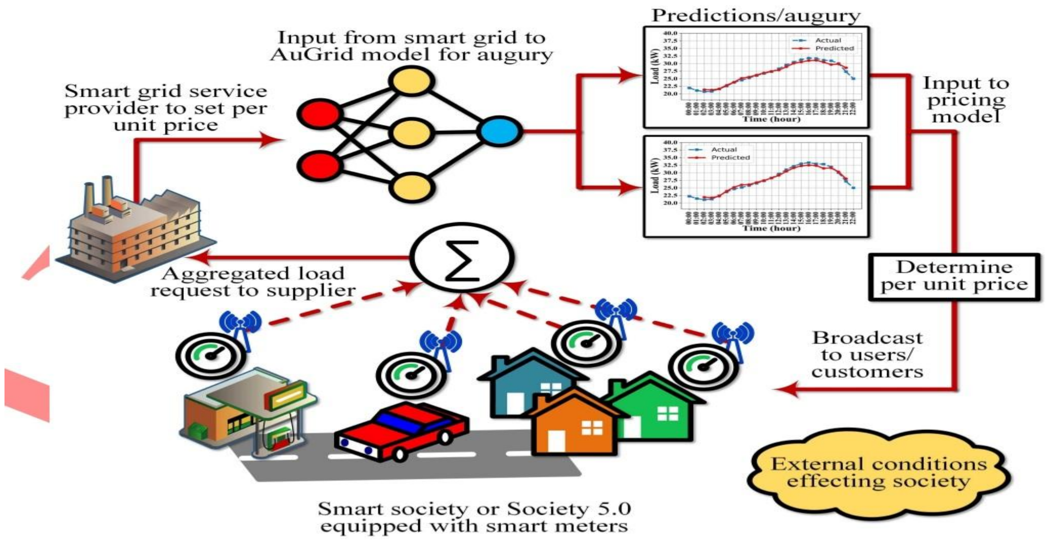



Figure 1: Overview of the proposed AuGrid system.

In this method also by transferring energy it will get wasted and it leads to loss.There is a solution for this prosumer need to generate energy capability this will solve the problem.But the prosumer doesn't cooperate they have a plan to store the energy at the end and not supplying required energy to the microgrids. We require a high quality of service of energy management so what we need to do is tell prosumer to act in cooperation but problem there is no such scheme which concentrates on prosumer.So we introduce a pricing scheme called smartprice.It is based on single leader and followers respectively stackelberg game.It is one of the best method as both microgrids and prosumers will get more benefits so there is a chance of prosumer to act cooperatively. At a smart price to ensure high quality of service, microgrids provide cooperatively prosumers in the form of revenue so that they can act cooperatively. So there are some of the primary contributions so let's see how it works. We present a smart grid for energy consumption to prosumers so that the prosumers can store energy in cloud enabled smart grid. In smart price prosumers and microgrid act as a leader and followers respectively this is the advantage over microgrid where it based on single leader and multiple followers.Finally to obtain the optimal solution prosumer need to request quantity of energy from microgrid then microgrid decides the price to be charged from the prosumer.If microgrid requires any energy it request from the prosumers and decides the amount to detected from prosumer and based on that prosumer will decide whether to act cooperatively or not. So finally we have presented the existing works on the area of pricing.

# MOTIVATION

Energy conservation and the use of renewable resources are available for an hour. With this in mind, the available literature offers a wide range of customer profile solutions by providing their load requests. In addition, Some of the solutions also aim to investigate how isolated electrical equipment such as air conditioners, refrigerators, and other similar items are used. These methods generate privacy problems, necessitating the need for secure and dependable solutions. Furthermore, price models that are purely based on load requests and electricity generation are ineffective in assisting in making educated judgments.because of uncertainty about the longer term. Such challenges encourage us to develop the proposed AuGrid system for predicting public responsibility profiles from a supplier's perspective based on previous requests and to set the cost per unit accordingly. It does not require a user profile at the individual level. Flexible price models are helpful in managing user usage. In the future energy management system, load management has an important role.The use of renewable sources and the total energy conservation are the main factors to be considered in load management these days. Some of the articles have some comparisons of load management techniques with latest technologies and the challenges of implementation in the smart grid.For example,dynamic pricing based and incentive based. All the existing articles offer so many solutions for consumers for achieving their load requests. And some solutions not only focus on load requests, but also study the consumption by individual appliances. For example, refrigerators,AC etc. It is not 100% secure because of privacy issues. So we need secured solutions for this.we don't know what is gonna happen in the future,so pricing models which only depend upon energy consumption and load requests are not gonna help. This motivates us to develop the AuGrid technology for forecasting load requirements from suppliers based on prior requests and calculating the cost per unit. This model helps in balancing the consumption.

For the past few years, we have seen the emergence of one of the most powerful technologies of modern times called intelligent grid (SG). It can be considered a modern force, an advanced grid with communication infrastructure used for double flow direction in the middle end users and service providers. It provides trust and an inexpensive demand response among end users as well service providers may be located in different geographic areas. Contrary to the traditional power grid, it has advanced switching and sensor devices (sensors and actuators) to produce and transmit this two-dimensional flow of power. In the SG environment, there are different levels of flow of information management management response to need. First The level of information flow is between sensors and smart devices in terms of smart meters using short distance connections such as Zigbee, 6LowPAN, Bluetooth, and Infrared. The second level is between smart meters to go to resources, once data centers, where different types of medium and long broadband networks such as WiFi, WiMax, LTE / LTE-A, and cellular networks are used. These different flow rates information narrows the gap between demand and response by making wise management decisions. However, it requires analyzing intelligent data to maintain controlled flow from support service providers to end users.

# LITERATURE SURVEY

Power consumption forecasting in smart grids benefits both customers and service providers.We targeted on air conditions associate degreed projected an ARIMA-based model for predicting the next day's energy use Ways to reduce electricity use, on the other hand, make it easier to make better choices than the selected ones. We used a multi-dimensional LSTM to achieve this.We profiled the energy usage in step with The user characteristics were analyzed, and an auction-based method was presented to optimize the energy transaction between the user and the supplier. The customers square measure oblivious to the pooled infrastructure and different proceedings. However, though explicit as a and. Their research only evaluates the current status of the system and does not forecast long-term outcomes. We believe that having a long-term perspective is beneficial. creating higher choices, particularly once coping with renewable sources. Conventional neural networks are a unit incapable of exploiting past observations and selections. whereas repeated neural networks overcome this issue, they can not depend on states that area units on the far side in the recent past.

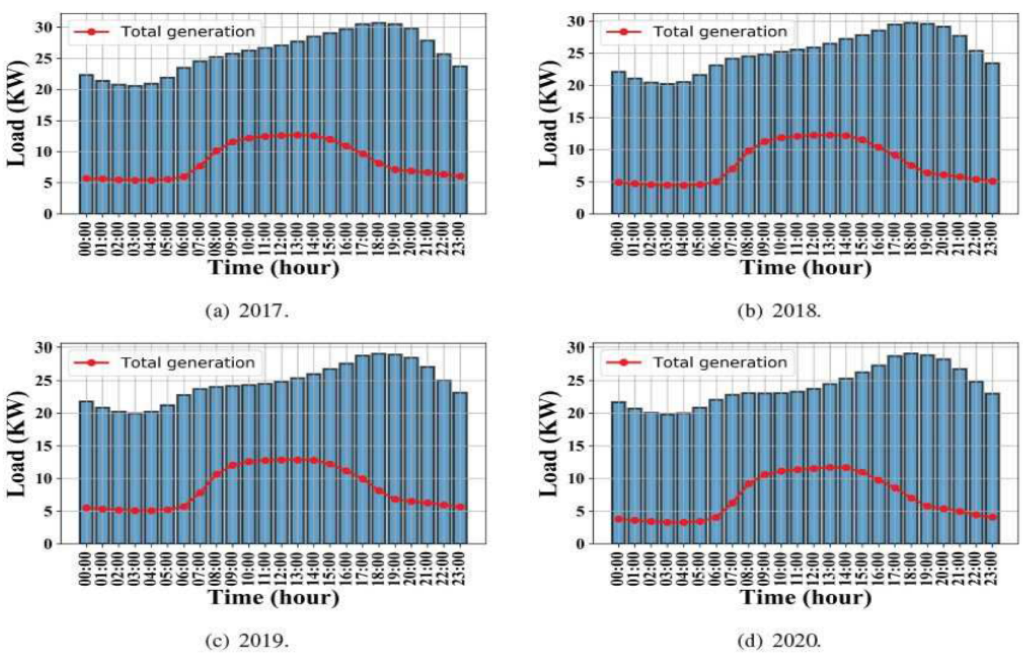



Figure 3: Load (bars) versus total renewable power (line).

LSTMs are unique RNNs that use extra gates and options to overcome such challenges. When the forget gate layer receives a new input, it determines the content that must be forgotten first. This is accomplished through the use of a sigmoid. It then employs an input gate layer to extract the required data from the new input, as well as a tanh layer to create a unique vector illustration of the new input. Before adding to the prior cell state from the forget gate layer, it mixes the two. The LSTM then delivers its results, which are a filtered form of the sigmoid and tanh functions combined.

The studies of forecasting the masses also are important to spot attacks in smart grids. One in every of the common attacks is load redistribution, where the attackers inject load across different buses, without exceeding the entire production.Before deciding the worth compatible with the load request, this proposed a categorization model for identifying the type of consumers that supported their consumption profile and device ownership. While such solutions are promising and effective, they also expose users to security risks and privacy violations. Researchers are working on strategies to flatten the generation-consumption curve, according to our findings. These efforts are aimed at forecasting load requests so that facultative service providers can be prepared. To help, some writers have provided methods for identifying clients and their energy consumption, as well as the instrumentation they utilize. This allows for strategic energy collection. Furthermore, we frequently develop various versions of valuation models with varied characteristics to aid in the optimization of client and repair supplier incentives, so each party is happy.

The consumers' need for energy will help to improvise energy management in SG . Previous work took the same customer-based approach driven by data. Although such methods seem beneficial, and raises concerns about data privacy as well, consumers may not want to share what is needed. Other works proposes a A Markov-based approach, which considers energy consumption systems, random power applications, and current status making management decisions. They look at the cell phone network setup, which works with a renewable enabled source grid that is smart, and they connect to each other to respond to flexible usage policies. Moreover, the authors build an image-based grid-based simulation,develop, and evaluate power management systems.

Few Contributions in this field:

1. *Data representation is done using tensors and pre-data processing performed involving null removal and repetitive values and interpolation, data normalization, measurement and size reduction.*
2. *The size reduction is applied using HOSVD. It increases data processing efficiency.*
3. *A comprehensive RNN-LSTM learning model is proposed analyzing the energy consumption of smart homes which predicts future use in small amounts of errors and high accuracy.*

Related Works in the field:

1. *Smart Grid and applications*
2. *Energy management in smart Grids*
3. *Security in smart grids*
4. *Pricing Model in smart Grid*
5. *Synthesis in Smart Grids*

# HARDWARE REQUIREMENTS

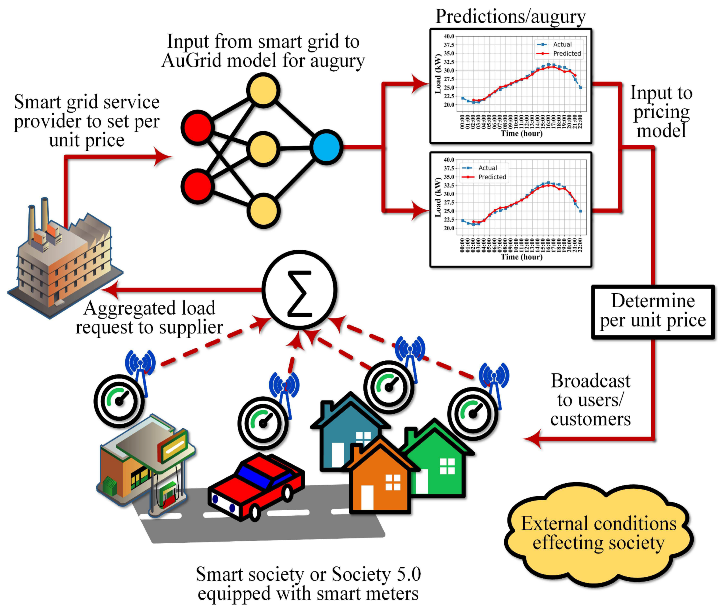
| Time/Usage | I5 PCs | Single Processor Boards |
|---|---|---|
| **Training Time** | 47.442s | 180.694 s |
| **Prediction time** | 1.68 s | 26.40 s |
| **Model size** | 40 KB | 35KB |
| **CPU usage** | 64.21% | 40.24% |
| **RAM usage** | 71.99% | 34.61% |
| **CPU usage** | 46.11% | 26.03% |
| **RAM usage** | 67.14% | 39.36% |

# SOFTWARE REQUIREMENTS

Python is a programming language that distinguishes itself from other programming languages by its flexibility, simplicity, and reliable tools required to create modern software. Python is consistent and is anchored on simplicity, which makes it most appropriate for machine learning.

- Features:
    - Independence across platforms
    - Consistency and simplicity
    - Frameworks and libraries variety

# ARCHITECTURE




AuGrid as a prediction method loads requests to customers per hour monthly at the end of the provider. Au in AuGrid is Augury (or forecast) and Grid represents intelligent grids. We consider providers who are aware of the location giving the service to some of the users. They are part of the IoT-enabled and intelligent environment meters. We create a model to allow the supplier to guess integrated local applications for hourly uploads from consumers. Using long-term memory (LSTM) -based on the recurrent neural network (RNN) load reporting applications,we are doing this.. LSTM helps to make predictable predictions of preceding upload requests. Here we will aim to implement a  Dynamic pricing system to control it as well control the overall supply of power. AuGrid helps us to predict the load requests and costs in accordance with forecasts, in contrast to dependence only with load applications and power generation. Data Visualization, Analysis and RNN LSTM model for Hourly Energy Consumption.

## Recurrent Neural Network (RNN Model)

- Recurrent Neural Networks (RNNs) rely on the premise of conserving and restoring layer output to forecast layer output.
- It is a normal function of the feedforward neural network with internal memory.
- The environment is repeated because RNN performs the same function on all data inputs, and the output of current inputs is dependent on the previous single calculation.
- After the output is output, it is copied and returned to the normal network.
- The RNN can process input sequences using its internal memory (memory). This allows it to do non-separate attention, writing attention, and speech recognition.
- In some neural networks, all inputs are independent of each other, but in RNN all inputs are related to each other.

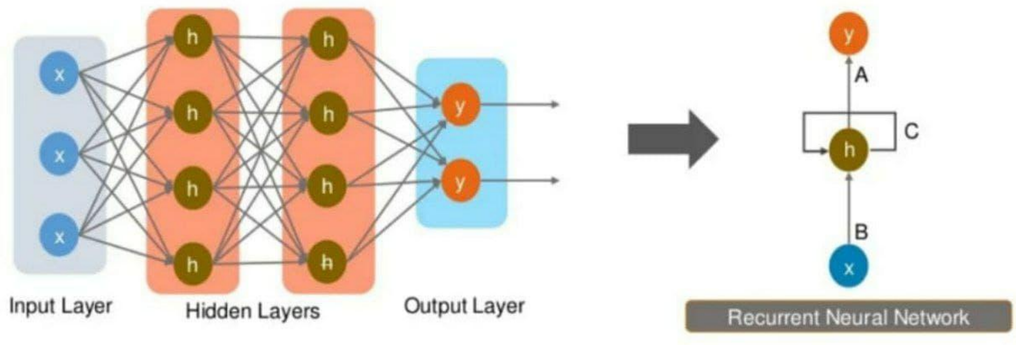



*Fig: RNN Architecture*

## Long-Short Term Memory (LSTM)

- ➔ LSTM networks are specifically designed to overcome the long-term dependence problem faced by conventional neural RNN networks.
- ➔ LSTMs are excellent at processing data sequences such as text, speech and standard timeline.
- ➔ LSTMs have feedback responses that make them different from traditional feedforward neural networks.
- ➔ LSTMs use a series of gateways that control how data in a series of data enters, stores and leaves the network.
- ➔ There are three gates for the standard LSTM - forget it, the input gate and the exit gate. These gates can be thought of as filters and each is its own neural network.
- ➔ LSTMs have responsive connections that make them different from normal neural feeds networks.This feature allows LSTMs to process complete data sequences without managing each point independently, but rather, storing useful information about previous data sequentially to assist in processing new data points.

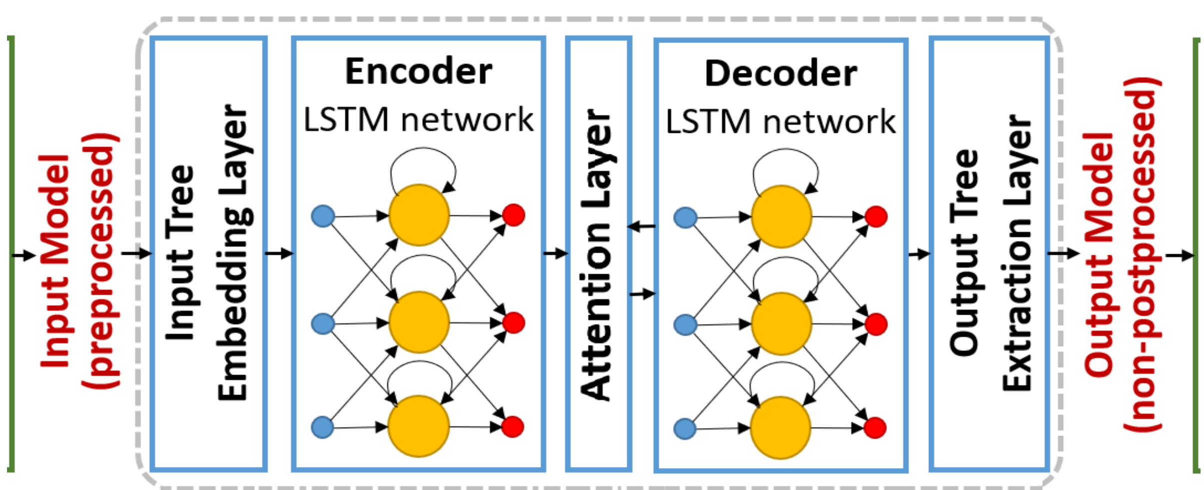



*Fig: LSTM Mode*

# WORKFLOW

In our view, it is useful to statistically measure predictions in the sequence of time series as loading profiles using losses (square errors mean) instead of accuracy. We see that the loss of your training in both backward values remains constant.While comparing a model with backward value 1 and backward value 2, the model which has backward value 1 has more loss.. Because of seasons, holidays, electronics, customer numbers, etc,the upload profiles change. More than 1 previous value is required. Interestingly, we see a loss of approximately 0 in When the retrospective value equals 2 in 400 epochs, the data and then the model converges to 400-500 epochs approximately.. As we find the merger, we should limit our representation to look back at 2 which will help in the easy representation. By looking into this clear observation, we are setting the look back as 2 which means we need two loading requests to start predicting more. As an example ,we would look at load requests from 01:00 and 02:00 hours to predict those from 03:00 hours. After that we slide to the next hour forecast and repeat the same on every other day. Hourly data from jan 2017 we use here to train our model.

- **DATASET USED**

| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | | | Datetime | AEP_MW | | | |
| 2 | 0 | 31-12-2017 | 01:00:00 | 13478 | | | |
| 3 | 1 | 31-12-2017 | 02:00:00 | 12479 | | | |
| 4 | 2 | 31-12-2017 | 03:00:00 | 11480 | | | |
| 5 | 3 | 31-12-2017 | 04:00:00 | 13431 | | | |
| 6 | 4 | 31-12-2017 | 05:00:00 | 13882 | | | |
| 7 | 5 | 31-12-2017 | 06:00:00 | 12403 | | | |
| 8 | 6 | 31-12-2017 | 07:00:00 | 13484 | | | |
| 9 | 7 | 31-12-2017 | 08:00:00 | 13400 | | | |
| 10 | 8 | 31-12-2017 | 09:00:00 | 13486 | | | |
| 11 | 9 | 31-12-2017 | 10:00:00 | 12487 | | | |
| 12 | 10 | 31-12-2017 | 11:00:00 | 12988 | | | |
| 13 | 11 | 31-12-2017 | 12:00:00 | 13489 | | | |
| 14 | 12 | 31-12-2017 | 13:00:00 | 13490 | | | |

# RESULTS AND DISCUSSION

## Algorithm and Coding

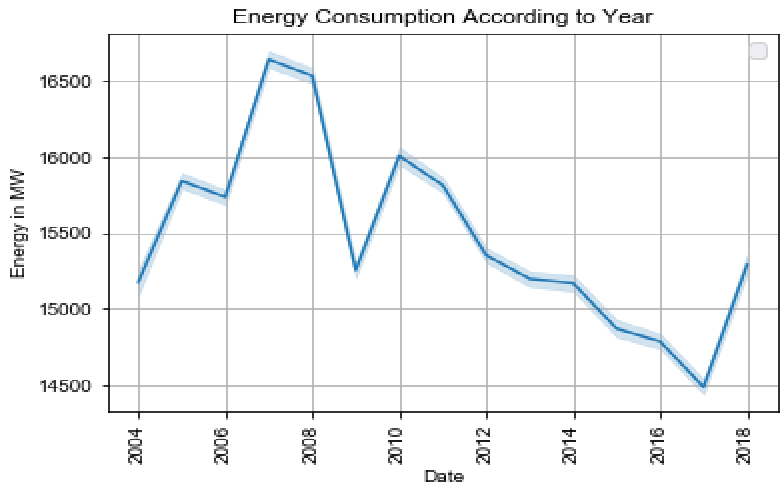
- **Step 1: Import Library**
  - *import pandas as pd*
  - *import numpy as np*
  - *import matplotlib.pyplot as plt*
  - *import seaborn as sns*
  - *from sklearn.preprocessing import MinMaxScaler*
  - *from sklearn.cluster import KMeans*
  - *import pprint*
  - *from keras.models import Sequential*
  - *from keras.layers import Dense*
  - *from keras.layers import LSTM*
  - *from keras.layers import Dropout*

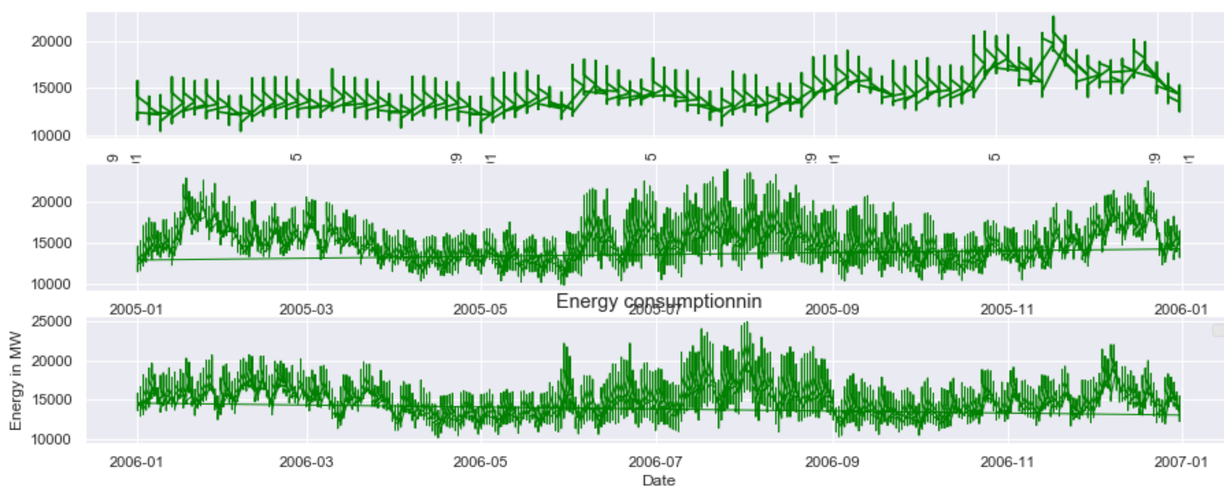
- **Step 2: Reformat the Date Time Columns**
  - Data is reformed into tabular format with MW usage, Month, Year, Date, Time, Week and Day as legends. The data is reformed for a better view.

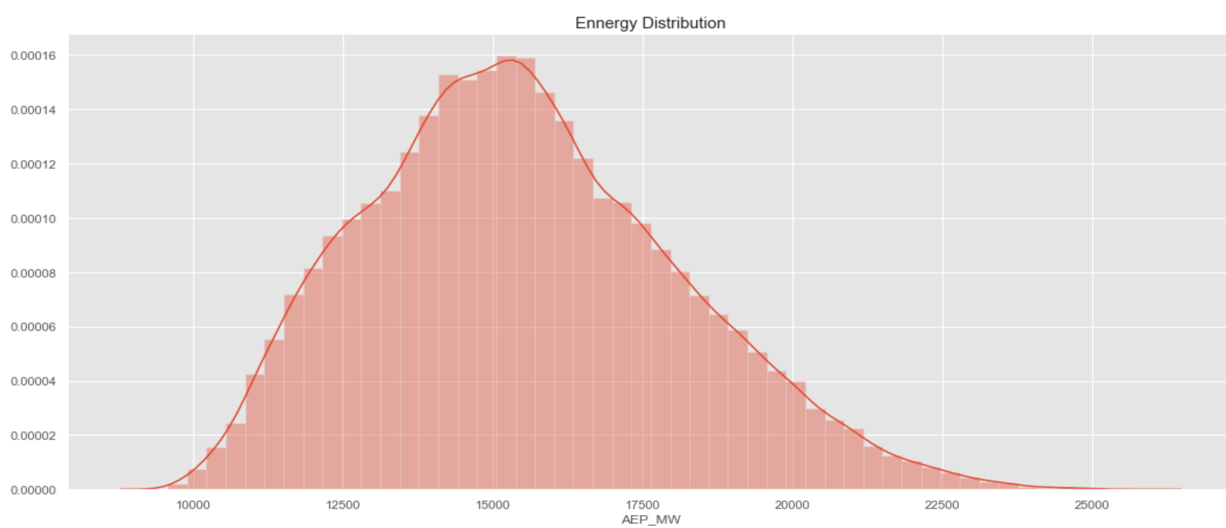
```
# Extract all Data Like Year MOnth Day Time etc
dataset = df
dataset["Month"] = pd.to_datetime(df["Datetime"]).dt.month
dataset["Year"] = pd.to_datetime(df["Datetime"]).dt.year
dataset["Date"] = pd.to_datetime(df["Datetime"]).dt.date
dataset["Time"] = pd.to_datetime(df["Datetime"]).dt.time
dataset["Week"] = pd.to_datetime(df["Datetime"]).dt.week
dataset["Day"] = pd.to_datetime(df["Datetime"]).dt.day_name()
dataset = df.set_index("Datetime")
dataset.index = pd.to_datetime(dataset.index)
dataset.head(1)
```

| | AEP_MW | Month | Year | Date | Time | Week | Day |
|---|---|---|---|---|---|---|---|
| **Datetime** | | | | | | | |
| **2004-12-31 01:00:00** | 13478.0 | 12 | 2004 | 2004-12-31 | 01:00:00 | 53 | Friday |

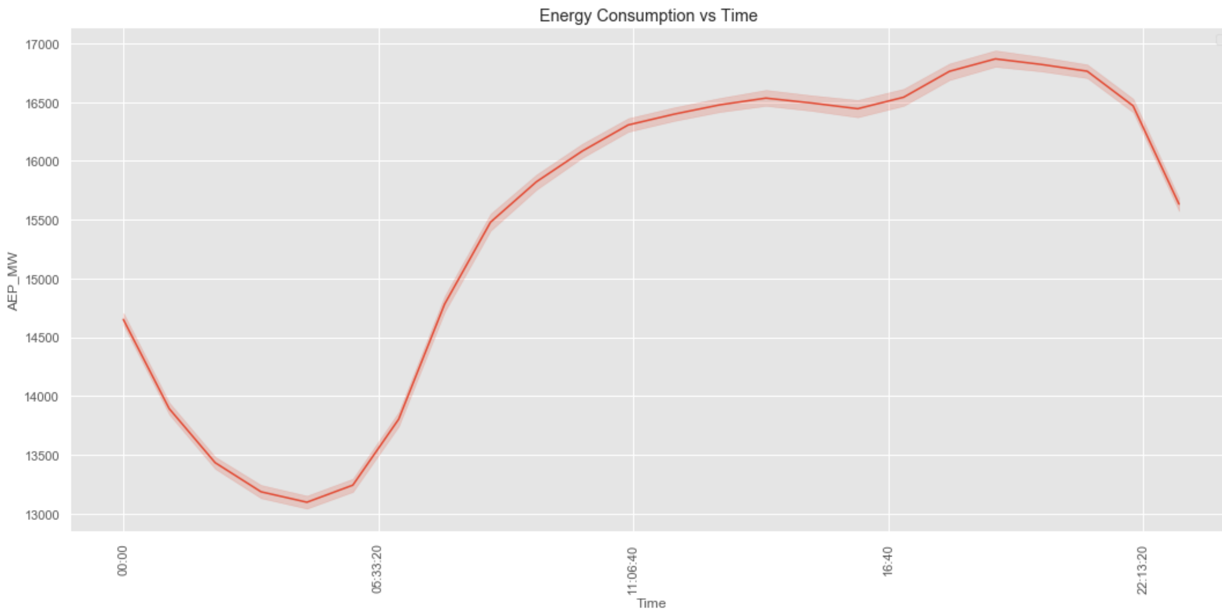
- **Step 3: Calculate and Plot the energy consumption Each Year**



- **Graph - Energy with Respect to Time**




- **Applying RNN-LSTM Model on the Dataset:**

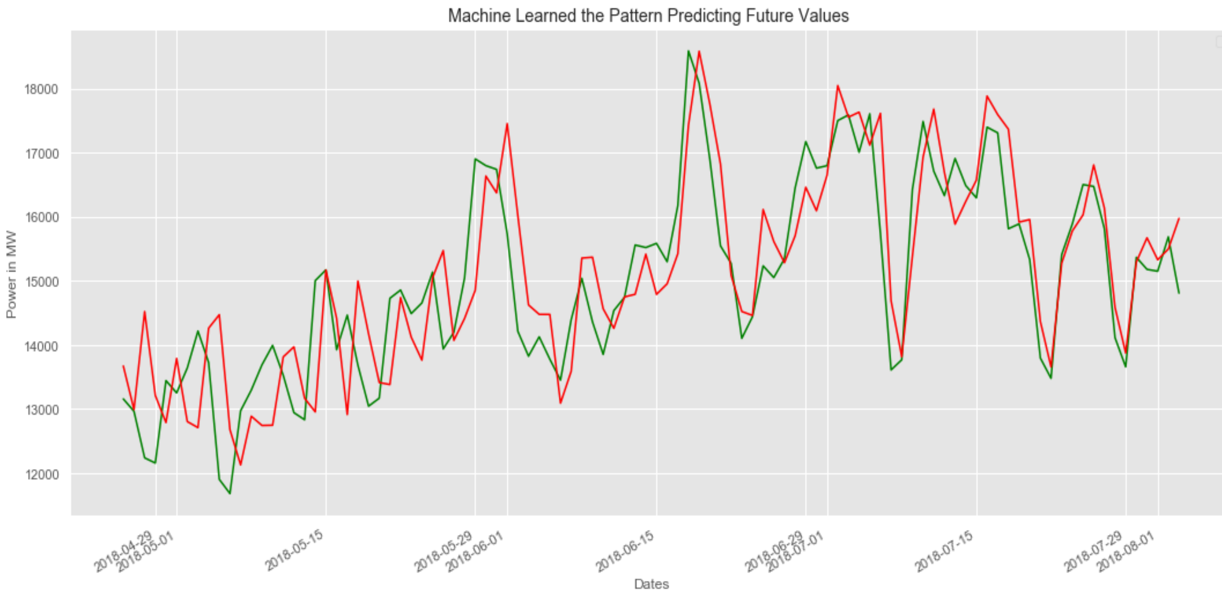
```
regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_Train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

- **Future Predicted Data on RNN-LSTM Model from AuGrid**

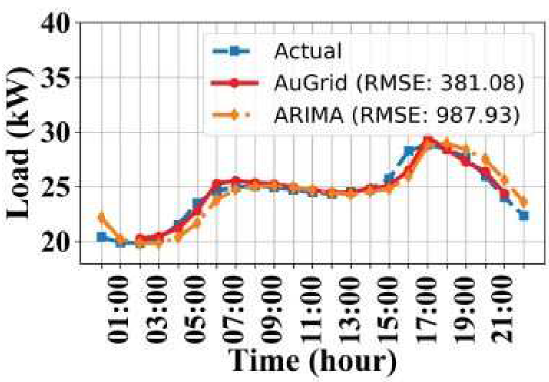
| | Date | TrueMegaWatt | PredictedMeagWatt |
|---|---|---|---|
| 0 | 2018-04-26 | 13157.791667 | 13671.706055 |
| 1 | 2018-04-27 | 12964.000000 | 12991.945312 |
| 2 | 2018-04-28 | 12237.583333 | 14521.591797 |
| 3 | 2018-04-29 | 12156.791667 | 13211.944336 |
| 4 | 2018-04-30 | 13443.500000 | 12788.455078 |
| 5 | 2018-05-01 | 13251.875000 | 13789.046875 |
| 6 | 2018-05-02 | 13641.166667 | 12804.154297 |
| 7 | 2018-05-03 | 14217.250000 | 12709.704102 |
| 8 | 2018-05-04 | 13725.625000 | 14261.728516 |
| 9 | 2018-05-05 | 11902.166667 | 14472.195312 |
| 10 | 2018-05-06 | 11680.083333 | 12677.794922 |
| 11 | 2018-05-07 | 12972.500000 | 12127.531250 |
| 12 | 2018-05-08 | 13295.083333 | 12887.196289 |
| 13 | 2018-05-09 | 13688.750000 | 12743.552734 |
| 14 | 2018-05-10 | 13993.250000 | 12747.035156 |
| 15 | 2018-05-11 | 13525.166667 | 13814.033203 |

We train the model on the load data. The graph represents all the predictions. We check that the forecasts match the education records almost well, confirming our observations i. We chose one month at random from each of the last 12 months (2017 - 2018) to illustrate our observations on formulating predictions based on unseen statistics. We discovered that the predictions almost perfectly match, regardless of month, year, season, or other possible relationships. It may be referred to that there aren't any predictions for 00:00 and 01:00 hours. That is because the trained model wishes to record factors for making the predictions.Furthermore,after obtaining the dropping trend (factor of inflection) at 17:00 or 18:00 hours, we stop from finding predictions at 22:00 and 23:00 hours. The car-Regressive included shifting average (ARIMA) version is another well-known method for anticipating information sequences. When it comes to LSTMs, neural networks and gates are no longer necessary. Rather, it uses regressions, integrations, and shifting averages to do a statistical analysis of the data (because the name indicates). The autoregression can be used to regress lagged and earlier values. The integration is unique in that it makes it easier to convert non-desk bound data to desk bound data. sooner or later, Because of the contrast between lagged observations and residual Errors, the moving common aids in smoothing the outcomes. We take into account the highlighted circumstances and return to the LSTM-based forecasting method. Finally, we set up the suggested version's performance and provide projections for all months from 2017 to 2020.

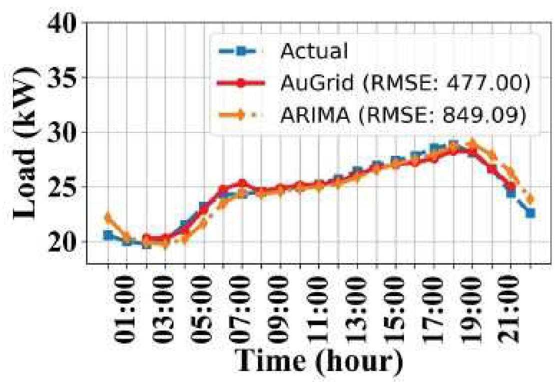
# OUTPUT



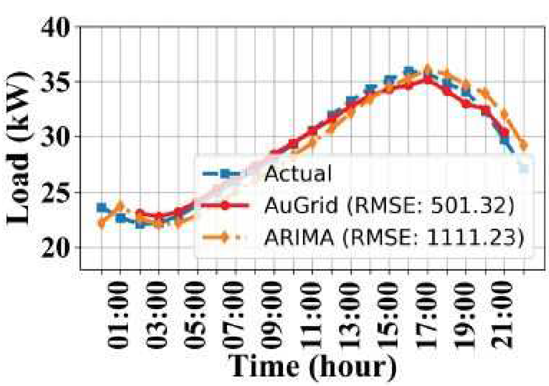

## Future Predicted data (in kW) for 3 years



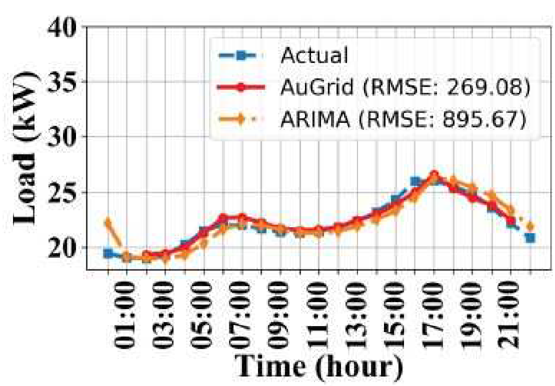

(a) January 2017.




(b) October 2018.




(c) July 2019.




(d) November 2020.

# CONCLUSION

We have proposed a Long-Short Term memory-based load request prediction model called AuGrid for smart grid services and service providers. We observed that the micro-grids ensure cooperation among the prosumers. In SmartPrice, using the cloud infrastructure, the micro-grids determine the optimal price for the unit quantity of energy to be charged from the prosumers and paid to the prosumers, respectively. On the other hand, we observed that the prosumers, who are non-cooperative by virtue, are motivated by the micro-grids to act cooperatively. We've also built pricing models based on AuGrid forecasts instead of models that are primarily determined by load demand and generation rates Our test results corroborate the notion that service providers give higher rates and rates when the future is known, as well as the stability of the suggested model. Using real-world datasets, we established the viability and robustness of the proposed AuGrid system. We also demonstrated deployment and deployment with minimal hardware usage on both resource-rich and resource-constrained devices. Despite the fact that we've noticed an increase in training and prediction delays on single-board processors, this delay is tolerable since we are making predictions. hourly guessing, no real-time needed. In the future, taking into account user heterogeneity, we plan to expand our individual pricing operations accordingly. We are also planning further improvements to AuGrid to provide better monthly forecasts. This work can be extended in the future by studying the nature of the energy distribution while introducing a bidding strategy so that the prosumers also have active participation in deciding the price for the unit quantity of energy. This work also can be extended while introducing a broker in between the micro-grids and the prosumers. This broker may act as a third-party entity that ensures the anonymity of the prosumers. Conclusion. There's little doubt that the long run belongs to the good Grid, which power generation can modify considerably by the time it becomes a reality. giant power plants can still make sure the basic offer, however there'll even be renewable energy sources, inflicting fluctuations within the grid. In conclusion, the sensible grid could be a necessary next step to the present power system. the various advantages that the new technology will bring to an area unit important to maintaining with the energy demand that's solely growing. larger communication between parts and additional automation of the ability grid system will solely be accomplished with innovations in electrical and pc engineering information. The worldwide sensible Grid initiative involves an entire transformation of the networking infrastructure accustomed to managing the facility grid with billions of connected devices to realize higher energy management, reduced carbon footprint, support of recent sources of renewable energy with a particularly high level of reliability, and reduction of value. The quantity of applications wherever sensible objects can play a key role in our future is merely delimited by our imagination. After implementation of good grid Indian facility can have good options like load management, price of preventive maintenance is not up to price of repair, participation of client, inexperienced power, management peak demand by handiness primarily based tariffs, automation to cut back force prices, watching of service request standing by client, distributed computing, net primarily based info, and GIS mapping of assets.

# FUTURE SCOPE

This work can be expanded in the future by studying the nature of power distribution while introducing a bidding strategy so that prosumers(producers and consumers) can also play a significant role in personal use only to determine the price of a unit of energy. This function can also be extended when introduced by the vendor in the middle microgrids and prosumers. This broker can act as an outside company business that verifies the anonymity of prosumers.We intend to develop this project by considering the variety of consumers and adjusting unit rates accordingly. We also intend to improve the AuGrid in order to produce more accurate monthly forecasts.

In the future the algorithm may be proposed in a cloud-based pricing system, called SmartPrice, forcing cooperation between prosumers to ensure a high level of service provided by small grids. In SmartPrice, using cloud infrastructure, each small grid counts the reward feature of each prosumer based on his behavior to force cooperation between them. We model the communication between each subnet and the consumers using the leader Many fans of the game Stackelberg, where the micro networks and prosumers act as leaders and followers corresponding. Each mini-grid defines the number of electricity units to pay/pay and each searcher determines the amount of power unit to be paid / paid and each researcher determines the amount additional power will be provided to ensure maximum revenue. So, SmartPrice forces cooperation between small grids as well as prosumers. Additionally, using SmartPrice, unit price power charged on prosumers decreased by 23.37-35.63%, thus ensuring higher income and the number of prosumers the supply of small grids increases by 38.19-53.14%.

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***ABDUL RAHMAN M***

***AJMAL A***

***ARYAN KUMAR***

***B K LIKHITH KUMAR***

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