ENERGY CONSUMPTION FORECAST USING MACHINE LEARNING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report "ENERGY CONSUMPTION FORECAST USING MACHINE LEARNING" is the bonafide work of JAYESH PRASAD A & BEZAWADA VENKATA SIVASAI who carried out this project work under my supervision.

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VIVA-VOCE EXAMINATION

The Viva-Voce Examination of the following students who have submitted this project work is held on **_22ND SEPTEMBER 2020_**.

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ABSTRACT

To Forecast the Energy usage of households on an hourly basis based on the data fetched through Smart Energy Meters and to study the trends of the area observed. Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development.

Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), ARIMAX (autoregressive integrated moving average with exogenous variables) and SARIMAX (Seasonal autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. SARIMAX uses the time and load data as the only input parameters for forecasting. The forecast can be developed using Python with statistical libraries for the SARIMAX Time Series Analysis and can be achieved to predict the future consumption data into required formats.

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INTRODUCTION

GENERAL

As a nation, INDIA is progressing towards Digital India, a flagship programme of the Government of India with a vision to transform India into a digitally empowered society and knowledge economy.

It has become a necessity to move towards a Digital Future, in order to improve the quality of reducing man-work.

One of the ways to inculcate these is to improve The Electrical Energy Sector, where there is lots of scope to produce digitally enabled solutions.

DISCUSSION AND EXCERPTS

EESL SUCCESSFULLY INSTALLS AND OPERATIONALISES 5 LAKH SMART METERS ACROSS INDIA ECONOMIC TIMES

MMENT The programme was aimed at retrofitting conventional meters with smart variants to improve billing efficiency.

Energy Efficiency Services Limited (EESL) has installed over 5 lakh smart meters in Uttar Pradesh, Delhi, Haryana, Bihar and Andhra Pradesh. These meters have been distributed under the Smart Meter National Programme (SMNP). The smart meters operational in these states aim to enhance consumer convenience and rationalise electricity consumption, an EESL statement said.

The Smart Meter National Programme that aims to retrofit 25 crore conventional meters with smart variants will lead to 80-100 per cent improvement in billing efficiency.

These smart meters are installed as per guidelines issued by the Central Electricity Authority. Smart meters are part of the overall Advanced Metering Infrastructure solution (AMI) that measures and records consumers' electricity usage at different times of the day and sends this information to the energy supplier through GPRS technology, EESL said.

SMART METER NATIONAL PROGRAMME EESL INDIA

With electricity demand expected to rise by 79 percent in the next 10 years, India is on a path of transforming its energy mix with innovation. Along with enhancing energy production, the nation also needs to cut Aggregate Technical and Commercial (AT&C) losses to below 12% by 2022, and below 10% by 2027.

Enabling India to achieve this imperative is the smart grid, the first step of which, is the creation of Advanced Metering Infrastructure. A new range of 'smart meters' can bring efficiency to how India manages its electricity, by checking data-entry errors and billing efficiencies, and cutting the costs of manual meter reading through web-based monitoring system.

With its pioneering role in India's energy efficiency journey, EESL's Smart Meter National Programme (SMNP) is working to eventually replace 25 crore conventional meters with smart meters across India.

By bringing standardized solutions based on the GPRS technology, these meters will ease integration in the sector, while cutting capital costs and boosting efficiency in billing and collection. Customers will also benefit from accurate bill readings, and real-time understanding of their electricity usage, catalysing a pan-India movement towards energy efficiency.

Our proven model of bulk procurement, aggregation of demand, and monetisation of savings will be the approach to roll out smart meters. This roll-out is proposed under the Build-Own-Operate-Transfer (BOOT) model, wherein EESL will undertake all the capital and operational expenditure with zero upfront investment from states and utilities. EESL will therefore, receive a nominal Internal Rate of Return that is reflected in a mutually agreed upon, automated payback structure.

In the larger scheme of things, the programme will holistically promote the Indian manufacturing industry while creating more direct and indirect jobs. The programme is expected to better billing efficiency by 75 to 100 percent while increasing the revenues of the utility companies to Rs. 1,38,100 crores.

UNION BUDGET: RS 22,000 CRORES TO POWER AND RENEWABLE SECTOR ECONOMIC TIMES

Our Hon'ble Finance minister Mrs. Nirmala Sitharaman allocated Rs 22,000 crores for the power and renewable sector and has urged state governments to implement smart meters in three years, which would give the consumers the right to choose suppliers and the rate.

The power distribution companies are under financial stress and the power ministry has been trying to implement smart meters, she said in her Budget speech.

"Ï urge the states to replace conventional energy meters with smart meters in next three years. This would give the conumers the freedom to choose the supplier and the rate as per their requirement," Sitharaman said.

The Union Budget proposes to allocate Rs 22,000 crore to power and renewable sector.

L&T WINS RS 1,000 CRORE CONTRACT TO MAINTAIN 5 MILLION SMART METERS ECONOMIC TIMES

Larsen & Toubro (L&T), India's biggest infrastructure and project execution company, has won a Rs 1,000-crore contract to maintain 5 million smart meters in Uttar Pradesh and Bihar over the next eight years, sources said.

The smart meter tender, floated by state-owned Energy Efficiency Services Limited (EESL) earlier this year, was divided into two parts — meter procurement and systems integration. The latter exercise would involve meter installation, data storage on Cloud and preparing dashboards, among other things.

"L&T has won the bid, and the cost has been arrived at through a competitive bidding process. They will be paid over the course of the next eight years," Saurabh Kumar, managing director of EESL, confirmed to ET.

L&T, Keonics, and China-based IESLAB had shown interest in the systems integration part of the tender, ET had reported on December 8.

As a systems integrator, L&T will provide the GPRS-based solution that requires the placing of a SIM card in the meter for communication.

Major telecom operators, including Airtel, Vodafone, Idea and BSNL, have been roped in for supplying 5 million SIM cards for the smart meters.

“The number of SIM cards to be supplied by each telco will be decided during the project execution phase,” said another person aware of the matter.

Smart meters are a part of the overall advanced metering infrastructure solutions (AMI) aimed at better demand response designed to reduce energy consumption during peak hours.

The cost has taken different components of systems integration into consideration, including installation of the meters, integrating them with the AMI software, providing GPRS solution, and O&M services. The original cost of the contract is `863 crore, to which 18% GST will be added, bringing the total cost to around Rs.1,020 crore.

L&T had also initially won the contract for supplying 2.5 million smart meters, but later lost out to state-owned Indian Telephone Industries (ITI) Limited, which quoted a price of Rs 2,503 per meter in a reverse auction conducted by EESL. L&T had originally quoted Rs 2,722 for each meter. The smart meters order by EESL is the largest in the world, the government has said.

New Delhi is seeking to bring down aggregate technical and commercial (AT&C) losses of state utilities through smart metering, which will increase billing efficiency.

‘INDIA IS LOSING RS 100,000 CRORES IN UNBILLED ELECTRICITY. THE SOLUTION IS SMART METERS’ SCROLL.IN

In conversation with **Saurabh Kumar, Managing Director at the Energy Efficiency Services Ltd** , headed by the power ministry.

In a bid to improve power utilities’ financial health by increasing their revenues through efficient billing, India plans to replace the existing 250 million traditional electricity meters with smart meters that use digital technology to enable a two-way flow of electricity and information. Traditional meters only record energy consumption for billing purposes.

Smart meters are crucial for reducing electricity distribution companies’, or discoms’, losses. In the financial year 2018-’19, these stood at Rs 27,000 crore, four-times the allocation for the renewables ministry in 2020. They do this by not only improving billing and revenue collection but also reducing the difference between the cost of supply and the revenue collected. A smart, automated metering system, without manual intervention, would reduce meter-reading and data-entry errors and costs.

These meters would also estimate consumer demand, letting utilities forecast and contract for power requirements more accurately. This is essential for integrating renewable energy into the grid using the “time of the day” policy, as we further explain.

To smoothen the transition and create an ecosystem for smart meter use, the Central Government, in 2017, created the Energy Efficiency Services Ltd or EESL, a joint venture between several public-sector enterprises helmed by the power ministry. EESL’s best-known success has been speeding up the adoption of fuel-efficient LED lights by bringing prices down by 80%. The company floated its first tender for smart meters in August 2017. On February 24, it announced that it has successfully installed one million smart meters in the country.

States that have installed smart meters include Uttar Pradesh, Haryana, Bihar and Delhi. Some discoms using smart meters have increased their per-meter, per-month revenue by Rs 200, said Saurabh Kumar, managing director at EESL. This increase in discoms' revenue is mostly due to improved monitoring efficiency of per-unit electricity supplied and improved billing due to smart meters, he added.

Kumar has worked with the government in various capacities. At the Bureau of Energy Efficiency, he led the implementation of the world's largest Clean Development Mechanism-efficient lighting project to reduce carbon emissions. An electrical engineer from the Indian Institute of Technology, Kanpur, Kumar has a postgraduate degree in public policy from the National Graduate Institute for Policy Studies, Tokyo, Japan.

Edited excerpts from the interview:

How many smart meters has EESL installed so far?

So far, we have successfully installed 1.10 million smart meters. We have completed a project in the New Delhi Municipal Corporation area about a year ago, with some 55,000 smart meters installed. Our projects are on in Uttar Pradesh, with all five distribution companies in the state; in Haryana, we are working with both the distribution companies. We have just started in Bihar.

Are these smart meters showing results? How are they improving discom revenues?

With these 1.10 million meters, the average increase in revenue per month per meter is Rs 200 [when the national average bill is about Rs 450, assuming average consumption of 90 units per month at Rs 5 per unit]. The highest increase was recorded for NDMC, around Rs 500, and the lowest would be in Kanpur and Meerut, about Rs 130. What we are charging to these discoms is Rs 85 for a single-phase meter and about Rs 105 for a three-phase meter.

Numbers are clearly showing that discoms' revenue is up and there are two main reasons. The first is the elimination of incidences of suppressed demand load. Let's understand this with a very simple example: Let's say you took an electricity connection five years ago when you had one air conditioner in your house, and we all know that there is a two-part tariff [i.e. if a discom gives you a 2.5-kilowatt sanctioned load for your house, you will pay some demand charge for it]. Now, over the next five years, you added three more ACs, which means your actual load has gone up from 2.5 kilowatts to about seven kilowatts. But there is no way, in the manual system, to check this. The moment we installed smart meters and put the data online, the discom knew the exact load used in a premise. Therefore, the fixed charges for sanctioned loads go up, increasing the revenue. In fact, [New Delhi Municipal Corporation] and Uttar Pradesh are the biggest benefactors of this.

The second reason is very crucial because a lot of discoms are still saying that they do not need smart meters because their billing efficiency is 99%. [New Delhi Municipal Corporation's] billing efficiency is 99.8% today and its average bill has gone up by 25%. The reason is, in the manual system you may be billing 99% of consumers, but there is no way of ensuring that the quality of billing is good. There are hundreds of dysfunctional meters and discoms continue to bill at flat rates. Just because you are generating a bill does not mean that you are getting all the revenue that you need to bill for.

The third benefit of a smart meter is transparency. About 99% of consumers in UP who have smart meters are now paying their bills on time–urban and rural. This is because now they know exactly what their consumption is, they do not have to wait for the bill to come after three months. We are now encouraging everyone to download a mobile app through which they can see their daily electricity consumption. Because of this transparency, disputes over bills have also gone down dramatically.

In Bihar, we are taking this one step further. We are going for a prepaid model there. You pay upfront for the energy you would like to consume in the near future [which helps consumers plan and regulate their energy use and bills]. If this happens, imagine how much it will benefit the discoms –they will need no working capital because they get the money upfront before you buy electricity. The need for a huge working capital is exactly the problem they are struggling with today. I would say the exercise has been an enormous success.

How will these smart meters improve the electricity sector in general? How can renewables benefit from them?

Let me first start by telling you why smart meters are a critical element in the future health of the sector. The average billing efficiency in India is 83%, which means that 17% of the electricity in the country is not billed for, forget about revenue collection. This 17% means a staggering loss of Rs 100,000 crore [equivalent to India's education budget for 2020], if I calculate the per-unit cost at Rs 5. There is only one solution to plug this: smart meters. We have seen smart meters solving the problem in UP, where Aggregate Technical and Commercial losses [the difference between the total electricity units supplied by a discom and the total units billed for] have gone down by 36% in certain feeders [transmission lines that take electricity from the spot of generation to distribution points].

Now coming to renewables, what is the problem today? Why are states reluctant to take renewables? Because renewable power generation mostly happens during the time [of the day] when I don't need it, not even with the per-unit cost of Rs 2.44 [because there is not enough demand given Indian usage patterns]. The solution to this is the "time of the day" policy [under which different rates apply at different times of the day. Usually, under this policy, the rate of the electricity is kept cheaper during off-peak demand hours to compel users to shift most of their non-essential power usage in that time-frame. This helps a user save money along with helping a discom reduce pressure on its grid during peak hours.]

Now, how do you implement "time of the day" policy? You tell a consumer that I will give you electricity at a cheaper price of Rs 3 per unit between 11am and 4pm, so shift your non-essential usage to these hours. But this can only be done with smart meters because it provides you with real-time flexibility. The other benefit of smart meters is incentivising people by demand response, which means that everyone wants to switch on their AC at 6pm...If I tell a consumer to switch on the AC at 9pm and he [or] she will get a rebate of Rs 1 per unit for those three hours, the load on the grid will shift. This can only happen in real-time with smart meters.

What are the challenges that Energy Efficiency Services Ltd faced with smart meters?

The first major challenge we faced had several ramifications. It was about the integration of the data that is coming out of smart meters to the head-end system [hardware and software that receives the stream of meter data] to the metre data management system [which helps process the received meter data for insights] and then the legacy software of billing and collection. But I am very proud to say that we overcame that challenge.

Now we have been able to standardise the process up to the meter data management system. So now when we start working with a new discom, the only challenge we face is integrating the entire system to their legacy billing software because all discoms use unique billing software. The other challenge we faced was the supply of smart meters in such huge numbers. The supply, however, has now improved considerably. At the moment there are six- [to] seven-metre manufacturers who have got certification from the Bureau of Indian Standards [the national standards body under the Ministry of Consumer Affairs]. We cannot install any metre that is not certified by the [bureau]. In fact, the minister and secretary of power have been meeting with metre manufacturers on a constant basis and we are seeing the results. The number of people on board is increasing by the day.

So is EESL trying to figure out a single solution that works with all the legacy billing software of discoms? Or is it using a different integration exercise for every discom?

It all depends on what softwares the discoms are using. Up to the meter data management system, we have achieved standardisation because it is either us or our partners who are controlling the infrastructure. The only thing that belongs to the discoms is their own billing software. For example, in [Uttar Pradesh], the five discoms have been using three platforms. We are trying to make it common. In the end, UP's discoms would like to see a consolidated dashboard with all the data about electricity consumption and trends and that is what our endeavour is.

We are bringing all the meter data on a common platform and further, we are planning to have different buckets for different discoms in a virtual framework because all of it is cloud-based. And to achieve this exact model took us a while because no one has ever done such an exercise at such a massive scale in India.

Why GPRS, why not other advanced technologies like radio frequency mesh that experts believe is better, as IndiaSpend reported? [Radio frequency mesh technology uses radio waves to communicate among groups of meters that send data to a data concentrator unit with a SIM card which then forwards it through the telecom network to the discom's main server. This is unlike the GPRS technology where each smart meter needs its own individual SIM card to communicate with the server.]

We are going with GPRS and possibly looking at the [Narrow Band-Internet of Things], which is a specialised band only for machines on a GPRS kind of a network. [Radio frequency] is a good technology but it does not suit our business model because it is capex heavy [requires capital expenditure to build a new network] due to which our cost-per-meter would go up to Rs 6,000 per meter. It is Rs 2,500 in the GPRS system.

Also, with RF, I will have to build institutional capacity to maintain that network. The benefits of GPRS technology is that I am getting data cost at a very reasonable price of Rs 4 per SIM card per month. And the availability of the GPRS network is 98.5% in the country.

I am not saying that moving forward we may not look at other technologies. We may. For example, in multi-storeyed buildings you can have an [radio frequency]-technology network because the data from all the apartment meters will come to a single DCU and from there go to the GPRS network. So we may look at a combination of network technologies going ahead.

Telecom companies are moving beyond 2G and 3G. Will that not cause a problem?

Our first tender was for 3G network technology. Let us look at what is in it for a telecom operator. An operator is currently getting only 1.1 million consumers for data, whose bandwidth requirement is so small, probably comparable to a credit card swiping machine, that an operator would never want to discard it. Secondly, for an operator these consumers are for life. EESL may get out of the scene but that SIM card will remain in a consumer's house forever.

Is connectivity not a problem for rural areas?

As I said before, all we need is a telephone line because the data requirement of these meters is very low. And we have worked in rural areas of Haryana and Uttar Pradesh. So far, we did not face any issue with network connectivity. In Bihar, the network coverage is about 99%. In rural Uttar Pradesh, it is almost the same.

What do the next couple of years look like for smart meters?

The government has come out with a very ambitious plan of replacing all 250 million meters in the country with smart meters in the next three years. For this, the government has spoken to the entire meter industry to gear up for this drive. The good part is that most meter manufacturers said that they only need three-six months' time to be ready to deliver 60 million [to] 80 million meters every year.

All the discoms that we are working with understand that they do not have the internal capacity to manage a project like this. They have tried to issue tenders to install smart meters on their own, but failed. But now they are seeing the results. We are also taking steps to build capacity within these discoms so that even after we leave there will still be people working there who understand this technology and how to take it forward.

Also, in our past experience of procuring meters and system integrators, we have identified a very large opportunity in the sector going forward. So last November we tied up with the National Investment and Infrastructure Fund, which manages the sovereign wealth fund of India, to establish a special purpose entity [a subsidiary], the Intellismart Infrastructure Private Limited, only for the purpose of implementing the smart meter project. The vision behind this move is that Intellismart will be the biggest system integrator in the country which will provide high-quality service in the transition period at a very affordable rate.

How is EESL preparing itself to ramp up meter installation?

Now, we are at a stage where it is simply a question of how many meters you can install per day. Today, I think we are at a rate of about 8,000 meters per day and the plan is to ramp it up to 15,000 to 20,000 in the next two-three months. By the end of this calendar year, we want to reach 70,000-100,000 meter installations per day. Currently, we have UP installing four million meters with us, as per the existing agreement. With Haryana, the agreement is of one million meters, but there are another one million consumers for which we are already in discussion with the state. In Bihar, we are currently installing about 1.8 million meters.

As for our new projects, we have signed an agreement with Port Blair. In Rajasthan, we have actually won a competitive bid to install 500,000 smart meters. We are also in conversations with Arunachal Pradesh, West Bengal and Telangana for hundreds of thousands of meters.

CAN SMART METERS SOLVE INDIA'S ELECTRICITY PROBLEM?

HINDUSTAN TIMES

Rahul Tongia is fellow, Brookings India, and **was technical advisor of the Government of India's Smart Grid Task Force**. He is also the founding advisor of the India Smart Grid Forum**.** His personal views are,

Much has changed in the electricity sector in the last few years. Electricity generation capacity is now surplus after years of deficits, and the price of solar power has fallen by 70%. But one thing that has barely changed is the performance of the electricity distribution companies (discoms), which continue to bleed money. They also face operational challenges, despite some improvements in the reduction of losses (and, importantly, 100% electrification). There are now proposals to install 250 million smart meters across all users to try and radically improve the discoms. While a top-down push is important, unless there is bottom-up buy-in, such solutions will likely be under-effective, or worse, crowd out parallel or complementary efforts.

A Smart Grid is a transformation of the electricity grid where digital communications and control enable a more nimble, resilient, flexible, and efficient grid. It's this last point that is pushing smart meters, which can be a tool for cutting down losses, which span under-billing, under-collection, and outright theft. Given the state of technologies and metering deployments across discoms, it's inevitable to try and leapfrog to smart meters.

Smart meters could help improve detection of theft (a necessary but not sufficient condition for viable discoms), but they can't accurately pinpoint all forms of theft alone. The two things really needed are on the ground action (vigilance) as well as analytics. Before discoms take the plunge in paying for smart meters, they have to ensure that vigilance improves through political will and analytics get incorporated in business practices regardless of the level of smart metering. Before asking for smart meters, planners should answer if utilities are harnessing the data they already have.

Prepaid meters are another major thrust. While this could help improve collection, one has to be willing to disconnect non-payers. Automation can make it easier, but it's political will that's needed for both automated and manual systems. Note that in a number of regions, the largest defaulter is the government itself. Most honest consumers actually prepay today through a deposit. Instead of the focus on prepaid, such functionality should be viewed as a subset of smart meters. We should also not implement prepaid meters in a standalone manner such as through a keypad for inputting payment codes. Not only is this inconvenient, utilities lose visibility of consumption and they can't easily offer differential tariffs for users.

There are few arguments against making discoms smarter and the impending need for smart meters. But we should focus on not just "yesterday's problems" such as billing and loss reduction, but also on tomorrow's challenges such as renewable energy, electric vehicles, consumer choice and competition. This emphasises that different discoms have different drivers and expected functionalities from their smart systems.

Why did many earlier IT-driven discom projects not reach their potential or even languish? It was because of a lack of preparedness. This same challenge remains for blanket smart meter roll-outs. While volume makes smart metering hardware cheaper, the real challenge remains integration with existing (legacy) systems. Without solving this challenge, no drop-in solution can work well.

Smart meter roll-outs are not quite like LED bulb procurements. Meters are more of an ecosystem, probably closer to smart cities. Volumes and standardisation help, but only up to a point. There is also a new option of third party deployers who invest, and then take a monthly charge. This seems to help liquidity issues more than solvency issues, i.e. business model issues more than business case issues, and it could transfer some risk depending on the contract design. But the utility still pays, today in the order of ~100 per month (including GST). Is the value proposition greater than this? The average Indian household bill is around ~500 per month, and we can't expect 20% efficiency gains to be revenue-neutral across India purely through smart meters.

There will be pockets and regions where high losses, high renewables, or something else drives more rapid deployment. The best way forward will be what some call “leopard spots” of deployment by geography — intensive deployment in selected areas, growing over time to cover the entire discom. This plan begins with a combination of most prepared discoms and highest urgency areas. This also gives utilities time to do their homework — finish standardising databases and billing platforms and GIS (digital mapping) efforts, not to mention enhance their staffing. Leadership continuity with political backing is another key ingredient for success. With this, even without smart meters, Haryana halved its losses in three years.

Smart meters fail when the technology and price points are off, but they succeed when consumers (and the utilities) ask for them. Instead of just looking at sticks like theft detection, we should also push carrots. These can include guaranteed zero load-shedding (with lifeline supply even during shortfalls), ability to easily integrate electric vehicles and renewables, as well as the potential to save money through time of day pricing.

Much of the focus has been on efficiency, but the real value proposition comes from a transformation, including one with dynamic pricing, and where consumers respond to incentives such as by shifting their loads to off-peak prices. These require awareness, incentives, and regulatory approvals, which will take time. Ultimately, smart meters are a valuable tool for improved discoms, but they are not a panacea for all ills. We should harness, but not rely on technology to solve what are fundamentally governance failures.

SMART ENERGY METER

SINGLE PHASE SMART METER – AURORA

Our single phase smart meter provides full smart functionalities in accordance with the latest IS standards and CEA guidelines. These smart meters can be integrated into a complete AMI solution for achieving Smart Grid benefits by customers.

SALIENT FEATURES

- Complying to IS 16444 Part 1
- Full smart functionality
- Communication options including optical, RF and GPRS
- Load connection/disconnection via relays in phase and neutral
- Tamper alerts available
- Data logging for instantaneous parameters, billing parameters and energy backups
- Event logging with active energy, voltage and current snaps available
- Power fail alerts (Last Gasp)

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L&T Meters®
THE RIGHT MEASURE

Specifications

Connection	1 Phase 2 Wire
Standards Applicable	IS 16444 Part 1
Accuracy Class	Cl 1.0
Rated Voltage	240V (P-N)
Voltage Variation	-40% to +20%
Current Rating	10-60 A
Starting Current	0.2% of basic current
Accuracy up to	120% of maximum current
Frequency	50Hz
Frequency Variation	-5% to +5%
Power Consumption	As per IS 16444 Part 1
Operating Temperature	-10°C to +55°C
Ingress Protection	IP 51

Supported parameters (As per customer requirement)

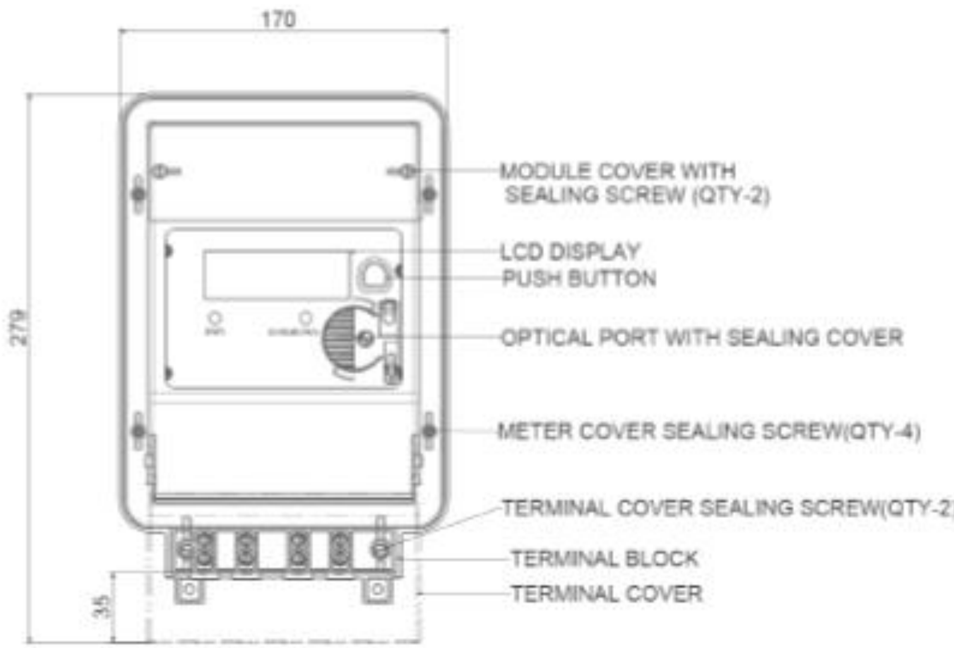
Instantaneous	Voltage, phase and neutral Current, PF, active power, reactive power and apparent power Frequency
Energy Measurement	4 quadrant measurement of kWh, kVArh, and kVAh
Maximum Demand	kW and kVA along with date and time
Time of Day	Up to 4 registers, profiles and seasons

Display

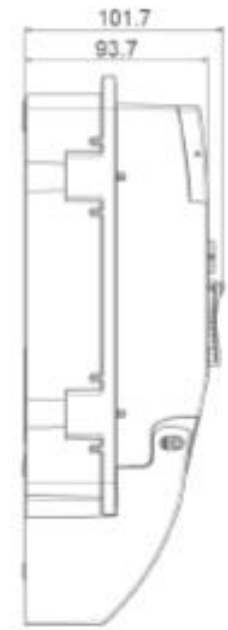
LCD	8 digit backlit display
LCD Indicators	Indication for relay status and tampers
Display mode	Auto scroll, push button and high resolution modes
LED	Pulse LEDs for kWh and KVArh

Smart Features

Alarms and alerts	Alarm/alert for power on/off, over voltage and over current
Load control	Disconnection provided for: Over current and Over load conditions For selected tampers Disconnection signal from utility
Relay	Provided in both phase and neutral complying to IS15884 with UC1/UC2/UC3; status available on display and data downloading; connection/ disconnection are logged as events
Data security	Multi-level password for data reading and programming
Communication	Optical port for local communication with DLMS NAN over 865-867 MHz RF complying to IS 15959 Part 2 Inbuilt GPRS Modem
Prepayment	Prepaid function as per IS15959 Part 2 (optional)



FRONT VIEW



SIDE VIEW

AUTOMATIC METER READING SIMULATION

This example shows you how to use Communications Toolbox™ to read utility meters by processing Standard Consumption Message (SCM) signals and Interval Data Message (IDM) signals which are emitted by Encoder-Receiver-Transmitter (ERT) compatible meters. You can either use recorded data from a file, or receive over-the-air signals in real time using the RTL-SDR Radio or ADALM-PLUTO Radio.

Required Hardware and Software

To run this example using recorded data from a file, you need the following software:

- Communications Toolbox™

To receive signals in real time, you also need one of the following SDR devices and the corresponding support package Add-On:

- RTL-SDR radio and the corresponding software Communications Toolbox Support Package for RTL-SDR Radio
- ADALM-PLUTO radio and the corresponding software Communications Toolbox Support Package for ADALM-PLUTO Radio

For a full list of Communications Toolbox supported SDR platforms, refer to Supported Hardware section of the Software Defined Radio (SDR) discovery page.

Background

Automatic Meter Reading (AMR) is a technology that autonomously collects the consumption and status data from utility meters (e.g. electric, gas, or water meters) and delivers the data to utility providers for billing or analysis purposes. The AMR system utilizes low power radio frequency (RF) communication to transmit meter readings to a remote receiver. The RF transmission properties include

- Transmission frequency within range: 910-920 MHz
- Data rate: 32768 bps
- On-off keyed Manchester coded signaling

The SCM and IDM are two types of the conventional message types that the meters send out. The SCM packets are used with a fixed length of 96 bits, whereas IDM packets are used with a fixed length of 736 bits. The packet format of the SCM and IDM messages are shown below [1]:

SCM Packet Format			
Field	**Length (bits)**	**Fixed Value**	**Notes**
Sync bit	1	1	
Preamble	20	0xF2A60	
ERT ID MS bits	2		MSBs of the meter serial number
Reserved	1		
Physical tamper	2		
ERT type	4		determines the commodity type, e.g., electric
Encoder tamper	2		
Consumption data	24		Actual meter reading
ERT ID LS bits	24		remaining bits of the meter serial number
Checksum	16		A BCH(255, 239) shortened to message length of 59 with genrator polynomial g(X) = $(267543)_8$

IDM Packet Format			
Field	**Length (bytes)**	**Fixed Value**	**Notes**
Training sync	2	0x5555	
Frame sync	2	0x16A3	
Packet type	1	0x1C	
Packet length	2	0x5CC6	The first byte is the number of total bytes and the last byte is the Hamming code of the first byte.
Application version	1	0x04	
ERT Type	1	0x17	The last 4 bits determines the commodity type, e.g., electric
ERT serial number	4		
Consumption interval count	1		Incrementing interval counter that increments at the end of each interval and rolls over to 0 after 255
Module programming state	1		
Tamper count	6		
Async count	2		
Power outage flags	6		
Last consumption count	4		
Differential consumption intervals*	53		47 intervals, represented by 9-bit integers
Transmit time offset	2		Time elapsed since the last interval ended
Serial number CRC	2		CRC-16-CCITT of ERT serial number
Packet CRC	2		CRC-16-CCITT of packet starting at Packet type
* Each integer shows the amount of the metered quantity that was consumed during each interval. Units will vary based on meter type and version. The leftmost interval is the most recent.			

Meters capable of sending both SCM and IDM messages transmit them on the same channel with separation of roughly 275 msec. Each meter transmits the SCM and IDM messages over multiple frequencies using a hopping pattern. The actual transmission frequencies, the frequency hopping pattern, and the time interval between transmissions are random to avoid interference from other transmissions.

Run the Example

To run the example, type AMRExample in the MATLAB® Command Window.

The signal source default is 'File'. To specify a different signal source, change the setting for signalSource in the helperAMRInit.m file. Valid options for signalSource are 'File', 'RTL-SDR', and 'PlutoSDR'.

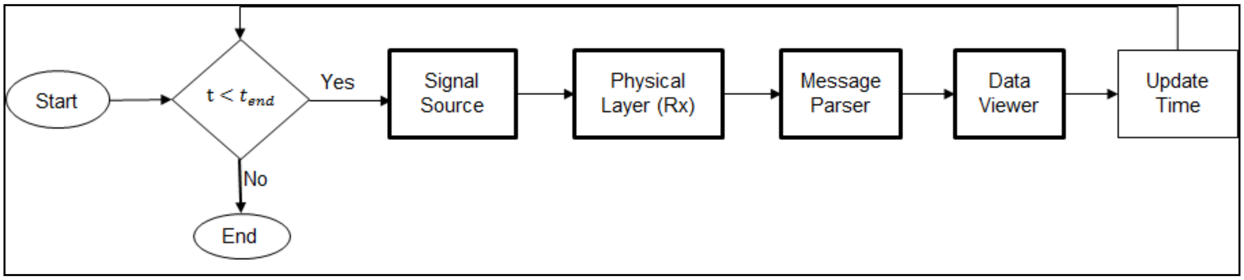
The receiver initializes the simulation parameters and calculates the AMR parameters. A data viewer display shows the meter ID, consumption information, and commodity type. The simulation loop calls the signal source, physical layer, message parser, and data viewer. The processing loop keeps track of the radio time using the frame duration. * The display updates for each data capture, showing unique meter IDs with the latest consumption information.

Initialize Parameters Valid inputs for signalSource are 'File', 'RTL-SDR' and 'ADALM-PLUTO'

```
signalSource = 'File';
initParam = helperAMRInit(signalSource);

% Calculate AMR system parameters based on the initialized parameters
[amrParam, sigSrc] = helperAMRConfig(initParam);

% Create the data viewer object
viewer = helperAMRViewer('MeterID', initParam.MeterID, ...
  'LogData', initParam.LogData, ...
  'LogFilename', initParam.LogFilename, ...
  'Fc', amrParam.CenterFrequency, ...
  'SignalSourceType', initParam.SignalSourceType);

start(viewer);
radioTime = 0; % Initialize the radio time

% Main Processing Loop
while radioTime < initParam.Duration
  rcvdSignal = sigSrc();
  amrBits = helperAMRRxPHY(rcvdSignal, amrParam);
  amrMessages = helperAMRMessageParser(amrBits, amrParam);
  update(viewer, amrMessages);
  radioTime = radioTime + amrParam.FrameDuration;
end

stop(viewer); % Stop the viewer
release(sigSrc); % Release the signal source
```

Receiver Code Structure

The flow chart summarizes the receiver code structure. The processing has four main parts: Signal Source, Physical Layer, Message Parser and Data Viewer.



Signal Source

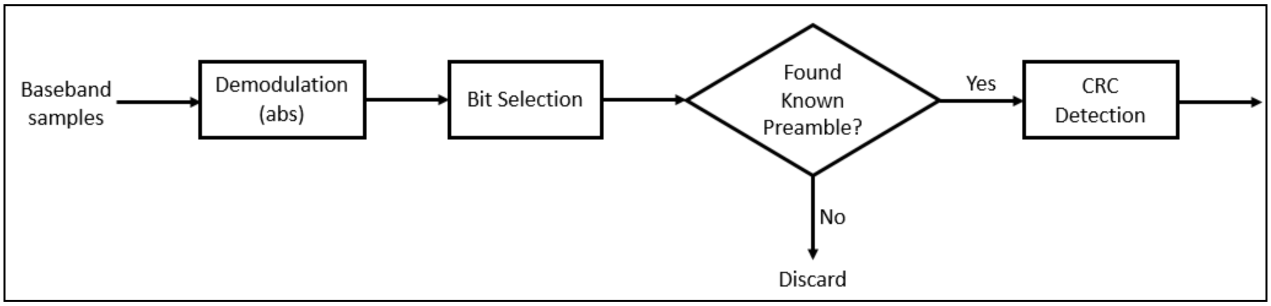
This example can use three signal sources:

1. "File": Over-the-air signals written to a file and read using a Baseband File Reader object at 1.0 Msps
2. "RTL-SDR": RTL-SDR radio at a sample rate of 1.0 Msps
3. "ADALM-PLUTO": ADALM-PLUTO radio at a sample rate of 1.0 Msps

If you assign "RTL-SDR" or "ADALM-PLUTO" as the signal source, the example searches your computer for the radio you specified, either an RTL-SDR radio at radio address '0' or an ADALM-PLUTO radio at radio address 'usb:0' and uses it as the signal source.

Physical Layer

The baseband samples received from the signal source are processed by the physical layer (PHY) to produce packets that contain the SCM or IDM information. This diagram shows the physical layer receive processing.



The RTL-SDR radio is capable of using a sampling rate in the range of 225-300 kHz or 900-2560 kHz and the ADALM-PLUTO radio is capable of using a sampling rate in the range of 520 kHz-61.44 MHz. A sampling rate of 1.0 Msps is used to produce a sufficient number of samples per Manchester encoded data bit. For each frequency in the hopping pattern, every AMR data packet is transmitted. The frequency hopping allows for increased reliability over time. Since every packet is transmitted on each frequency hop, it is sufficient to monitor only one frequency for this example. The radio is tuned to a center frequency of 915 MHz for the entire simulation runtime.

The received complex samples are amplitude demodulated by extracting their magnitude. The on-off keyed Manchester coding implies the bit selection block includes clock recovery. This block outputs bit sequences (ignoring the idle times in the transmission) which are subsequently checked for the known preamble. If the preamble matches, the bit sequence is further decoded, otherwise, it is discarded and the next sequence is processed.

When the known SCM preamble is found for a bit sequence, the received message bits are decoded using a shortened (255,239) BCH code which can correct up to two bit errors. In the case where the known IDM preamble is found, the receiver performs a cyclic redundancy check (CRC) of the meter serial number and of the whole packet starting at the Packet type (the 5th byte) to determine if the packet is valid. Valid, corrected messages are passed onto the AMR message parser.

Message Parser

For a valid message, the bits are then parsed into the specific fields of the SCM or the IDM format.

Data Viewer

The data viewer shows the decoded packets on a separate MATLAB figure. For each successfully decoded packet, the meter ID, commodity type, AMR packet type, consumption information and the capture time is shown. As data is captured and decoded, the application lists the information decoded from these messages in a tabular form. The table lists only the unique meter IDs with their latest consumption information.

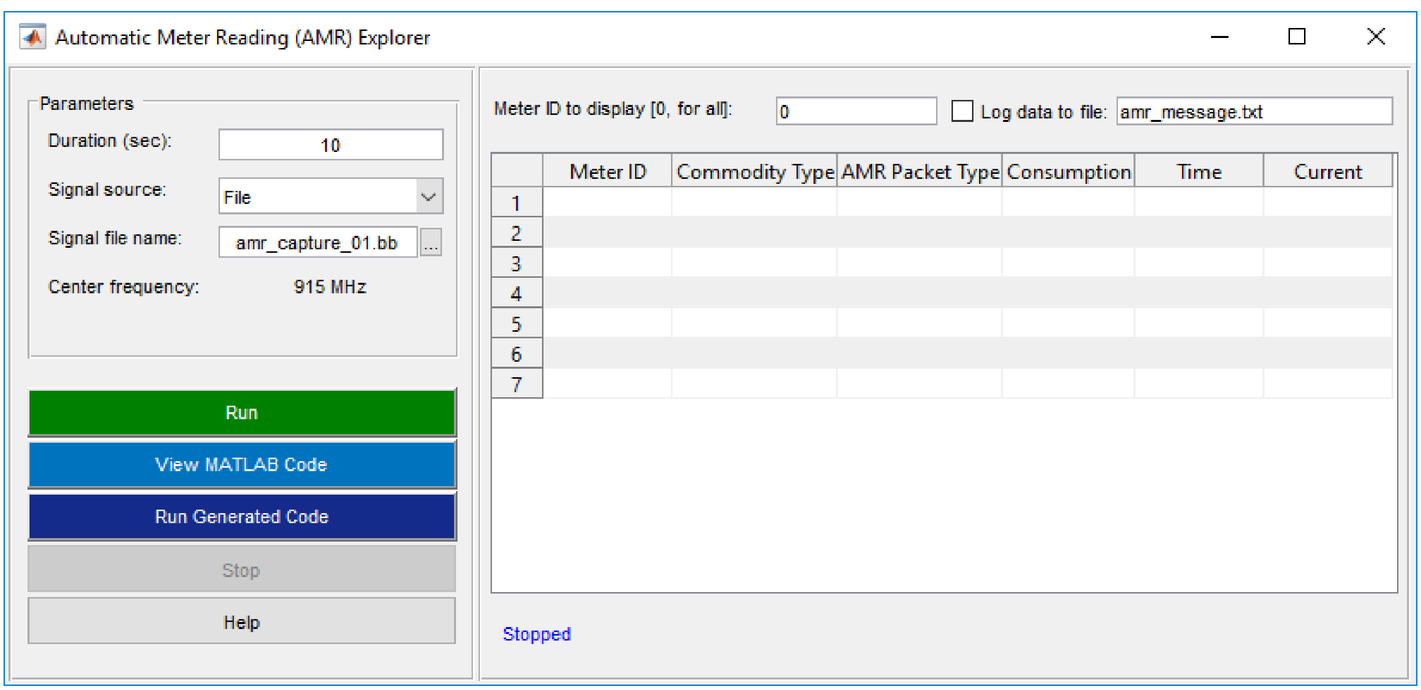
You can also change the meter ID and start text file logging using the data viewer.

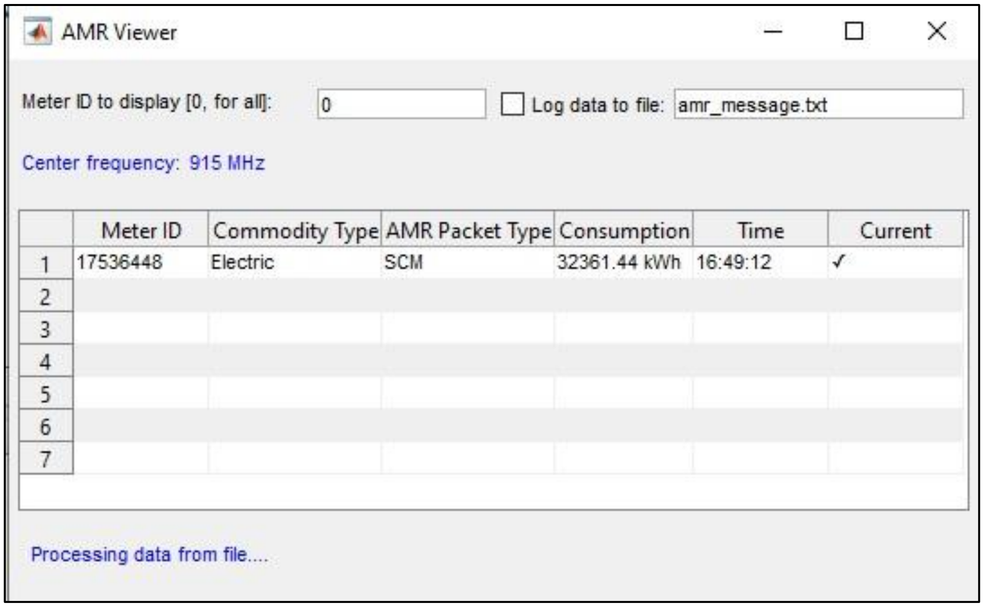
- **Meter ID** - Change the meter ID from 0, which is the default value and is reserved for displaying all detected meters, to a specific meter ID which you would like to be displayed.
- **Log data to file** - Save the decoded messages in a TXT file. You can use the saved data for post processing.

Further Exploration

The data file accompanying the example has only one meter reading and has been captured at center frequency of 915 MHz. Using RTL-SDR or ADALM-PLUTO, the example will display readings from multiple meters when it is run for a longer period in a residential neighborhood.

You can further explore AMR signals using the AMRExampleApp user interface. This app allows you to select the signal source and change the center frequency of the RTL-SDR or ADALM-PLUTO. To launch the app, type AMRExampleApp in the MATLAB Command Window or click the link. This user interface is shown in the following figure





RESULTS

The Meter Readings can be logged to a Text file for further uses.

Meter ID,	Commodity Type,	AMR Packet Type,	Consumption [	unit],	Time(hh:mm:ss),
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:42:52 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:42:57 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:42:57 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:42:58 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:42:58 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:42:59 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:00 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:00 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:01 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:01 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:02 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:02 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:02 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:03 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:03 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:03 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:04 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:04 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:04 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:05 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:05 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:05 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:06 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:06 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:07 ,
17536448,	Electric,	IDM,	32361.44 [	kWh],	20:43:07 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:08 ,
17536448,	Electric,	SCM,	32361.44 [	kWh],	20:43:08 ,

LITERATURE SURVEY

Smart Meter Energy Consumption Data in London Households
UK Power Networks

Energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014.

Readings were taken at half hourly intervals. Households have been allocated to a CACI Acorn group (2010). The customers in the trial were recruited as a balanced sample representative of the Greater London population.

The dataset contains energy consumption, in kWh (per half hour), unique household identifier, date and time, and CACI Acorn group. The CSV file is around 10GB when unzipped and contains around 167million rows.

Within the data set are two groups of customers. The first is a sub-group, of approximately 1100 customers, who were subjected to Dynamic Time of Use (dToU) energy prices throughout the 2013 calendar year period. The tariff prices were given a day ahead via the Smart Meter IHD (In Home Display) or text message to mobile phone. Customers were issued High (67.20p/kWh), Low (3.99p/kWh) or normal (11.76p/kWh) price signals and the times of day these applied. The dates/times and the price signal schedule is available as part of this dataset. All non-Time of Use customers were on a flat rate tariff of 14.228pence/kWh.

The signals given were designed to be representative of the types of signal that may be used in the future to manage both high renewable generation (supply following) operation and also test the potential to use high price signals to reduce stress on local distribution grids during periods of stress.

The remaining sample of approximately 4500 customers energy consumption readings were not subject to the dToU tariff.

CONTEXT

To better follow the energy consumption, the government wants energy suppliers to install smart meters in every home in England, Wales and Scotland. There are more than 26 million homes for the energy suppliers to get to, with the goal of every home having a smart meter by 2020.

This roll out of the meter is led by the European Union who asked all member governments to look at smart meters as part of measures to upgrade our energy supply and tackle climate change. After an initial study, the British government decided to adopt smart meters as part of their plan to update our ageing energy system.

In this dataset, you will find are factorised version of the data from the London data store, which contains the energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014. The data from the smart meters seems associated only to the electrical consumption.

There is information on the ACORN classification details that you can find in this report or the website of CACI.

The data contains nearly a million values of Energy consumption each taken at an half-hourly basis of 30 Households. It is about 60MB in size and is in the format of CSV (Comma Seperated Values).

COMPUTER SPECIFICATIONS

PC Specifications:
Processor: Intel i5 430M 2.27GHz, RAM:4GB, Graphics: NVIDIA GT 330M 1GB

Implementation of the Solution was done on Cloud Kaggle Kernel with Hardware Specifications: (Using Cloud Kernel provided by www.kaggle.com)

RAM – 16 GB

DISK – 5 GB

UK ENERGY CONSUMPTION DATA EXPLORATION (Sample 22 Rows)

LCLid	stdorToU	DateTime	KWh	Acorn	Acorn_grouped
MAC000002	Std	10/12/2012 11:30	0.143	ACORN-A	Affluent
MAC000002	Std	10/12/2012 12:00	0.663	ACORN-A	Affluent
MAC000002	Std	10/12/2012 12:30	0.256	ACORN-A	Affluent
MAC000002	Std	10/12/2012 13:00	0.155	ACORN-A	Affluent
MAC000002	Std	10/12/2012 13:30	0.199	ACORN-A	Affluent
MAC000002	Std	10/12/2012 14:00	0.125	ACORN-A	Affluent
MAC000002	Std	10/12/2012 14:30	0.165	ACORN-A	Affluent
MAC000002	Std	10/12/2012 15:00	0.14	ACORN-A	Affluent
MAC000002	Std	10/12/2012 15:30	0.148	ACORN-A	Affluent
MAC000002	Std	10/12/2012 16:00	0.154	ACORN-A	Affluent
MAC000002	Std	10/12/2012 16:30	0.137	ACORN-A	Affluent
MAC000002	Std	10/12/2012 17:00	0.493	ACORN-A	Affluent
MAC000002	Std	10/12/2012 17:30	0.354	ACORN-A	Affluent
MAC000002	Std	10/12/2012 18:00	0.228	ACORN-A	Affluent
MAC000002	Std	10/12/2012 18:30	0.195	ACORN-A	Affluent
MAC000002	Std	10/12/2012 19:00	0.527	ACORN-A	Affluent
MAC000002	Std	10/12/2012 19:30	0.886	ACORN-A	Affluent
MAC000002	Std	10/12/2012 20:00	0.198	ACORN-A	Affluent
MAC000002	Std	10/12/2012 20:30	0.243	ACORN-A	Affluent
MAC000002	Std	10/12/2012 21:00	0.193	ACORN-A	Affluent
MAC000002	Std	10/12/2012 21:30	0.342	ACORN-A	Affluent
MAC000002	Std	10/12/2012 22:00	0.27	ACORN-A	Affluent

DESCRIPTION OF THE DATA

COLUMNS:

1. **LCLid**

   It is the ID of the House being recorded.

2. **StdorToU -** Standard/Dynamic

   It is the type of Consumption Tariff taken by the Consumer.

3. **DateTime –** mm/dd/yyyy hr:mm format

   Half hour period of Date and time

4. **KWh –** Energy consumption unit

   It is the Energy usage of the house in half-hourly basis.

5. **Acorn and Acorn-grouped**

   Acorn segments postcodes and neighbourhoods into 6 Categories, 18 Groups and 62 types, three of which are not private households. By analysing significant social factors and population behaviour, it provides precise information and in-depth understanding of the different types of people. Household Acorn segments households to provide more refined targeting.

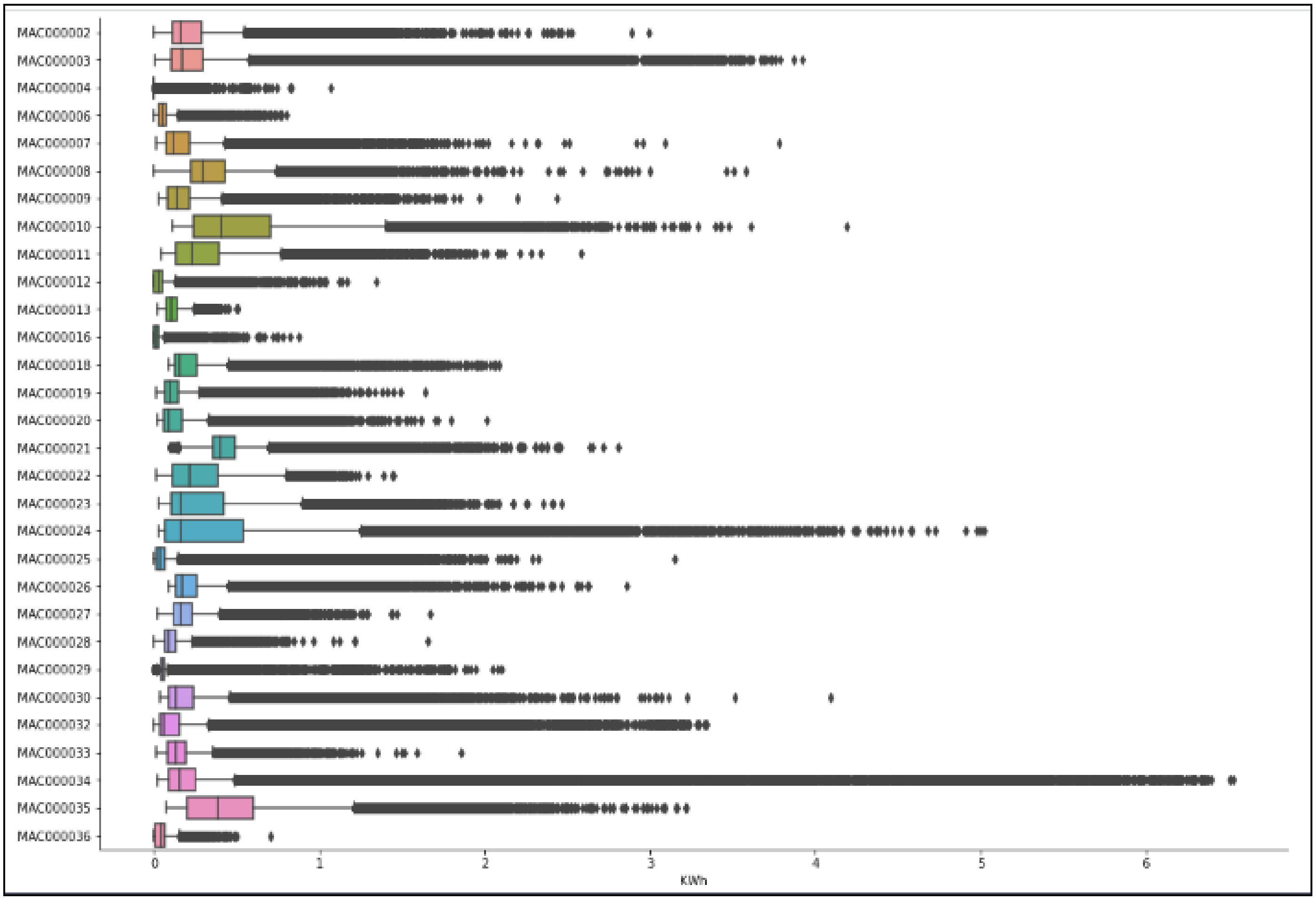
Since the aim of the project is to forecast the Energy consumption of the Households, it is sufficient to utilize the 'LCLid', 'DateTime', 'KWh' columns only.

DESCRIPTION

	DateTime	LCLid	KWh
count	999971	999971	999971.000000
unique	39095	30	NaN
top	2012-10-20 00:00:00.0000000	MAC000018	NaN
freq	58	39081	NaN
mean	NaN	NaN	0.239580
std	NaN	NaN	0. 387533
min	NaN	NaN	0.000000
25%	NaN	NaN	0.060000
50%	NaN	NaN	0.129000
75%	NaN	NaN	0.255000
max	NaN	NaN	6.528000

DATA VISUALISATION

BOX PLOT House-ID vs KWh plot



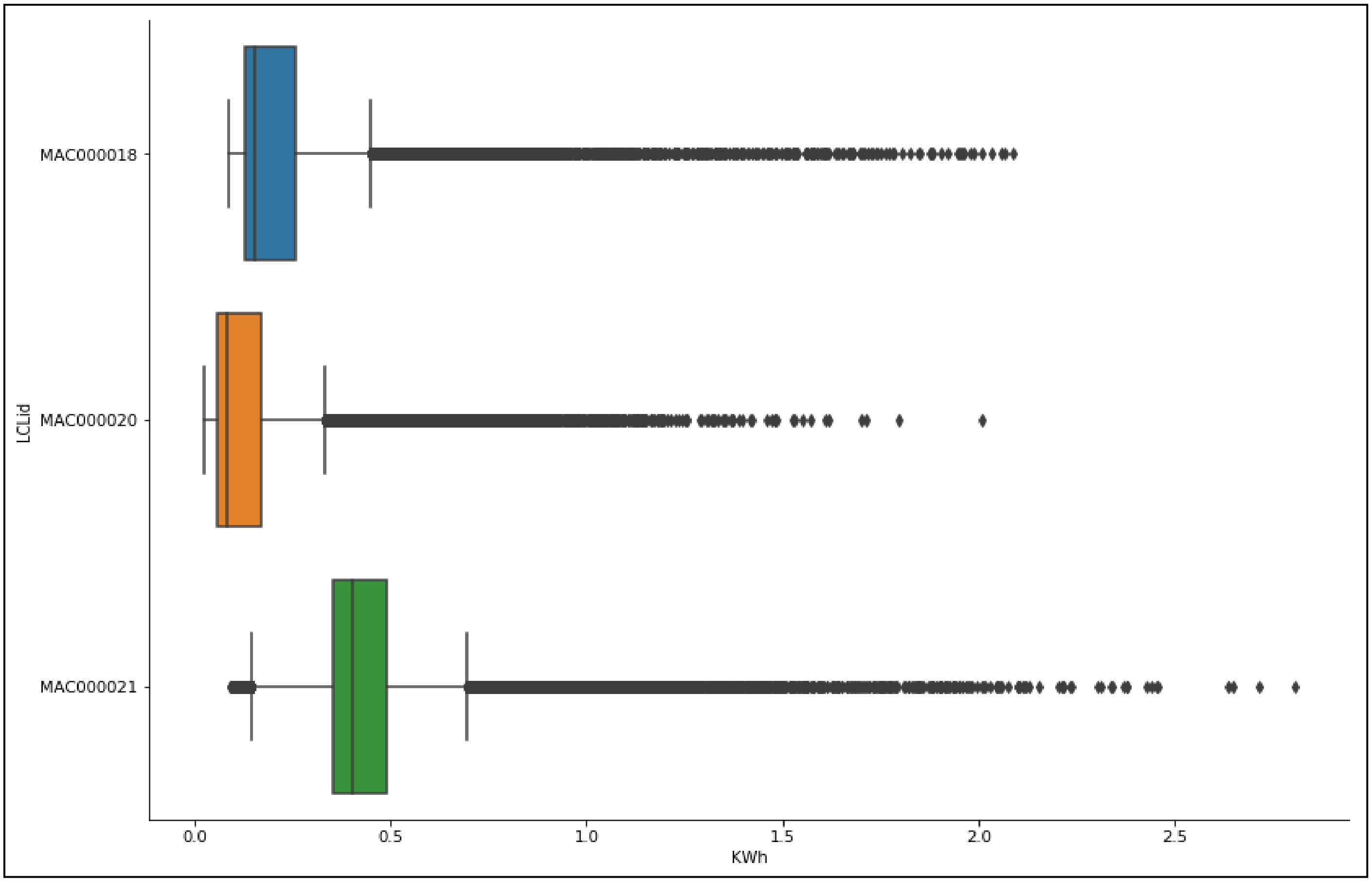
As the dataset contains data of 30 households totaling around **1 million** values of data, we will be focusing on the **TOP 3 Households** having the highest number of consumption data due to limitations in resources.

House ID	Number of Values of Data	Energy Consumed per household (KWh)
MAC000002	24157	6101.14
MAC000003	35468	14104.43
MAC000004	31676	1120.79
MAC000006	36460	2168.32
MAC000007	25045	4954.02
MAC000008	26012	9445.01
MAC000009	25237	4514.97
MAC000010	25048	13786.28
MAC000011	23704	7450.14
MAC000012	24669	1086.83
MAC000013	29613	3259.81
MAC000016	19523	533.97
MAC000018	39081 I	8748.45
MAC000019	39070	5061.87
MAC000020	39078 II	5344.03
MAC000021	39078 III	18323.18
MAC000022	39071	10216.11
MAC000023	39068	11668.20
MAC000024	39026	16944.26
MAC000025	39064	3879.52
MAC000026	39064	10141.91
MAC000027	39068	7292.63
MAC000028	32157	3221.82
MAC000029	39063	2764.48
MAC000030	39066	9277.97
MAC000032	39068	10452.43
MAC000033	39070	6162.76
MAC000034	39069	22145.14
MAC000035	39023	18473.80
MAC000036	16175	928.55

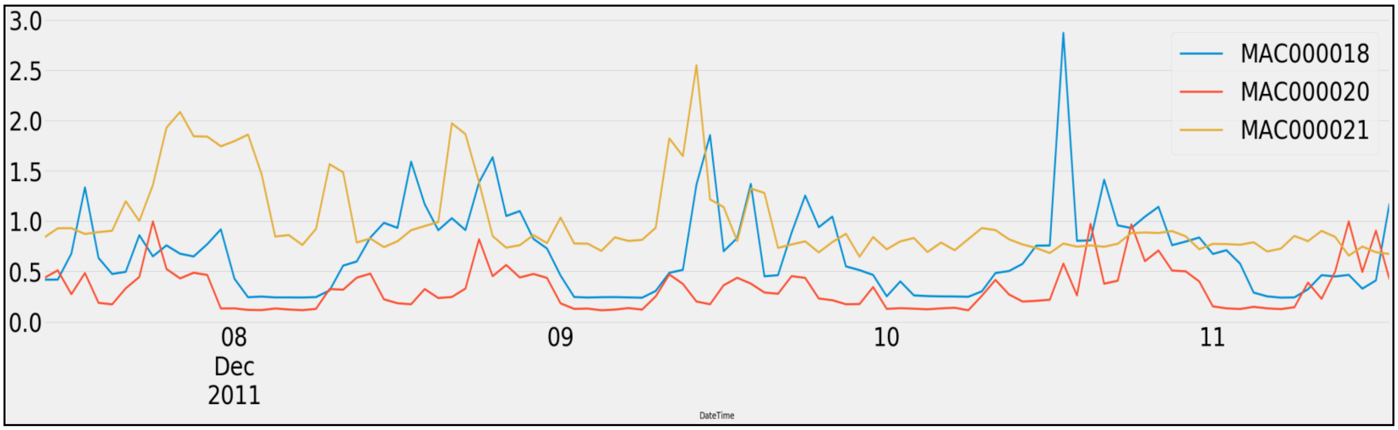
From the above table it is clearly understood that the Households **MAC000018**, **MAC000020** and **MAC000021** are the TOP 3 households having the maximum number of values of data.

DATA VISUALISATION OF TOP 3 HOUSEHOLDS

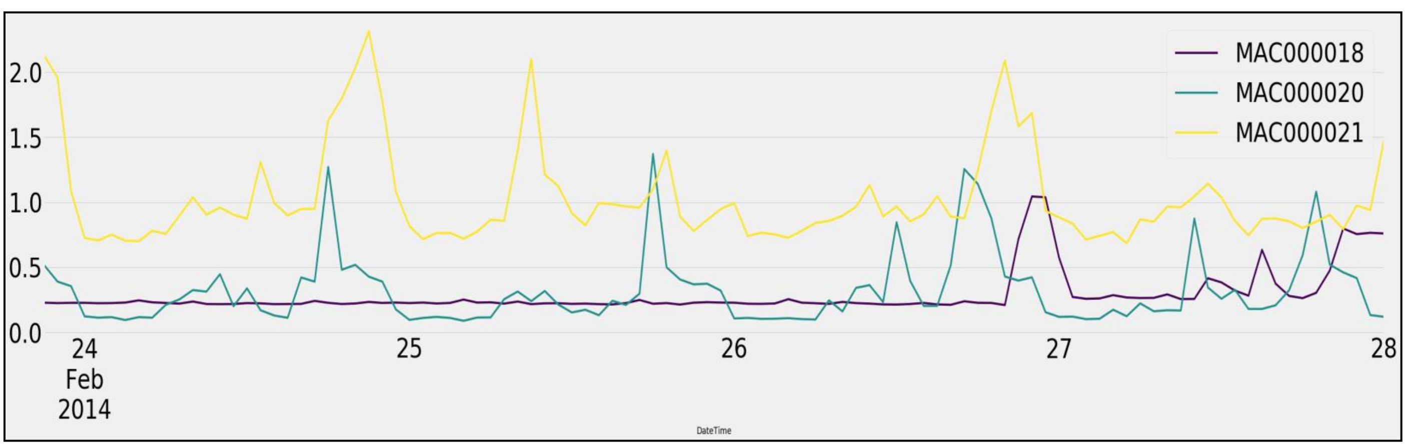
BOX PLOT House ID vs KWh



First 5 Days Plot KWh vs DateTime

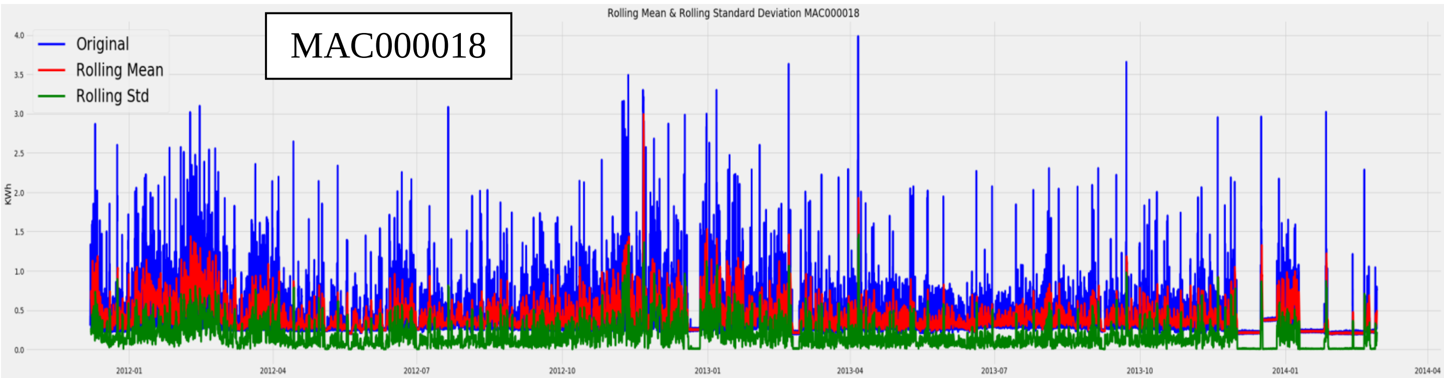


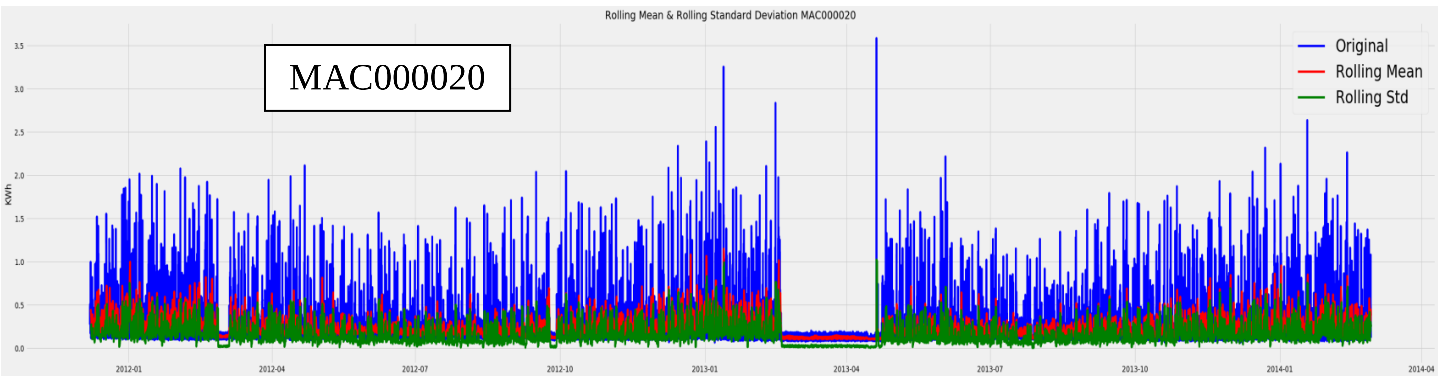
Last 5 Days Plot KWh vs DateTime

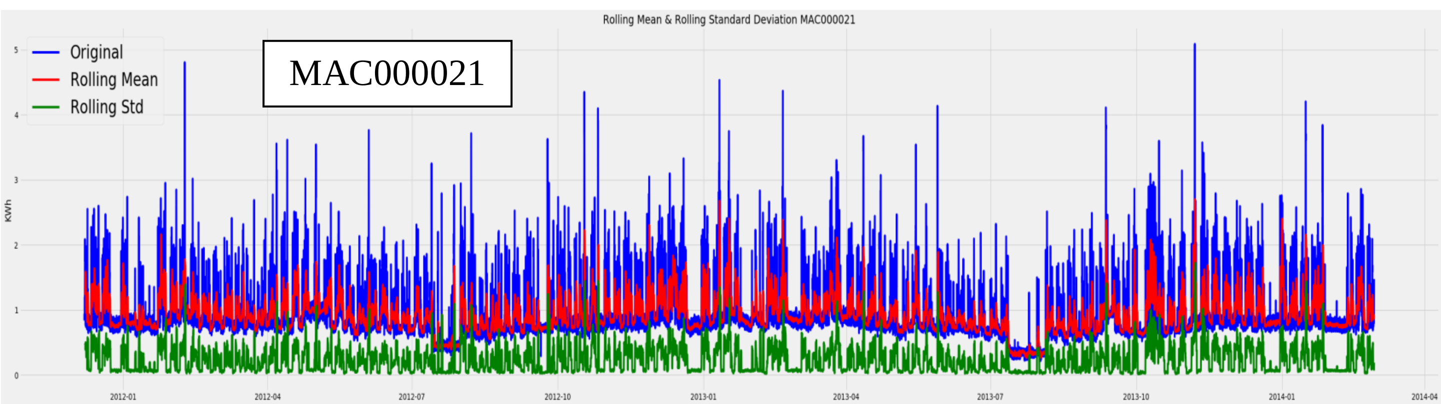


Whole KWh vs DateTime Plot

KWh vs DateTime MEAN & STANDARD DEVIATION PLOT







STATIONARITY IN TIME SERIES ANALYSIS

A *stationary* time series is one whose statistical properties such as **mean, variance, autocorrelation, etc. are all constant over time**. Most statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary (i.e., "stationarized") through the use of mathematical transformations. A stationarized series is relatively easy to predict: you simply predict that its statistical properties will be the same in the future as they have been in the past! The predictions for the stationarized series can then be "untransformed," by reversing whatever mathematical transformations were previously used, to obtain predictions for the original series. Thus, finding the sequence of transformations needed to stationarize a time series often provides important clues in the search for an appropriate forecasting model. Stationarizing a time series through differencing (where needed) is an important part of the process of fitting an **ARIMA model**.

Another reason for trying to stationarize a time series is to be able to obtain meaningful sample statistics such as means, variances, and correlations with other variables. Such statistics are useful as descriptors of future behavior *only* if the series is stationary. For example, if the series is consistently increasing over time, the sample mean and variance will grow with the size of the sample, and they will always underestimate the mean and variance in future periods. And if the mean and variance of a series are not well-defined, then neither are its correlations with other variables. For this reason you should be cautious about trying to extrapolate *regression* models fitted to nonstationary data.

Most business and economic time series are far from stationary when expressed in their original units of measurement, and even after deflation or seasonal adjustment they will typically still exhibit trends, cycles, random-walking, and other non-stationary behavior. If the series has a stable long-run trend and tends to revert to the trend line following a disturbance, it may be possible to stationarize it by de-trending, perhaps in conjunction with logging or deflating. Such a series is said to be **trend-stationary**. However, sometimes even de-trending is not sufficient to make the series stationary, in which case it may be necessary to transform it into a series of period-to-period and/or season-to-season *differences*. If the mean, variance, and autocorrelations of the original series are not constant in time, even after detrending, perhaps the statistics of the *changes* in the series between periods or between seasons *will* be constant. Such a series is said to be **difference-stationary**.

As the data we are using is having Mean, Variance and Autocorrelation being constant all over its timeline, the data is said to be **Stationary**. Also to double check the stationarity of the data, a statistical test can be performed on the data.

AUGMENTED DICKY-FULLER TEST

The Augmented Dickey Fuller Test (ADF) is unit root test for stationarity. Unit roots can cause unpredictable results in your time series analysis.
The *Augmented* Dickey-Fuller test can be used with serial correlation. The ADF test can handle more complex models than the Dickey-Fuller test, and it is also more powerful. That said, it should be used with caution because—like most unit root tests—it has a relatively high Type I error rate.

Hypotheses
The hypotheses for the test:

- The null hypothesis for this test is that there is a unit root.
- The alternate hypothesis differs slightly according to which equation you're using. The basic alternate is that the time series is stationary (or trend-stationary).

Choosing Models and Lags
Before you run an ADF test, inspect your data to figure out an appropriate regression model. For example, a nonzero mean indicates the regression will have a constant term. The three basic regression models are:

- No constant, no trend: $\Delta y_t = \gamma y_{t-1} + v_t$
- Constant, no trend: $\Delta y_t = \alpha + \gamma y_{t-1} + v_t$
- Constant and trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + v_t$

The Augmented Dickey Fuller adds **lagged differences** to these models:

- No constant, no trend: $\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant, no trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant and trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

TESTING OUR DATA WITH THE AUGMENTED DICKY-FULLER TEST

MAC000018

- (**-10.759048973499379, 2.5486015095819113e-19,** 45, 19482, {'1%': -3.430685702793611, '5%': -2.8616883686189465, '10%': -2.566848972599547}, -2844.0235449517495)
- 1st element is test statistic (-10.75):
- More negative the test statistic, more likely the data is stationary.

- 2nd element is p-value: (2.5e-19):
- If p-value is small → reject null hypothesis. Reject non-stationary.

- 5th element is the critical test statistics.
- Therefore the data is stationary.

MAC000020

- (**-12.877514154650884, 4.734810119516972e-24,** 45, 19482, {'1%': -3.430685702793611, '5%': -2.8616883686189465, '10%': -2.566848972599547}, -5771.464795964712)
- 1st element is test statistic (-12.87):
- More negative the test statistic, more likely the data is stationary.

- 2nd element is p-value: (4.7e-24):
- If p-value is small → reject null hypothesis. Reject non-stationary.

- 5th element is the critical test statistics.
- Therefore the data is stationary.

MAC000021

- (**-12.054883868739621, 2.547099857389433e-22,** 45, 19481, {'1%': -3.4306857200282006, '5%': -2.8616883762355876, '10%': -2.5668489766537537}, 5154.755395986191)
- 1st element is test statistic (-12.05):
- More negative the test statistic, more likely the data is stationary.

- 2nd element is p-value: (2.5e-22):
- If p-value is small → reject null hypothesis. Reject non-stationary.

- 5th element is the critical test statistics.
- Therefore the data is stationary.

TIME SERIES FORECAST

TYPES

1. Autoregression (AR)
2. Moving Average (MA)
3. Autoregressive Moving Average (ARMA)
4. Autoregressive Integrated Moving Average (ARIMA)
5. Seasonal Autoregressive Integrated Moving-Average (SARIMA)
6. Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors (SARIMAX)

AUTOREGRESSION (AR)

The autoregression (AR) method models the next step in the sequence as a linear function of the observations at prior time steps.

The notation for the model involves specifying the order of the model p as a parameter to the AR function, e.g. AR(p). For example, AR(1) is a first-order autoregression model.

An autoregressive model of order p, abbreviated AR(p), is of the form

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + w_t = \sum_{i=1}^{p} \phi_i X_{t-i} + w_t$$

where Xt is stationary, wt ∼ wn(0, σ2 w), and φ1, φ2, . . . , φp (φp 6= 0) are model parameters. The hyperparameter p represents the length of the “direct look back” in the series

The method is suitable for univariate time series without trend and seasonal components.

MOVING AVERAGE (MA)

The moving average (MA) method models the next step in the sequence as a linear function of the residual errors from a mean process at prior time steps.A moving average model is different from calculating the moving average of the time series.

The notation for the model involves specifying the order of the model q as a parameter to the MA function, e.g. MA(q). For example, MA(1) is a first-order moving average model.

$$X_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q} = w_t + \sum_{j=1}^{q} \theta_j w_{t-j}$$

The method is suitable for univariate time series without trend and seasonal components.

AUTOREGRESSIVE MOVING AVERAGE (ARMA)

The Autoregressive Moving Average (ARMA) method models the next step in the sequence as a linear function of the observations and resiudal errors at prior time steps.It combines both Autoregression (AR) and Moving Average (MA) models.

The notation for the model involves specifying the order for the AR(p) and MA(q) models as parameters to an ARMA function, e.g. ARMA(p, q). An ARIMA model can be used to develop AR or MA models.

$$X_t = w_t + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j w_{t-j},$$

The method is suitable for univariate time series without trend and seasonal components.

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) method models the next step in the sequence as a linear function of the differenced observations and residual errors at prior time steps.

It combines both Autoregression (AR) and Moving Average (MA) models as well as a differencing pre-processing step of the sequence to make the sequence stationary, called integration (I).

The notation for the model involves specifying the order for the AR(p), I(d), and MA(q) models as parameters to an ARIMA function, e.g. ARIMA(p, d, q). An ARIMA model can also be used to develop AR, MA, and ARMA models.

$$\Delta\hat{y}_{t-d} = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

The method is suitable for univariate time series with trend and without seasonal components.

SEASONAL AUTOREGRESSIVE INTEGRATED MOVING-AVERAGE (SARIMA)

The Seasonal Autoregressive Integrated Moving Average (SARIMA) method models the next step in the sequence as a linear function of the differenced observations, errors, differenced seasonal observations, and seasonal errors at prior time steps.
It combines the ARIMA model with the ability to perform the same autoregression, differencing, and moving average modeling at the seasonal level.

The notation for the model involves specifying the order for the AR(p), I(d), and MA(q) models as parameters to an ARIMA function and AR(P), I(D), MA(Q) and m parameters at the seasonal level, e.g. SARIMA(p, d, q)(P, D, Q)m where "m" is the number of time steps in each season (the seasonal period). A SARIMA model can be used to develop AR, MA, ARMA and ARIMA models.

The method is suitable for univariate time series with trend and/or seasonal components.

SEASONAL AUTOREGRESSIVE INTEGRATED MOVING-AVERAGE WITH EXOGENOUS REGRESSORS (SARIMAX)

The Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors (SARIMAX) is an extension of the SARIMA model that also includes the modeling of exogenous variables.

Exogenous variables are also called covariates and can be thought of as parallel input sequences that have observations at the same time steps as the original series. The primary series may be referred to as endogenous data to contrast it from the exogenous sequence(s). The observations for exogenous variables are included in the model directly at each time step and are not modeled in the same way as the primary endogenous sequence (e.g. as an AR, MA, etc. process).

The SARIMAX method can also be used to model the subsumed models with exogenous variables, such as ARX, MAX, ARMAX, and ARIMAX.

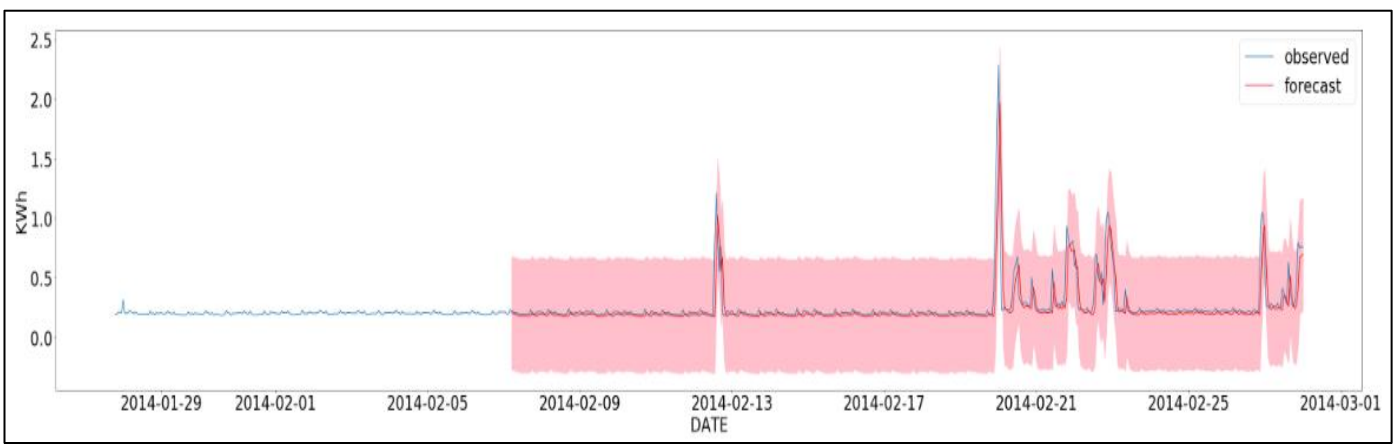
The method is suitable for univariate time series with trend and/or seasonal components and exogenous variables.

Since our data is non-seasonal and univariate without any trend, we will be forecasting using the ARMA method.

RESULTS

MAC000018

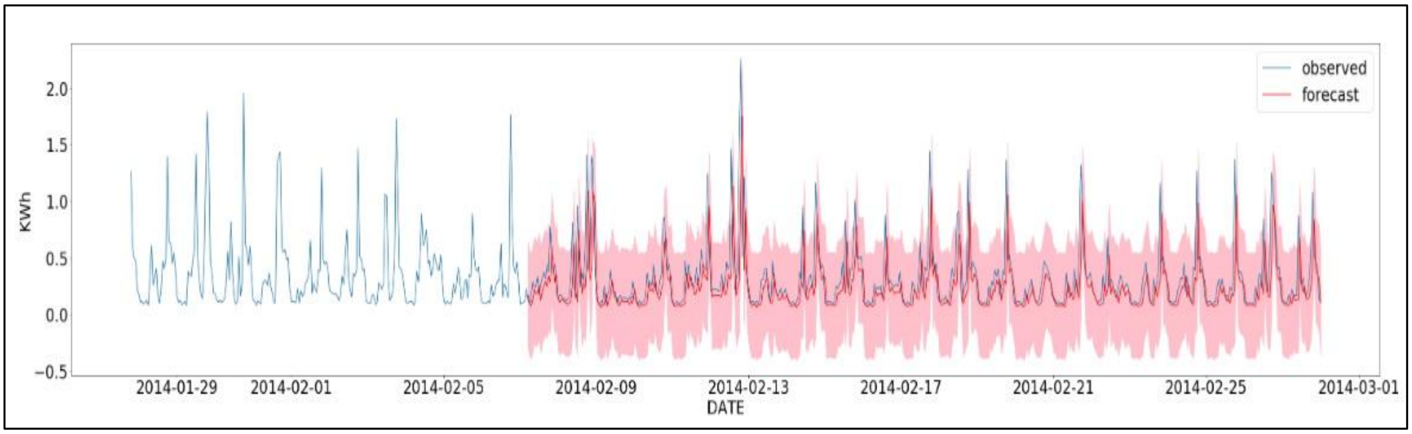
```
                           Statespace Model Results
==============================================================================
Dep. Variable:                    KWh   No. Observations:                19528
Model:               SARIMAX(1, 0, 1)   Log Likelihood                   5.664
Date:                Wed, 25 Mar 2020   AIC                             -5.329
Time:                        19:14:33   BIC                             18.310
Sample:                    12-07-2011   HQIC                             2.414
                         - 02-28-2014

Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9315      0.002    519.032      0.000       0.928       0.935
ma.L1         -0.1818      0.004    -47.653      0.000      -0.189      -0.174
sigma2         0.0585      0.000    325.972      0.000       0.058       0.059
==============================================================================
Ljung-Box (Q):                  1115.66   Jarque-Bera (JB):           343527.24
Prob(Q):                           0.00   Prob(JB):                        0.00
Heteroskedasticity (H):            0.55   Skew:                            1.47
Prob(H) (two-sided):               0.00   Kurtosis:                       23.34
==============================================================================
```



MEAN ABSOLUTE ERROR 0.12097408853300513

MAC000020

```
                           Statespace Model Results
==============================================================================
Dep. Variable:                    KWh   No. Observations:                19528
Model:               SARIMAX(1, 0, 0)   Log Likelihood                 390.571
Date:                Wed, 25 Mar 2020   AIC                           -777.142
Time:                        19:24:13   BIC                           -761.383
Sample:                    12-07-2011   HQIC                          -771.981
                         - 02-28-2014
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.7729      0.002    355.367      0.000       0.769       0.777
sigma2         0.0563      0.000    296.978      0.000       0.056       0.057
===================================================================================
Ljung-Box (Q):                     1875.11   Jarque-Bera (JB):           233113.03
Prob(Q):                              0.00   Prob(JB):                        0.00
Heteroskedasticity (H):               0.97   Skew:                            2.01
Prob(H) (two-sided):                  0.20   Kurtosis:                       19.44
===================================================================================
```



MEAN ABSOLUTE ERROR 0.12348569648741221

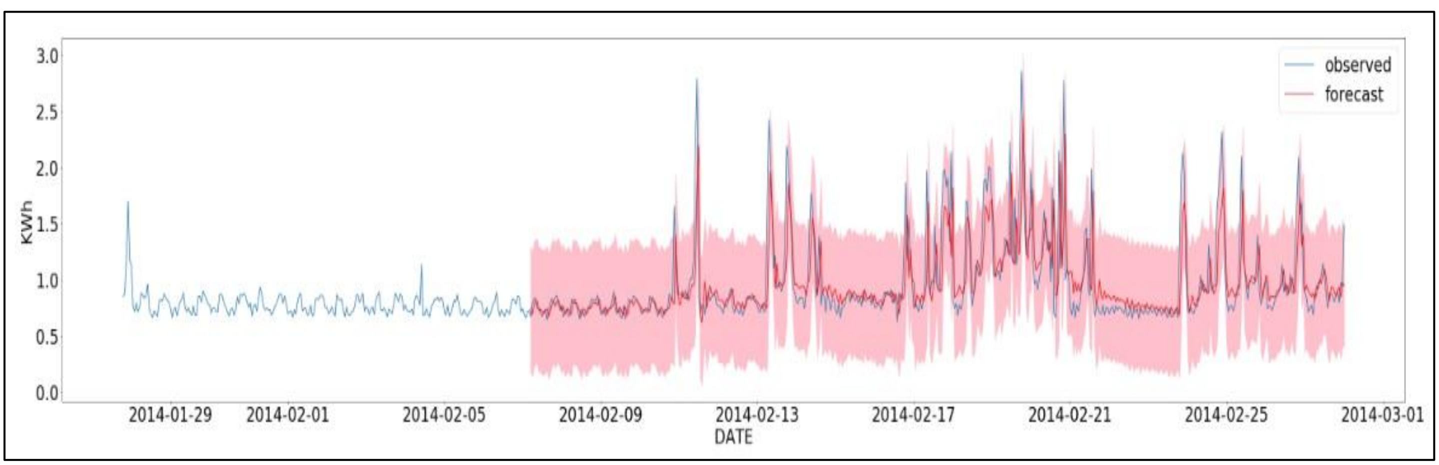
MAC000021

Statespace Model Results

Dep. Variable:	KWh	No. Observations:	19527
Model:	SARIMAX(1, 0, 4)	Log Likelihood	-3068.014
Date:	Wed, 25 Mar 2020	AIC	6148.028
Time:	19:34:41	BIC	6195.305
Sample:	12-07-2011	HQIC	6163.513
	- 02-28-2014		
Covariance Type:	opg		

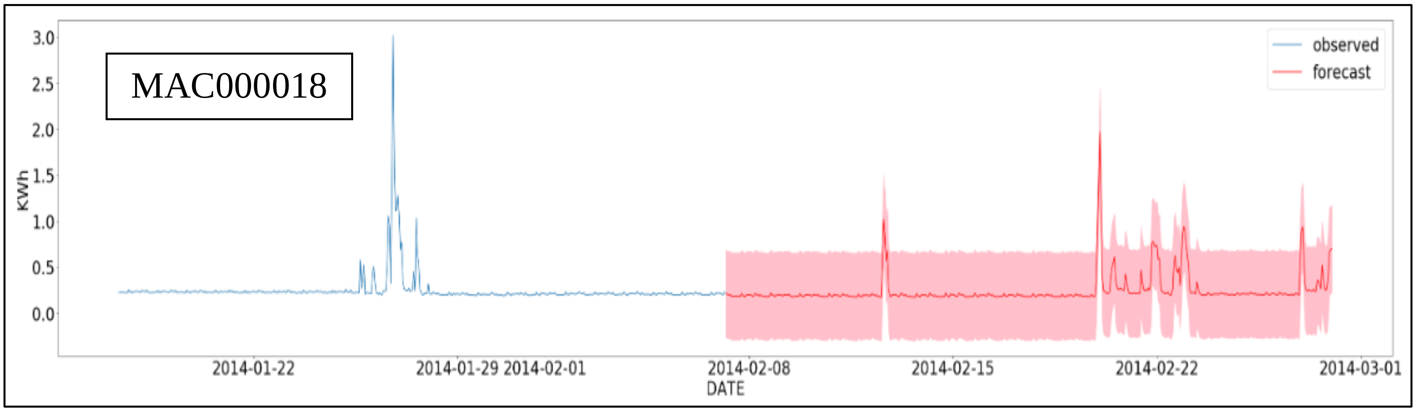
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9995	0.000	3214.765	0.000	0.999	1.000
ma.L1	-0.2698	0.004	-63.722	0.000	-0.278	-0.261
ma.L2	-0.2407	0.004	-56.806	0.000	-0.249	-0.232
ma.L3	-0.2073	0.005	-42.994	0.000	-0.217	-0.198
ma.L4	-0.1720	0.005	-33.106	0.000	-0.182	-0.162
sigma2	0.0802	0.000	213.074	0.000	0.079	0.081

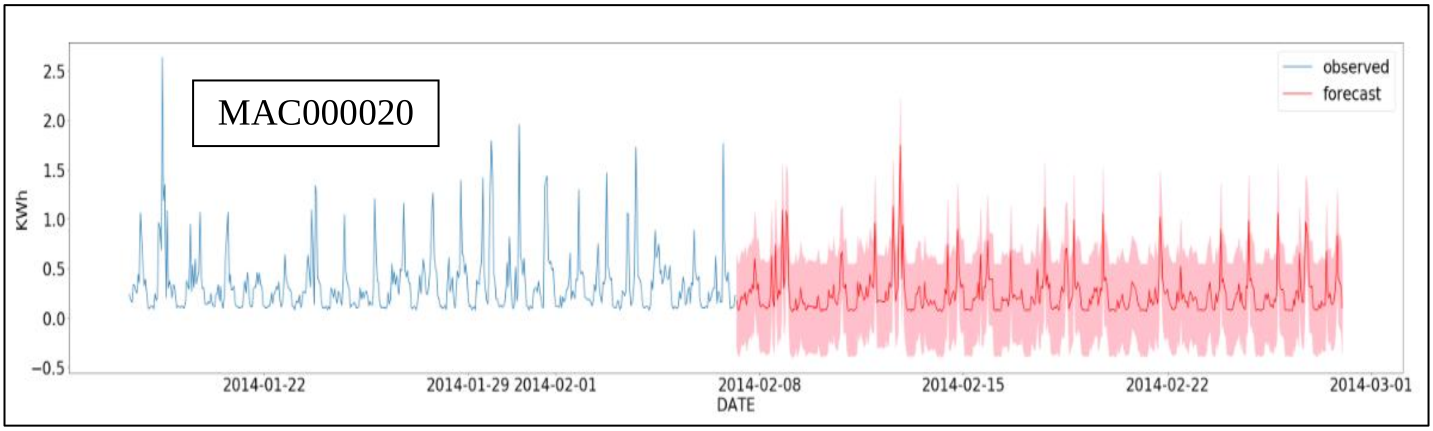
Ljung-Box (Q):	1175.02	Jarque-Bera (JB):	106053.39
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	1.01	Skew:	1.72
Prob(H) (two-sided):	0.74	Kurtosis:	13.89

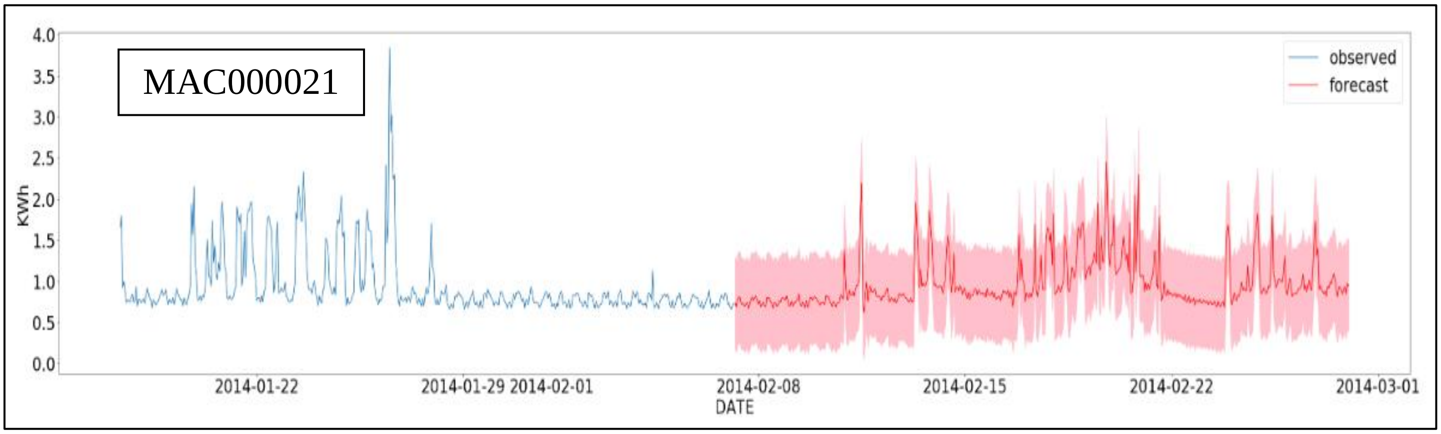


MEAN ABSOLUTE ERROR 0.1662678730275063

FORECAST OF ALL THREE HOUSEHOLDS







CONCLUSION

Energy usage of households is forecasted on an hourly basis based on the data fetched through Smart Energy Meters using Machine Learning Tools such as ARIMA and SARIMAX, using Python as programming language.

As the whole world is progressing towards Renewable Energy Sources for their production of Energy to meet their demand, in order to reduce Global Warming, production of Greenhouse Gases and also making our Earth's resources more sustainable. This project hopes to revert the disadvantage of Renewable Energy production to be reliable and predictable using this forecast of energy consumption.

This forecast provides usage to the Power Generation Corporation, for the production of required amount of Power for meeting the demand of the Consumers. It also provides an useful insight to the consumers on their usage in order to reduce the consumption of the Energy, thereby leading to Save Energy and Cost.

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