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SMART METERING SYSTEM USING AI TECHNIQUES

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Abstract- The economy of energy suppliers and countries may be significantly impacted by non-technical losses (NTLs) in the electrical distribution system, which mostly involve electrical theft. Non-technical losses include consumer dishonesty, unethical transmission line tapping, and hacking or tampering with energy meters. The smart meter, a crucial component of the smart grid, is anticipated to benefit several stakeholders on the economic, social, and environmental levels. Smart meter data analytics, which deals with data gathering, transmission, processing, and interpretation that benefits all stakeholders, is one of the crucial elements that will define the success of smart meters. An artificial neural network can be created in order to find and identify meter manipulation or energy theft. The outcomes can also be applied to larger real-world systems. Additionally, a communication network that satisfies the security requirements for smart grid communication must be properly chosen and implemented in order to deploy smart meters. This article discusses different problems and difficulties related to the development, implementation, use, and upkeep of the smart metering system.

Catchphrases- NTL, losses detection, Smart meter, Advanced Metering Infrastructure, Automatic Meter Reading, Neural Networks, Communication Systems, Energy Consumption Profiles.

1. INTRODUCTION

Anomalies of any kind (installation mistakes, meter parametrization mistakes, malfunctioning meters, or energy fraud) pose a serious issue for the utilities. They not only result in large revenue losses, but they can also have an impact on the management of the power system since they raise questions about actual usage. The electricity providers are very interested in reducing NTL because they account for a sizable portion of the overall power losses. Furthermore, since their usage accounts for roughly 55% of overall energy consumption, detecting NTL in industrial and large commercial users is of special relevance (EC). Undoubtedly, recovering substantially more money from an industrial customer's meter when an abnormality is found. [1].

It can be difficult to detect NTL using a supervised strategy because this is a very unbalanced classification problem. Naturally, a very small percentage of the world's electric supplies have any form of identified anomaly in developed nations. Additionally, as the customer samples are manually labelled by on-site inspections, human mistake is a possibility. It becomes more challenging for a machine learning (ML) algorithm to distinguish between classes when misclassified examples are included.

It can be difficult to detect NTL using a supervised strategy because this is a very unbalanced classification problem. Naturally, a very small percentage of the world's electric supplies have any form of identified anomaly in developed nations. Additionally, as the customer samples are manually labelled by on-site inspections, human mistake is a possibility. It becomes more challenging for a machine learning (ML) algorithm to distinguish between classes when misclassified examples are included. The detection and prevention of electricity power theft using AMI has not been considered, despite the substantial study on the large-scale implementation of smart meters and smart grids. Power Utilities is now working to address the serious problem of power theft. According to the World Bank, power theft accounts for up to 50% of the lost electricity in developing nations. Technical and Non-Technical losses are the two categories into which these power losses can be divided.

Unauthorized tapping of distribution lines and poles, refusal to pay bills, meter tampering and circumventing meters, official bribery, and defective meters are some examples of non-technical losses [2]. Non-technical losses are understudied, and the majority of power utilities do not keep records of these losses' data. Although even industrialised nations like the USA and UK report NTLs ranging from $1 to $6 billion [3], it is generally believed that NTLs are more prevalent in underdeveloped nations. Non-technical losses in India are thought to account for up to more than 50% of all power loss. India's power utility corporations have recorded annual losses of $4.5 billion. [4] The current artificial intelligence-based, state-based, and game theory-based methods for power theft detection employing AMI can be roughly categorised into these three categories.

1.1. AMI and Smart Meters:

Advanced Metering Infrastructure, or AMI, is recognised as the first step in the process that leads to the smart grid. It is renowned for its cutting-edge methods of electric grid-related transmission and distribution. Customers will be able to monitor how much energy they consume online using the computer application as a third party.

The AMI will have the capability to improve electricity quality. A two-way communication will be established between the smart maters and the central control stations. They can send the clients' billing information through these interactions. Individual residential loads can be controlled by the smart meter using their capacity. By the benefit of micro girds and the AMI’s network, we can possibly get the pattern of improved efficiencies and the moderating energy usage [11,12].(Figure 1: Flow of power in Advanced Metering Infrastructure).

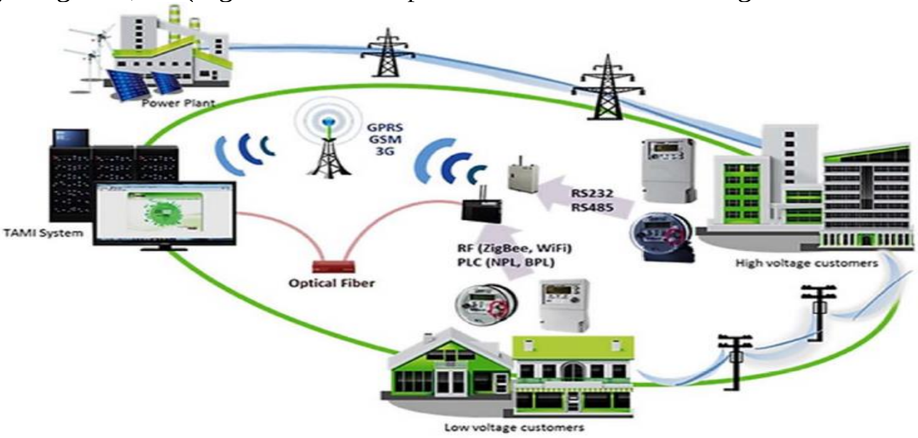

Figure 1: Flow of power in Advanced Metering Infrastructure [5]

Smart Meters record the use of the energy and then simultaneously it also sends the data back forth to the central server for the purpose of monitoring and analysis of the data. The major purposes of smart meters are to keep track of energy consumption statistics, set a reading interval, link with communication, connect and disconnect, remotely programme, and detect theft. There may be a cap on the power supply in some circumstances, and if it is exceeded by the smart meter, the electricity supply will be turned off.

Table 1: Types of Smart Meters categorized on their end user

Domestic Application	Industrial Application
Single phase/three phase, whole current counter/LCD type meters	Digital Panel meters
Dual source projection metering solutions	Digital energy meters
Special long range metering solutions	LT Tri-vector meter
Smart metering solutions	Single module meter
Prepayment metering solutions	Multi-function meter
DLMS metering solutions	Load manager and demand controller
RF/Optical port/LPR meters	Power factor control and regulators
	Prepayment metering solutions
	DLMS metering solutions
	Long range integrated metering solutions
	Net metering solutions
	Smart metering solutions

Smart meters can help the government achieve its energy management objectives. The distribution firms are currently faced with the difficulty of replacing the traditional meters with smart meters. The system is also updated using it. The largest benefit is the continuous and speedy receipt of data on energy use as well as the processing and transmission processes. The region will be able to be found and located when the distributed companies switch to smart meters, and it will then be regulated by the usage of power consumption.

The smart meter can be used to track daily energy consumption, including that of gas and electricity. It may also be able to track water consumption as well. We can lower the cost of meter reading and bill collection by utilising the smart meter. This function also helps the bill's accuracy and lowers the likelihood of error theft. The smart meter's architecture is shown in Fig. 2 and includes an energy meter, harmonic sensor, and circuit breaker. A workstation for the wireless transceiver and control system will be available. We can compute the problems with the control signals and the non-technical losses by using this workstation. The ECS will be able to manage and regulate the flow of power or the operation of any household appliances.

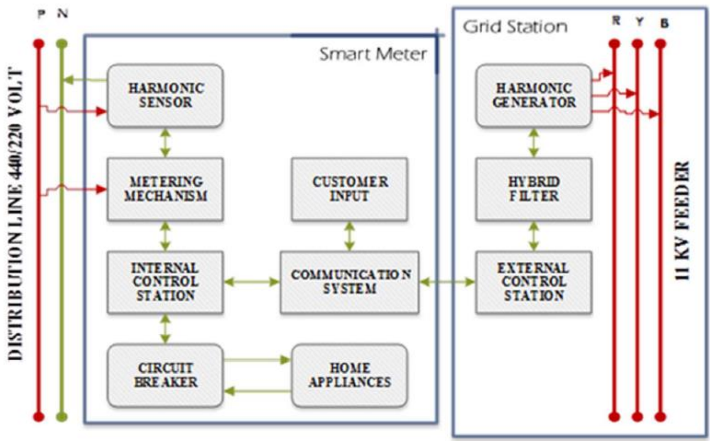

Figure 2: Model of Smart Metering Infrastructure

2. Literature Survey and Methodology Used:

2.1. AMR vs AMI:

Table 2: AMR vs AMI.

Process	AMR	AMI
Communication	One-way communication	Two-way communication
Data Collection	Monthly Data (Interval Data: 15/30 min)	15/30/60 min (Configurable) for applying dynamic pricing
Business Opportunities	Monthly consumption billing	• Consumer payment option • Pricing options • Utility operations • Demand response • Emergency response
Business Processes	Billing consumer information system	• Billing • Consumer Information system • Consumer data display • Outage Management • Emergency demand response
Consumer Participation	None	• In-home display • Demand response

2.2. Smart Meter Benefits [6]:

The smart meter benefits for the customers are:

A. If there is an outage, the smart meter will enable quicker outage detection and service restoration.

B. Customers will have more control over how much electricity they use on their own. Due to the various pricing plans that are offered to the customers and giving them more opportunities to check their electricity use and the bills received, they become available with the functions of time-based rates and the range expands.
C. Customers that receive smart meters will have access to the electricity used the day before, and usage will be tracked through the utility website.
D. By removing the need for new power plants, smart meters will benefit the environment. Utilities will refrain from using peaked plants to satisfy the increased demand since doing so would be environmentally detrimental because peaked plants often produce more greenhouse gases and other air pollutants.
E. Because information about power usage can be communicated in accordance with the automatic utility procedure of billing without on-site visits by the utility, it will increase privacy. The utility can check the meter.
F. The primary preference for a smart grid is smart metres. Every component of the sector, including production, distribution, transmission, and consumer interface, will integrate digital technology in order to use the smart grid. With the aid of the smart grid's sense, it is possible to observe what is occurring to the energy flows, maintain their balance, and subsequently increase their dependability.

2.3. Challenges faced in implementation of Smart Meters and AMI:

In lieu of redesigning the current grid, efficient grid management can be an alternate approach. The integration of the smart grid, however, represents a viable strategy for managing the current grid due to its technical benefits and improvements to operating capability. The design, implementation, and maintenance of the smart metre system, however, present numerous problems and difficulties.

Several billion dollars are needed to install and maintain the network in order to implement the smart metre technology in the distribution system. It is challenging to justify the investment. As a result, this expenditure must be achieved in proportion to the anticipated rise in energy demand and the share of distributed generation. [7].

The process of replacing the existing energy meters with a smart meter system will be a challenge for utility companies. Lack of proper infrastructure for synchronizing this new technology with the existing ones might interrupt the introduction of smart meters. Collection and transmission of energy consumption data is a continuous process that is done automatically, but it is a tedious and expense job. [8].

A smart metre and the server at the base station must send enormous amounts of data in order for the system to function. Data administration, maintenance, and storage may be a laborious task. The majority of smart metre communication networks have inadequate bandwidth, which results in excessive traffic and restricts the amount of data that can be sent. Energy consumption data transmitted through public communication networks like cellular networks might involve security risks. [7].

Smart meters are often located in open and insecure environments and need proper shelter to be physically secure. Quantification of the potential benefits is very difficult due to the lack of historical data. Future of smart metering depends on the policies of utility companies and respective governments. Figs. 3, 4, 5 illustrate various issues and challenges in design, deployment, utilization and maintenance of the smart meter system.

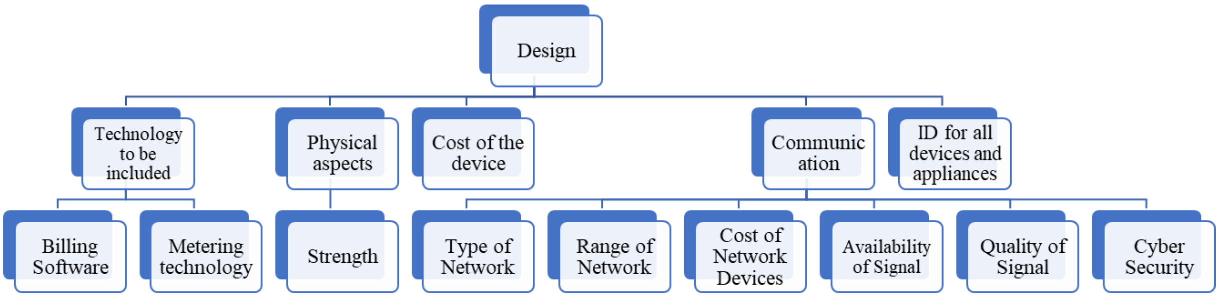

Figure 3: Design issues for a smart meter system

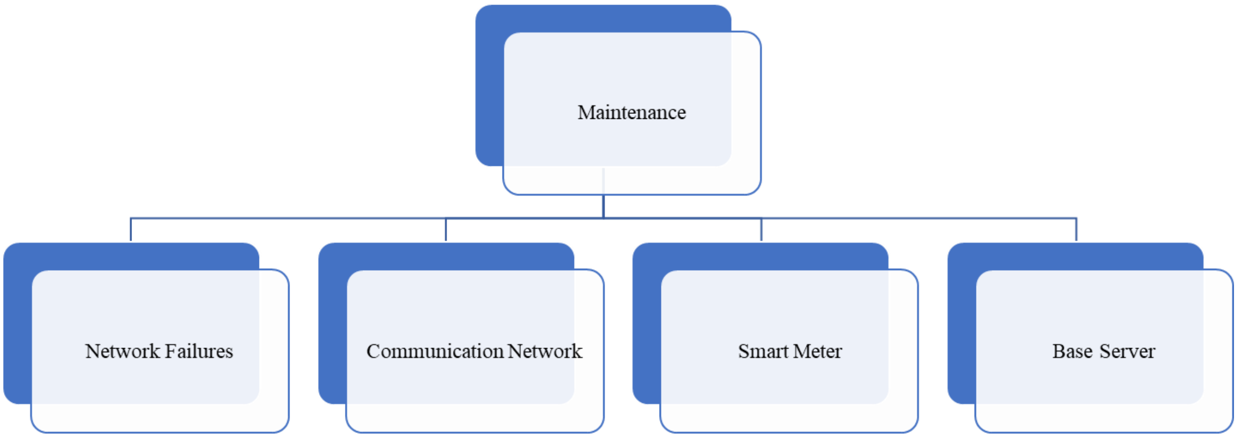

Figure 4: Maintenance Issues for a Smart Meter System

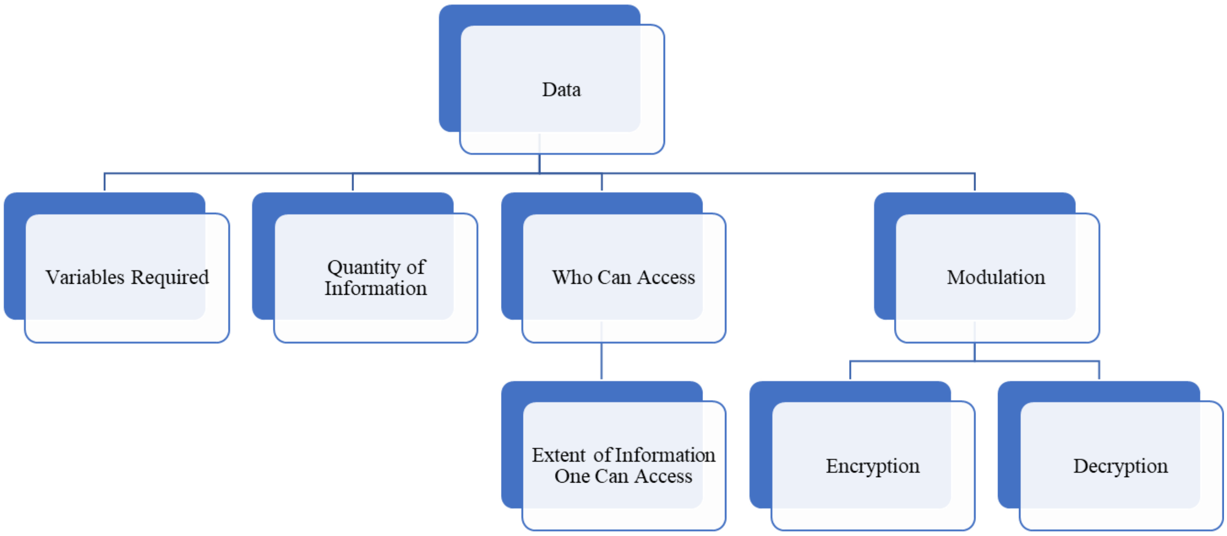

Figure 5: Challenges with data transfer for a smart meter system.

2.4. Communication technologies used in smart grid:

One of the most important achievements in smart grid is AMI system that is used to measure, acquire, and analyze the data about energy consumption and power quality of each consumer. Any SM with AMI infrastructure involves communication facility with metering devices on demand. The bidirectional communication is performed between utility supplier and consumer to improve maintenance, demand management, and planning capability of supplier [9].

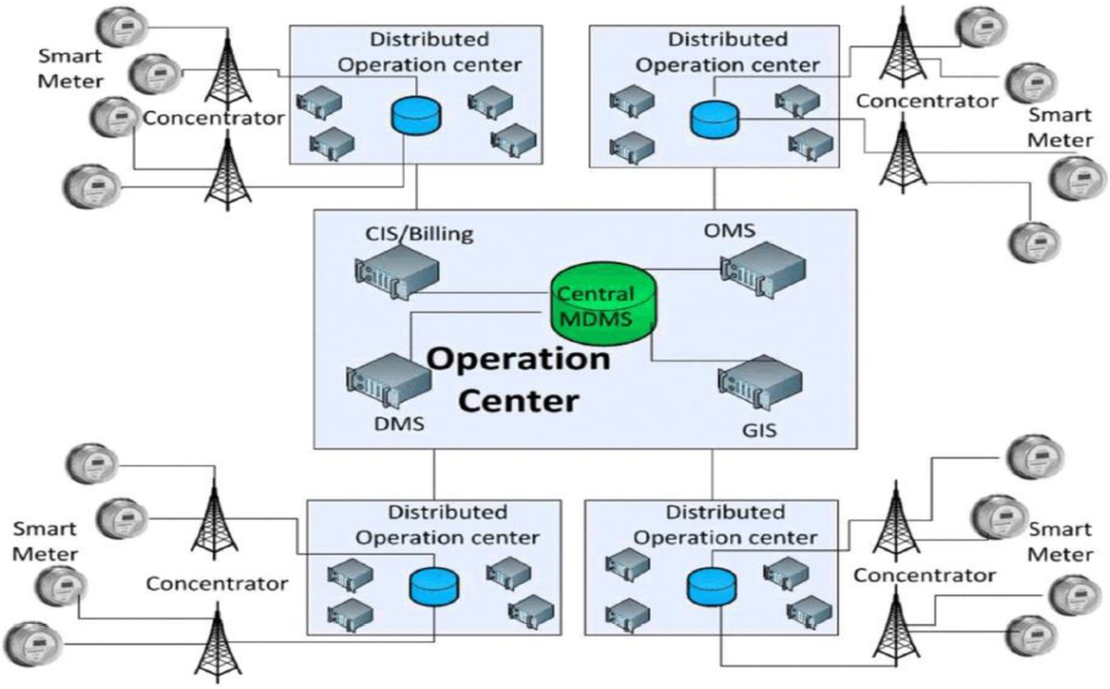

Figure 6: Distributed communication and management architecture in smart grid.

Because measured billing data plays such a major part in the smart grid, data management is one of the more crucial jobs. A metering data management system (MDMS), which handles data processing and storage, makes up the centre component. A MDMS is made up of the following components: a DMS, an outage management system (OMS), a GIS (geographic information system), a CIS (consumer information system), and an OMS (outage management system). [10].

MDMS can be viewed as a supervisor for the entire system, with responsibility for managing and forecasting power quality and load demand rates. Several distributed operation centres that are planned in the same MDMS framework as the central operation centre can be added to it. Data including utility location, usage rates, and billing information for SM and consumers must be collected using the GIS and CIS systems. [10].

The communication between operation centre and SM can be applied in several ways by using two ways such as wireline and/or wireless. Wire line communication is done by using transmission lines and widely known method is the PLC. PLC applications provide data transmission rates upto 200 Mbps for a single-phase system. It is also possible to use several wireless communication methods based on IEEE 802.22 protocol wireless regional area network (WRAN) or IEC 802.15.4 protocol that is wireless personal area Network (WPAN).

The communication architecture of the smart grid is defined by IEEE 2030-2011 standard that is important to understand applications and infrastructures at a hierarchical arrangement. The standard is intended to create a consensus on the numerous confusing descriptions by clearly indicating a logical structure for the different sub-networks. The last network type described by the standard is core network for the utility sections such as generation and transmission layers. It includes broadband communication architectures such as voice over internet protocol (VoIP) and GIS.

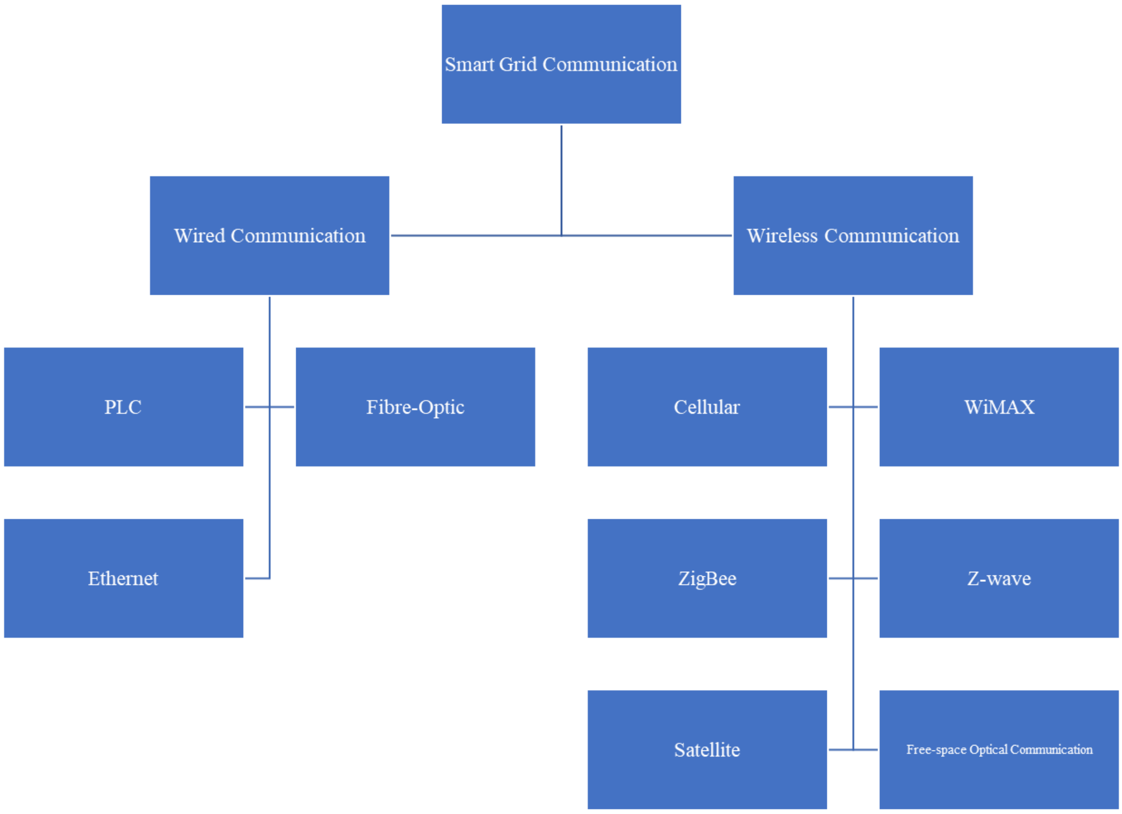

Figure 7: Smart Grid Communication Techniques

Table 3: Overview of network types and requirements [11]

Network Type	Coverage (km)	Data Rate Requirements	Data Rate	Technology Alternatives	
				Wireless	Wired
WAN	10-100	High data rate. Devices such as routers and switches.	10 MBPS – 1 GBPS	WiMAX, 3G, 4G, 5G.	Ethernet, Fiber Optic
NAN/FAN	0.01 – 10	Highly dependent on node density and topology.	100 KBPS – 10 MBPS	ZigBee, WiFi, WiMAX, Cellular	Power Line Communication
HAN/BAN/IAN	0.001-0.1	Dependent on application. Generally low data rate required.	10-100 KBPS	ZigBee, Z-wave, WiFi.	Ethernet, HomePlug, M-Bus

Table 4: Overview of wired communication technologies in SG [12]

Technology	Data Rate	Coverage	Application	Advantages	Disadvantages	Network Type
Ethernet	Upto 100 Gbps	Upto 100m	In-home communication, SCADA	Good on short distances	Coverage Limitations	Premise network, NAN/FAN, WAN
Broadband PLC	Upto 300 Mbps	Upto 1500m	SCADA, Backbone communication in power generation domain	Existing infrastructure standardized, High reliability	Noisy channel environment, Disturbance	NAN/FAN, WAN
Narrowband	10-500	Upto 3	SCADA,	Existing	Noisy channel	NAN/FAN,

PLC	Kbps	Km	Backbone communication in power generation domain	infrastructure standardized, High reliability	environment, Disturbance	WAN
HomePlug	4,5,10 Mbps	Upto 200m	In-home communication, Smart Appliances	Low cost, Low energy	Coverage Limitations, Disturbance	Premise Network
Fibre Optic	Upto 100 Gbps	Upto 100 Km	SCADA, Backbone communication in power generation domain	High bandwidth, High data rate, not susceptible to electromagnetic interference	Costly	WAN

Table 5: Overview of wireless communication technologies in SG [12]

Technology	**Data Rate**	**Coverage**	**Application**	**Advantages**	**Disadvantages**	**Network Type**
WiMAX	75 Mbps	Upto 50Km	In-home communication, Smart meter reading	Low cost, low energy	Not widespread ,Coverage Limitations	NAN/FAN, WAN
ZigBee	20-250 kbps	Upto 100m	In-home communication, Smart appliances, Home automation	Mesh capability, simplicity, mobility, Low cost, low energy	Low data rate, short range, interference	Premise network, NAN/FAN, WAN
Z-Wave	9-40 Kbps	Upto 30 m	Wireless mesh network	Mesh capability, simplicity, mobility, Low cost, low energy	Low data rate, short range, interference	Premise network
Wi-Fi	2Mbps-1.7 Gbps	Upto 100 m	In-home communication, Smart Appliances, Home automation, SCADA	Good on short distances	Security	Premise Network, NAN/FAN
3G	Upto 42 Mbps	70 Km	SCADA, Smart meter reading	Already existing network, high security, low cost, large coverage	Network shared with consumers may result in congestion	NAN/FAN, WAN
4G/LTE	Upto 979 Mbps	Upto 16 Km	SCADA, Smart meter reading	Already existing network, high security, low cost, large coverage	Network shared with consumers may result in congestion	NAN/FAN, WAN
LTE-M	7 Mbps	11 Km	Smart meter reading	Low cost, low energy, scalability,	Low data rate	NAN/FAN

				coverage		
NB-IoT	159 Kbps		Smart meter reading	Low cost, low energy, scalability, coverage	Low data rate	NAN/FAN
5G	Upto 20 Gbps		SCADA, Remote control , Smart meter reading	Low cost, low latency, high data rate, scalability		NAN/FAN, WAN
Satellite	50 Mbps		Backup, Remote location communication	Good when no other alternative is viable	High cost	WAN

2.5. Smart Metering Status in India:

There are total 10 smart grid pilot projects that are implementing by state-owned distribution utilities in India. All selected pilot Projects involve installation of Smart Meters for the purpose of reduction in distribution losses and reliability improvement. The development of smart metering system is still in the early stage. Table VI provides summary of the smart meter implementation across the country. [13].

Table 6:Overview of Smart Meter deployment in different states [13]

States	Major Utilities	Date of Award	Sanctioned Cost (Crores)	No. of Consumers
Assam	APDCL SGIA- Phoenix	Mar'15	29.94	15,083
Tripura	TSECL SGIA- WIPRO	Sep'15	24.08	42,676
West Bengal	WBSEDCL, SGIA- Chemtrols	Jun'15	7.03	5,275
Haryana	UHBVNL SGIA- NEDO, Japan	Apr'14	20.07	11,000
Himachal Pradesh	HPSEBL SGIA- Alstom	Feb'15	19.45	1,251
Punjab	PSPCL SGIA- Kalkitech	Mar'15	10.11	2,734
Puducherry	PED SGIA- Dongfang	May'16	46.11	34,000
Karnataka	CESCL SGIA - Enzen	Mar'14	32.59	21,824
Gujarat	UGVCL	July'15	48.78	39,422
Telangana	TSPDCL SGIA - ECIL	Oct'15	41.82	11,904

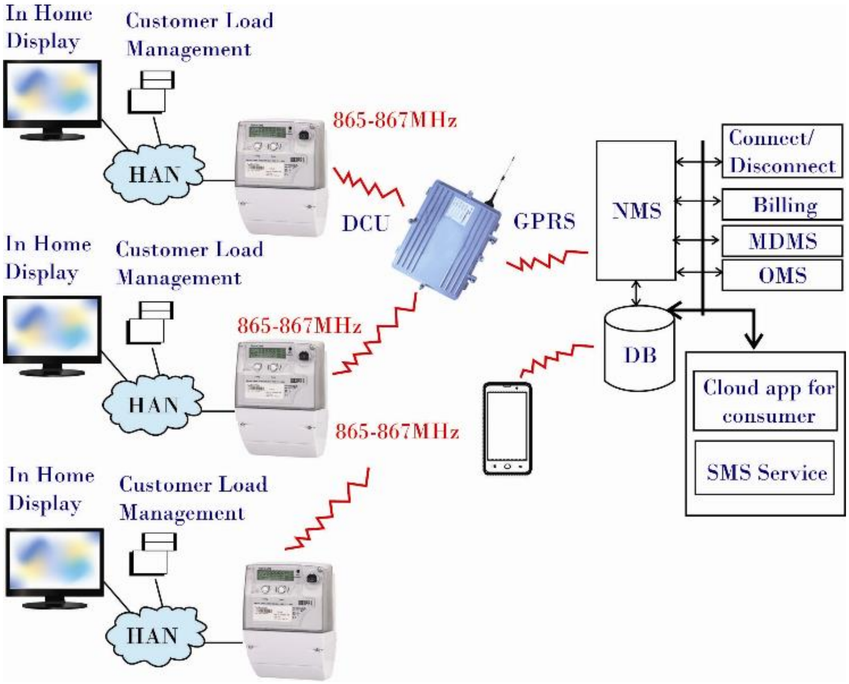

Figure 8: Conceptual architecture being deployed by the utilities

Mesh networking provides a means of connecting short-range communication to a wider geographic area. Mesh RF Technology typically operates at a frequency of 915 MHz and features acceptable latency and broad bandwidth. RF mesh technology is used to create a Neighborhood Area Network (NAN), in which data is sent from various meters to a DCU mounted on the poles. [14]

2.5.1. Key challenges for Smart Meter implementation:

Several distributed operation centres that are planned in the same MDMS framework as the central operation centre can be added to it [15]. The major challenges to be faced while implementing the smart metering technology are as follows.

- Power theft
- Lack of awareness
- Inadequate grid infrastructure
- Cyber security and data privacy
- Financial issue

Key Challenges during the pilot stage:

- Testing facilities for Smart Meters
- Interoperability Issues and Integration with existing system
- Adoption of Smart Grid Regulations
- Business Case on Smart Grid
- Skill development of utility staff

3. Neural Networks for NTL Detection:

3.1. Recurrent Neural Networks:

RNNs are a class of Neural Networks that deals with sequential data. Given a sequence of data, it holds memory of all previous computations and uses that for future calculations. Since RNNs can store memory, they have been very useful in Natural Language Processing and in Speech Recognition.

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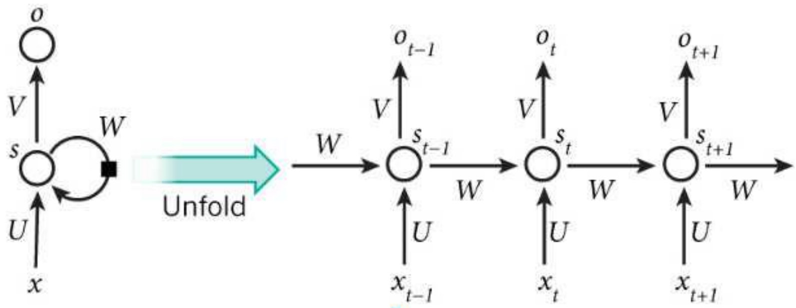

Figure 9: Framework of a Vanilla Recurrent Neural Network

The diagram above demonstrates how an RNN can be unrolled according to time steps or the quantity of sequences. For instance, the RNN can be unrolled into a 10-layer neural network if there are 10 sequences [16].

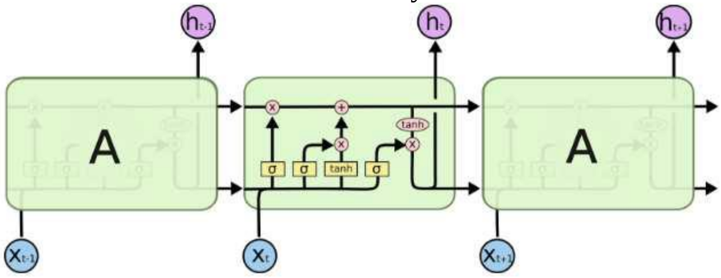

Figure 10: Long Short-Term Memory Architecture

- xt is the input at time step t. x is a vector of 6 data points which corresponds to the power consumption values for every half an hour.
- U is the weight associated with the input x. This indicates how strong the connection x is with the neuron s.
- st is the hidden state which is calculated at time step t and is responsible for the memory. Connection from the previous time step and the current time step are considered for calculating the hidden time step value.
- W is the weight associated with the incoming connection from the previous hidden state.
- The linear combination of [W × st−1] and [U × xt] is passed through an activation function to calculate the value of the present hidden state st. This function is calculated for all hidden states.
- ot is the output that is calculated by evaluating the SoftMax of st. In this case, ot will be a vector of probabilities, the highest value belonging to the class in which the predicted power consumption value lies.

3.2. Long-Short Term Memory:

A specialised recurrent neural network called Long Short Term Memory (LSTM) is capable of learning long-term dependencies [17]. The issue of vanishing and bursting gradients affects conventional RNNs. Weights in the network's early layers are updated by very small values in vanishing gradients, which causes the network to train very slowly. This is due to the fact that weight updates are inversely proportional to the gradient of the error function, and in the initial layers of backpropagation, gradients continually multiply with low activation levels, leading to further lower values. Similar to exploding gradients, it is more difficult to reach an optimal value since the gradients grow too wide and update the weight parameters by a significant amount.

$$i = \sigma(x_t U^i + s_{t-1} W^i) \quad (1)$$
$$f = \sigma(x_t U^f + s_{t-1} W^f) \quad (2)$$
$$o = \sigma(x_t U^o + s_{t-1} W^o) \quad (3)$$
$$g = \tanh(x_t U^g + s_{t-1} W^g) \quad (4)$$
$$c_t = c_{t-1} \circ f + g \circ i \quad (5)$$
$$s_t = \tanh(c_t) \circ o \quad (6)$$

3.3. Dataset [16]:

3.3.1. Sequential Dataset

Power consumption values are viewed as a collection of sequential patterns in this learning approach. The data is trained using the mathematical approach known as Sequence to Sequence Learning. The power being utilised now depends on the power that was consumed earlier because it is sequential. Future power usage figures follow the same pattern.

3.3.2. Intuition Behind Learning:

Utilizing a mathematical model that can recognise these patterns and retain some recall of the data's sequence is the aim. As soon as it has been trained, the model will accept a fixed vector of inputs and predict the best-possible value to come after the sequence. The next corresponding power output is predicted after the output is predicted, and the window of sequences is sided by one step. Once every projected value has been acquired, it is compared to actual values to identify any anomalies.

3.3.3. Data Pre-processing:

Since there was no power usage for numerous hours of that day, the dataset's original version had a large number of entries that were mostly zeros. This noise would be used to train the model. Zeros are eliminated, and outliers are substituted with the highest value determined using a box plot in place of outliers because the model is based on ideal power consumption numbers.

(1) Box Plot: A box-and-whisker plot is used to remove outliers in the data. All power values present in the database of a particular locality is taken in a single vector and sorted in ascending order. The median value is found out and is used to split the data in two parts. Using the median, the data is split and the corresponding medians are calculated for each part. These values are plotted as lower (Q2) and upper (Q3) quartiles respectively. Interquartile range (IQR) is found out by the difference in the quartiles [Q3 − Q2].The maximum value is calculated by [Q3 + 1.5 × IQR] and minimum value by [Q2 − 1.5 × IQR]. All power values lying outside this maximum-minimum range are considered as outliers. The power values above the maximum value are replaced with the maximum value itself and all power entries that contained majorly 0 are removed for better optimisation and generalisation of the model.

(2) Normalization: After data pre-processing has been performed, the data is normalised by dividing each power value by the maximum power value present in the training data.

$$Z_i = x_i / x_{max}$$

This value is the maximum value found by the box plot. The power values get squashed in the range (0, 1].

(3) Feature Adjustment: After data pre-processing and normalisation, all power values in the dataset are unrolled into a single vector. This vector is split into input-output pairs for the LSTM model. A single input will contain 6 continuous power values and its corresponding output will be the next power value in that sequence. The output is then concatenated with the input time sequence as the Tth time and the previous (T − 6)th value is removed from the input. It's output would be the next power value in that sequence. A stride of one is used to move the window over the vector. This is repeated for the entire dataset to form input-output pairs. Intervals ranging from 0-100, 100-200, 200-300, etc. are created. The output value is converted to a categorical value by mapping it to it's corresponding interval. It is then converted to a one-hot representation which is a vector consisting of 1 in it's interval index and 0 in other interval indexes. The input-output pairs are divided into training set, that will be fed to the Recurrent Neural Network for training; validation set, for choosing the optimum parameters and hyper-parameters; and test set, for determining the accuracy of the model.

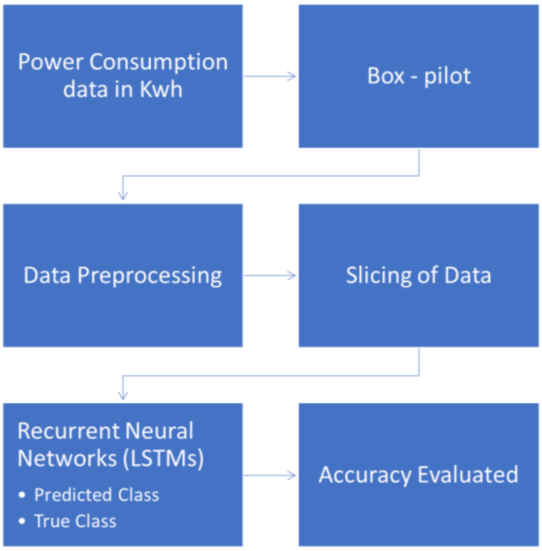

Figure 11: Proposed Model Architecture

The proposed model has LSTM layer(s), with each layer having certain number of cells. In the dataset, the rows denote data for a particular house on a particular day and the columns have power consumption values spaced at every half hour intervals. Since the architecture can model on data of a particular locality, we assume 5 households from the dataset that are in the same place at the same time.

A. Training process

1) Function Evaluation: Adam serves as the model's optimizer, and Categorical Cross Entropy serves as the loss function. When compared to Mean Squared Error, Categorical Cross Entropy performs better because Mean Squared Error places too much focus on examples that are erroneously categorised and may impede training. With a learning rate of 0.001, a fuzz factor of 1e08 and no learning rate decay, the experimental findings are optimised.
2) Experimental Values: Figure 15 shows the variation of the loss function with respect to the number of epochs. After 800 epochs, the loss function dropped to 0.5909.

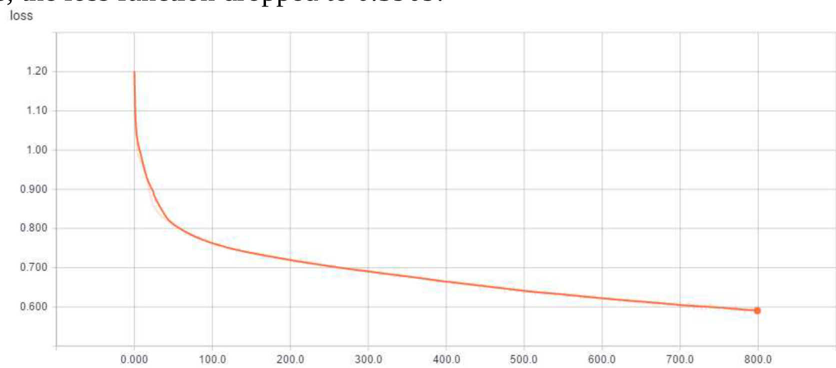

Figure 12: Training Loss vs Number of Epochs

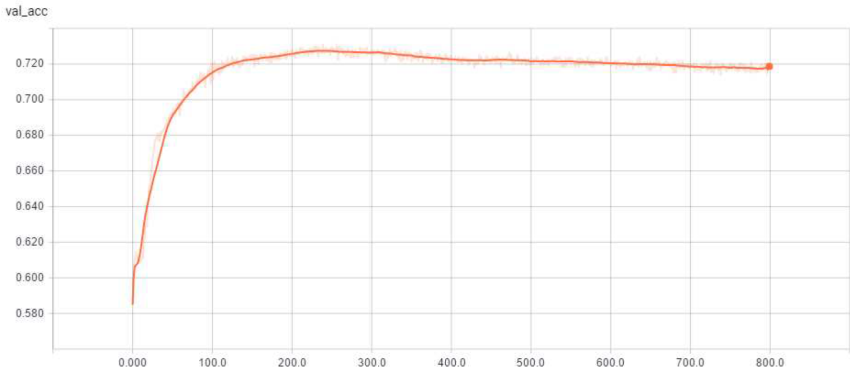

Figure 13: Validation Accuracy vs Number of Epochs

The training accuracy achieved after 800 epochs is 76.81%. The architecture that attained this accuracy consisted of two stacked Long Short-Term Memory (LSTM) units consisting of 64 nodes each. After 227 epochs, the weights are loaded and tested to give 73.45% on training accuracy and 72.93% on test data. The output that the model predicts belongs to classes 1 to 6, where each class denotes a lower bound and an upper bound value.

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