Feature Ranking for Energy Disaggregation

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Abstract - *The prominent escalation in installations of smart meters across residential and commercial building have induced interest in finding various new techniques for monitoring loads. This is primarily done to attain efficient service of quality and retrieve effective information about appliance utilization and valuable user consumption insights. The paper's literature survey demonstrates how Deep Neural Networks achieved phenomenal results by overcoming the limitations observed in Factorial HMMs. An overview was presented on the Non- Intrusive Load Monitoring Architecture along with the stages involved in this architecture. This work considers all the features implemented in energy auditing devices and it takes the number of organizations that have employed that feature in regard and finally ranks the features' significance. This constructively aids the consumers in stipulating the necessary features thereby scrutinizing his electricity bills appliance wise*

Key Words: **appliance-level, smart meter, NILM, energy disaggregation, neural networks, feature rank.**

1.INTRODUCTION

Manually reading a energy meter is contemplated to be a mundane and tedious task. After the evolution of smart energy meters traditional standard meters turned out to be obsolete due to their methodology that entails households to track their individual meter readings and finally propose them to their suppliers in order to receive accurate bills [1]. They usually deploy a secure national communication network which is called the DCC to wirelessly send your actual energy utilization readings by default to your desired supplier. It is quite unfortunate to realize that almost 39% of the energy being consumed in the domestic sector can go futile [4]. It has been showed by many studies that on providing feedbacks to consumers about their energy consumption information, energy can be saved effectively [5,6]. This renders the fact that households will no longer depend on reckoned energy bills or have the necessity to dispense their individual energy readings. The computational technique that estimates the power demanded by individual devices that have been connected to a single source meter which measures the entire power demand for all appliances as a whole is referred to as Energy Disaggregation.

In this work we performed survey on how NILM with deep neural networks established to be an efficacious technique when compared to the existing techniques. We have gathered all the features that are currently implemented by organizations that manufacture appliance-level energy monitoring devices also referred as energy auditors. On Acquisition of all the features with their respective organizations that implement those features, we ranked the features. Through this we can ascertain more prioritized features over the less significant features.

2. LITERATURE SURVEY

According to NILM researchers time and sequential data always appeared to be a prospective solution. Therefore, a higher attention was paid towards Hidden Markov Models (HMMs) by the researchers. The foremost work that was implemented in regard to HMM was in [7] , where the authors have applied Factorial HMM (FHMM) to perform the disaggregation of energy. Similarly, FHMMs were further investigated in [8] and [9]. Kolter and Johnson provided a public fundamental dataset [10] which proved to be efficacious for studies involving disaggregation of Energy. In [11] there was an application of Additive Factorial HMMs, in which an unsupervised method was used to select signal pieces with isolation of individual appliances. In [12] and [13] HMM based techniques were employed by Parson et al. where they performed an amalgamation of prior models which are for general device types like clothes dryers, refrigerators. Etc. Recently a new technique was being introduced in which both HMMs and Factorial HMMs were utilized to model appliances' load marks and a superimposition of these. This new method was called as Particle Filter Based Disaggregation of Load. A new system of electrical load disaggregation was proposed by Paradiso et al. in [14]. In this method FHMMs were utilized and investigation was done on context-based features. The representation of context data was in the form of power patterns and user presence. An unsupervised method for disaggregation was employed by the authors in [15], which was in regard to the communications between appliances which were framed using FHMM and Viterbi algorithm was deployed to implement the inference.

We have seen that, strategies that involves variations with HMM have gained much attention, but the underlying fact is that none of these models had the ability to overcome the main obstacles that incurred. The reason that made it complex to infer is that the number of the discrete state space augments was directly proportional to the complexity of the HMM based strategies.

Recent studies have manifested that in sequential models' phenomenal results can be achieved by deploying deep neural architectures. On endeavouring to find a solution of power decomposition, Kelly and Knottenbelt employed deep neural networks [3]. The authors presented three different proposals

(a) Denoising autoencoders were implemented to reduce noise;
(b) A regressive design to determine beginning time, ending time and each individual appliance's power request;
(c) Application of a specific RNN deploying LSTM nodes. In [16], a presentation of a well-defined deep recurrent network architecture with LSTM was performed by the authors whose main goal was to circumvent the issues that were incurred in the NILM strategies that were used previously. This solution had a criterion that each and every home device must have a linked network. Due to this reason the authors employed three networks because there were three appliances as target.

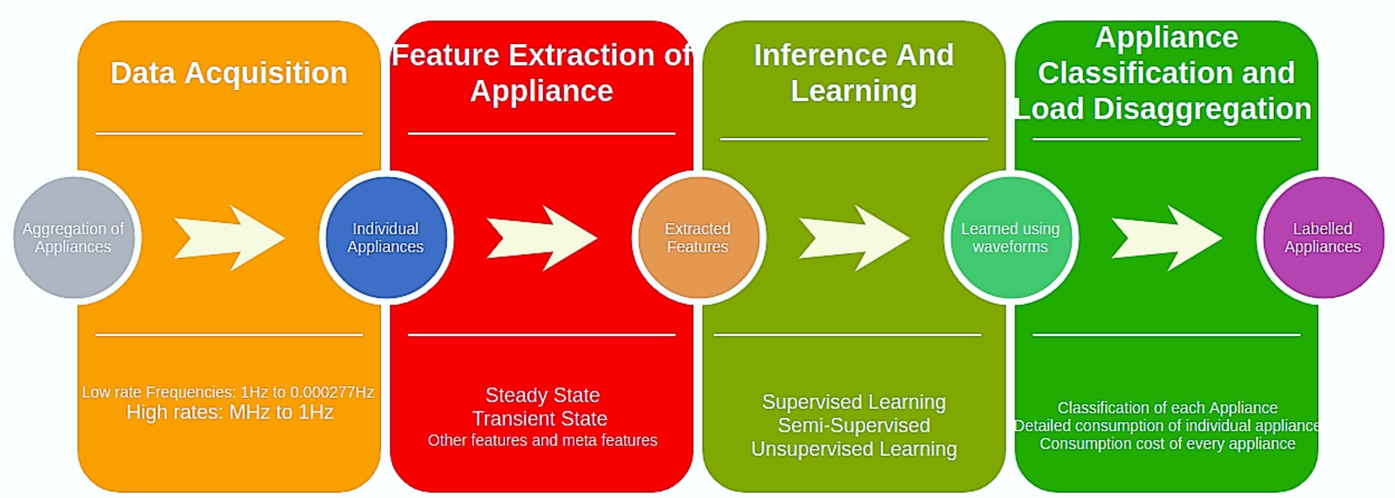

Fig -1: General Pipeline of NILM

3. NILM TECHNOLOGY

The kind of appliances that are being connected and the amount of energy they consume in an interval of time can be inferred by non-intrusive load monitoring approaches just by installing a metering device at the location. The paramount reason to use NILM techniques over the other techniques are primarily because of its less expensive and easy installation service, since only one metering device is being used for each energy entrance to the building instead of having one or more metering device for each room. Energy Disaggregation is assessed to be a computational technique in order to estimate the demand of power for individual appliances all connected to a single meter source that measures the comprehensive demand across several appliances.

The stages involved in the NILM Architecture are:

3.1 Data Acquisition

Procurement of data is done in three categories. First involves Measurements of basic parameters such as: Current(A), Voltage(V), Apparent Power(S) which is the product of current by voltage. The Second Category of Data being obtained involves the other measurements that are derived from the previous Measurements which are: real power also called average power (P) is the net transference of energy without taking the direction into consideration, power factor (PF), {(P/S) or cos(Θ) where Θ is the angle between voltage and current} the ratio between the real power and apparent power, reactive power (Q, measured in volt-ampere-reactive or VAR), which is the rate at which energy is stored and then delivered by inductors and capacitors. The third category involves other advanced measurements such as harmonic distortion [17], electric characteristic, electromagnetic interference (EMI) and transients. Eventually the energy consumed is the amount of power utilized over the time (Measured in kWh kilowatt-hour).

3.2 Feature Extraction

In order to detect appliance state transitions the features that are extracted are categorized into three major categories:

1) **Steady state:** Features which are derived from steady state operations of a device. Usually variations [18] in Reactive Power and Real Power are considered in order to detect varied state event operations of devices.
2) **Transient state:** Features Being derived from the operation of an appliance in transient state. They are less overlapping between devices when analogized to steady state features. Features such as transient response time, current spikes, repeatable transient power profiles, spectral envelopes, etc. come under this category.
3) **Non-traditional:** Features that refer to other new characteristics which are generated as the result of the other two kinds of characteristics or other such as on/off distribution, time of the day, use frequency of an appliance and the correlation of usage of multiple appliance.

3.3 Inference And Learning

The extracted features are now deployed to determine the appliances which are running at a particular time. The methods used can be both Supervised as well as Unsupervised or Semi-Supervised.
1) **Supervised**: It can be an
a.) Optimization Approach in which the features extracted are compared in order to explore the load features loaded in the database so that it can find the closest match possible b.)Pattern Recognition Approaches include the basic clustering approach like Hart [18], SVMs to classify the basic harmonic features and ANN [19] that manifested to have a great performance because of their capability to introduce state change and temporal information.
2) **Unsupervised**: These approaches require no pre training or information to be stored in the database. Due to their cost-effective, non-intrusive nature and short phase time to train for load identification algorithm they entice most of the companies.

3.4 Appliance Classification and Load Disaggregation

This is the rearmost phase in the NILM pipeline, after the completion of identification of the load phase, division of the entire consumption among the detected loads is necessary.

4. FEATURE CLASSIFICATION

After having listed the features provided by all the Energy Monitoring companies. The features provided by these smart energy meters from their respective companies have been categorized into three major categories. First category consists of all the features which is implemented by 4 or more companies, Second Category refers to the features provided by two or three companies and finally the Third category lists all those features provided by just one company thereby making the feature Unique to that particular Enterprise.

A. The most prioritized features are the ones that are deployed by 4 or more companies. Due to the high frequency of companies implementing these features, their importance in the market has raised significantly. These features are shown in Fig- 2:

- Provision of a Web Application and a Mobile Application to its consumers, so that it's easy-accessible and they can remotely glance through their meter bills at a particular instant and scrutinize their readings carefully.
- Historical Data Analysis must be provided to the consumer to make them ensure that they have a consistency in their energy consumption and also they can compare their current usage with the past utilization and reduce the energy bills.
- Custom Notifications for appliance level: Data processing is One of the brilliant advantages of an enterprise-grade IoT platform. It not just performs collections of data in a centralized manner from diverse source, but also configures consumer notifications and alerts them when necessary, it also sets up custom visualization dashboards.

- Assistance in Setting and Tracking Goals: It must let the users to set the goals that is energy conserving in nature and also monitor their usage as per their set goals whether they are using it as per the target or is there any deviations in the goals being set.

Features	Companies
Web App	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On,Green Turn Labs
Historical Data Analysis	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On,Green Turn Labs
Identifies Always ON Loads	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On,Green Turn Labs
Custom Notifications for appliance level	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On,Green Turn Labs
Mobile App	Sense,Smappee,Neurio,Curb,Eye Dro, Switch On, Green Turn Labs
Training & Collecting Model of the devices manually	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On
Identify Energy Hogs of appliances	Sense,Neurio, Bidgely,Eye Dro,Switch On, Green Turn Labs
Set and Track Goals	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On
Setup Billing Information	Sense, Bidgely,Eye Dro,Switch On, Green Turn Labs
Email Notifications & Monthly Reports	Sense, Bidgely,Eye Dro,Switch On, Green Turn Labs
OTA Upgrade	Sense, Smappee,Neurio, Curb, Eye Dro
Supports Three Phase	Smappee,Neurio, Bidgely, Eye Dro, Green Turn Labs
Load Management with Solar & usage	Sense,Smappee,Neurio,Green Turn Labs
Detects Energy Guzzlers	Sense,Smappee,Switch On,Green Turn Labs
Transfers data to the Cloud using WiFi	Sense,Smappee, Neurio, Eye Dro

Fig- 2: Category 1 Features

- Identification of loads that are always turned on is a very important feature that helps consumers to save their appliances and energy in a great amount.
- OTA Upgrade: On the Air Update proved to be proficient to fix the bugs in the software for the OEMs and in the updation of their software rather than manually updating it for each individual appliance deploying the software. Thereby this saves Money and time and also mitigates the Quality Assurance as well as the Software Development Process.
- Detects Energy Guzzlers.: Identification of energy Guzzlers proved to be significant for practical usages. This is primarily done to detect those appliances that consume huge amount of energy than that it was meant to consume. This is done to economize the electricity bill and also prevent disasters if the appliance is present in a vulnerable site and goes faulty.

B. The second most prioritized set of features are the following and they are implemented by 2 or three companies. These features as shown in Fig- 3 include:

Features	Companies
Interactive and customized graphs	Bidgely, Eye Dro, Green Turn Labs
Delete unused devices or report a problem	Sense,Smappee,Green Turn Labs
Bench Marking of Appliances	Sense,Switch On, Green Turn Labs
Data Export	Sense,Smappee,Neurio
Slab Rate Management	Sense, Bidgely,Eye Dro
Power events(Brown-outs, Blackouts Surges)	Sense, Bidgely, Switch On
Electrical problems (Tripping circuit, breakers, Flickerin	Sense, Bidgely, Switch On
Performs its disaggregation through meter data alone	Bidgely, Eye Dro, Green Turn Labs
Peak Temperature, Low Temperature	Eye Dro, Green Turn Labs
KWh Consumed, Kwh Generated	Eye Dro, Green Turn Labs
Demand ,Peak Voltage, low Voltage	Eye Dro, Green Turn Labs
Predict equipment failure at early-stages	Switch On, Green Turn Labs
Deep Neural Network used for predictive maintenance	Switch On, Green Turn Labs
Data access is available through Software, Cloud API,	Neurio, Eye Dro
Vacation detection	Bidgely, Eye Dro
Provides training through Skype	Smappee,Bidgely

Fig- 3: Category 2 Features

- Deletion of unused devices or Report an Issue: Companies such as Sense, Smappee and green Turn Labs have the feature to identify the appliances that have been idle for a long time and deletes the unused devices. They identify the idleness through their visualizations that they provide. In certain cases deletion of devices isn't permitted in which they report the issue to the user. Bench Marking of Appliances: A process that involves choosing the best companies for the product and then data is collected on their internal performance so that comparison between both the organizations is done in order to identify the gaps present in the company. This is done mainly to adopt policies and processes that enhances the position of the company in the market ranking.
- Data Export: A operation that exports reports or session data for long term storage. To a session archive solution, it appears to be an integral data as the exported session data through data export can be used to settle debates and dissension with customers.
- Slab Rate Management: It must maintain the consumers usage by prompting the users with regard to the next slab rate. By implementing this it ensures that the customers don't receive undesired bills and are completely aware of their usages and meter readings.
- Vacation Detection: When users are out of place it detects their absence with smart techniques such as Noise Monitoring or Appliance Usage monitoring. This prevents energy from being wasted unnecessarily and failure of appliances.
- Predictive Equipment Maintenance:
  A maintenance strategy that evaluates an appliance performance by monitoring it. After capturing the information from the device, it senses the areas that needs attention. Thereby we can prevent failures from occurring and increase the cost savings.
- Identification of Power Events: Brownouts are detected in which the voltage is reduced that can result in an unexpected behaviour in the appliance such as a motor running in its reverse direction.

C. The third category of features involves those that are used by just one organization. They are unique to the firm as shown in Fig- 4 and are implemented in that firm individually. They are:

- Log of Instantaneous values: It displays all the values of energy or power consumed by each appliance at a particular instant of time in the cycle. It also displays the average value which gives the average value of all instantaneous values during one alteration.

- Data is Highly secured: The data is stored in the Cloud that makes it highly secured. Encryption lies in the front line of defense. It is most preferable for data security as without the accurate decryption key its impossible to decipher the content. Cloud provides services in addition to storage such as backup and restoration of data.

Features	Companies
Log of instantaneous values	Smappee
Secures data and highly private	Smappee
Identify homes with a high potential to electrify appliances, and their potential effect on peak loa	Bidgely
Quantify the effect of solar production on transformer and substation peak load	Bidgely
Does not rely on meter type	Bidgely
Neurio uses weather data, combined with each home's historical solar generation to build its da	Neurio
Neurio forecasts peak demand and ensures the battery is sufficiently charged to handle it	Neurio
Considers all aspects of a Time Of Use bills when managing the battery, including Zero Export	Neurio
Instant glimpse of their energy generated from solar,	Neurio
Hourly, daily, monthly and yearly power consumption patterns Appliance usage characteristics Projected usage	Green Turn Labs
Detailed insights about Carbon Emissions	Green Turn Labs
Scalability and interoperability acheived through open APIs for interactions between customers	Switch On
End-to-End Enterprise-grade security implemented through HTTPS/SSL/HSTS/PKC	Switch On
Big Data Capability with Complete Industrial IoT cloud architecture capable of handling more th	Switch On

Fig- 4. Category 3 features

5.EXPERIMENTATION

Weighted Scored Ranking Method

Step 1: Now Since we have three different categories of features, we weight each category along with the frequency of the company appearing in that category.
Since Category 1 has the highest priority, it has the maximum weight W1. Similarly, we have W2 and W3.
Keeping the condition,

$$\sum_{j=1}^{n} w_j = 1$$

Where w_j is the weight of the j^{th} category and n is the number of categories.
So we assign W1 with the highest value 0.6, W2 with 0.3 and W3 with 0.1.

Organization	Weight	Weighted Score
Sense	14W1 + 6W2	10.2
Eye Dro	13W1 + 7W2	9.9
Green Turn Labs	11W1 + 9W2 + 2W3	9.5
Bidgely	10W1 + 7W2 + 4W3	8.5
Switch On	11W1 + 5W2 + 3W3	8.4
Smappee	12W1 +3W2 + 2W3	8.3
Neurio	12W1 +2W2 + 4W3	8.2
Curb	5W1	3

Fig- 5: Weighted Score values for Organizations

Step 2: For the Organization Sense, we have 14 features in Category 1 and 8 features in Category 2

$$\sum_{i=1}^{n} x_i w_i$$

where w_i is the weight of a particular category and x is the frequency of features appearing in that category.
The Weighted Score of Sense is 14W1 + 8W2, which is 10.8
Similarly, we calculate the Weighted score values for all the companies as shown in Fig- 5.

Step 3: Now we check each feature and look for the occurrence of a particular company for that feature, if the company is present in the corresponding companies list indicating that the feature is implemented by that company, then we add it to find the Score for that feature. Similarly we do it for all 47 features and calculate their scores. Based on the scores we Rank the features as shown in Fig- 6.

Features	Companies List	Weighted Score	Rank
Web App	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On,Green Turn Labs	66	1
Historical Data Analysis	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On,Green Turn Labs	66	2
Identifies Always ON Loads	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On,Green Turn Labs	63	3
Custom Notifications for appliance level	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On,Green Turn Labs	63	4
Mobile App	Sense,Smappee,Neurio,Curb,Eye Dro, Switch On, Green Turn Labs	57.5	5
Training & Collecting Model of the devices manually	Sense,Smappee,Neurio,Curb,Bidgely,Eye Dro, Switch On	56.5	6
Identify Energy Hogs of appliances	Sense,Neurio, Bidgely,Eye Dro,Switch On, Green Turn Labs	54.7	7
Set and Track Goals	Sense,Smappee,Neurio,Bidgely,Eye Dro, Switch On	53.5	8
Setup Billing Information	Sense, Bidgely,Eye Dro,Switch On, Green Turn Labs	46.5	9
Email Notifications & Monthly Reports	Sense, Bidgely,Eye Dro,Neurio, Green Turn Labs	46.3	10
Supports Three Phase	Smappee,Neurio, Bidgely, Eye Dro, Green Turn Labs	44.4	11
OTA Upgrade	Sense, Smappee,Neurio, Curb, Eye Dro	39.6	12
Transfers data to the Cloud using WiFi	Sense,Smappee, Switch On, Eye Dro	36.6	13
Detects Energy Guzzlers	Sense,Smappee,Switch On,Green Turn Labs	36.4	14
Load Management with Solar & usage	Sense,Smappee,Neurio,Green Turn Labs	36.2	15

Fig- 6: Ranks obtained by top features

6.CONCLUSION

Through this Survey we find out that certain features such as Ranking similar appliances based on their energy consumption are yet to be implemented. By reviewing each organization's energy monitors in detail and performing technical online survey we made a comparison between 8 products based on 47 different features and finally based on the score we rank the features. Thereby, we deduce that Provision of a Web Application and Performing Historical Data Analysis proves to hold the highest ranks because without these features performing energy disaggregation would be ineffective. Similarly we can perceive the features such as Big Data Capability with Complete Industrial IoT cloud architecture which is capable of handling more than 100 million events provided by the organization 'Switch On' and Providing Detailed insights about Carbon Emissions by 'Green Turn Labs' as low rank features because they are optional with low ranks.

7. FUTURE WORK

Our survey is solely based on the existing major energy auditing companies. There are a lot of evolving companies that are yet to launch their product into market. The accuracy of the ranks can further be increased by getting more information about the new companies that are yet to gain their recognition in the market. More product features can be taken into consideration in order to enhance insights on consumer's necessities.

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