2017 International Conference on Data Management, Analytics and Innovation (ICDMAI)
Zeal Education Society, Pune, India, Feb 24-26, 2017

Electric Vehicle Charging LoadFiltering by Power Signature Analysis

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***Abstract*—With the more increase in population which is leading to rapid fossil fuel depletion and adding more pollution into environment, there will be more demand of Electric Vehicle in the future and with the more EV's going to come on road having old power distribution infrastructure it will bring charging problem of EV. Home charging of EV will bring overloading of transformer thus producing adverse effect on smart grid. In such conditions monitoring of EV charging plays a vital role in EV charge Scheduling and to monitor the power loading pattern of different houses under a transformer while EV charging by monitoring the smart meter. In this paper by Non-Intrusive load monitoring (NILM) an algorithm is developed that will disaggregate EV charging load and kWh consumed by EV from the aggregated power signal (real power in watts) of many appliances. This algorithm can also identify EV in presence of other high wattage appliances. Advantage of this algorithm is that it even works with low sampling rate of per second data (1/60 Hz) and can be easily trained with the area specific EV charging known database thus giving high estimation accuracy. This algorithm is checked on a monthly data of a house giving accuracy of more than 90 percentage with the output information of how much kWh energy has been consumed by EV and the mean square error only 0.05 in disaggregating EV charging load.**

Keywords—Non-intrusive load monitoring (NILM);Power Signature; Electric Vehicle; Aggregated Power; Disaggregation; Smart Meter; Smart Grid.

I. INTRODUCTION

To implement smart energy-efficient behavior in household NILM is a powerful tool thus providing feedback on electricity consumption of appliances. These feedback has demonstrated to be impressive in energy management when it is detailed acquired and provided in a timely manner. Utilities having the energy consumption data of appliances help their costumers save electricity by giving individual appliance power consumption information as a service to their customers. With the help of sensors that monitor the consumption of individual appliance in the household, the data desired to provide such information can be obtained.

Non-intrusive load monitoring (NILM) is a powerful approach to identify appliance level electricity consumption from aggregated consumption data of households.

With the depletion of fossil fuels there will be more demand of Electric Vehicle in the future and with home charging EV entering the market makes Electric Vehicle charging load in future is going to become a more important load element for smart grid analysis[4]-[6]. As the number of EV's are growing day by day stepping towards greener future but it will produce impact on our existing distribution system, which is not designed taking into consideration of upcoming EV charging load in the future. However the gravity of this impact depends on time, duration of charging, level of charging, rate and season in this EV are charged [7]. Therefore tracking of EV charging load is the most urgent and important part of energy disaggregation.

Tracking EV charging load will also help in providing the house owner the actual energy consumption by EV. This feedback will help EV owners to manage EV charging to save energy as well as utilities can attract EV owners to charge their EV in off peak hours by giving discount and other offers to avoid overloading of transformer thus it will also play a vital role in charge scheduling.Many Algorithms are there for the energy disaggregation taking into consideration various residential loads like Weiss algorithm, HMM[4].

But there is no such algorithm specially designed for tracking EV charging load. Therefore a special Algorithm for tracking EV charging is needed giving all the energy related information of EV charging to save distribution system for non-marginal impact of EV charging load.

In this paper an algorithm specially designed for tracking EV charging load is presented. This algorithm can identify EV charging even in the presence of other high wattage appliances which is very important for load management during peak load hours. With upcoming new EV's and new battery technologies this algorithm can be easily modified to track EV charging.

Algorithm runs even with data sampled at 1/60 HZ(i.e. one sample a minute) which is the data extraction capability of many smart meters.

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II.CONCEPT AND DEFINATION

A. Power Signature

PS can be characterized as the electricalconsumption behaviour of respective appliance when it is in operation [4]. As each human is identified with their unique signature similarly each electrical device contains unique features in its consumption behaviour. This behaviour depend on what variable we monitor at the smart meter or any other point if interest. This variable can be Voltage, Power or Current.

Themathematical equation for PS of an appliance can be defined as-

$$\Psi\text{i}(\text{t}) = f_{i,1}\,(V\,,t), f_{i,2}(V,t), \ldots\ldots f_{i,M}\,(V,t)|\Delta t = T \qquad (1)$$

Where V is electrical measurement w.r.t time.
f(V,t) is the feature derived from V
M is the total number of features.
T is the sampling interval of V.

B. Composite Load

CL is defined as the composite behavior of more than one load operating together and their collective behavior measured at a single point. In mathematical form it can be expressed as:-

$$\Omega(t) = \{\textstyle\sum_{i=1}^{R} \Psi\text{i}(\text{t})|\,\Delta t = T\,\} \qquad (2)$$

R is the total number of appliances operating together.
CL is complicated to handle as the features of more than one appliances are present.

III. FEATURES OF POWER SIGNATURE

Many electrical appliances are being used by us today and with the growing number of appliances and its complexibility it is absurd to acquire a complete database of all. Therefore a particular feature of appliance can be extracted from conventional measurement (e.g. Power Waveform). Previous research has shown that using the real and reactive power (P and Q) features can track appliance usages [1]. P and Q with harmonics can also identify load [2]. Other features that can be considered under transient and steady state behavior are-

- Current consumption waveform
- Active and Reactive power
- Instantaneous admittance waveform
- Instantaneous power waveform
- Harmonics
- Power waveform
- Switching transient waveform

IV. POWER SIGNATURE ANALYSIS APPROACH

In this paper we have taken the kWfeature of EV battery charging to design a load disaggregation tool as shown in fig.1.

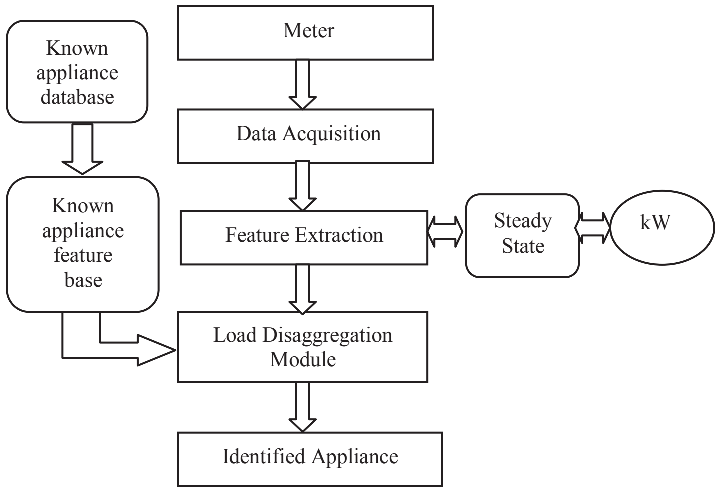

Fig. 1. The workflow of load disaggregation platform.

Everymodule of the platform plays an individual and correlated dependent role in load disaggregation.

V. DATA

Composite data and individual appliance data used to design this algorithm are real power signal(watt) acquired using wattmeter at the sampling rate of 1/60 Hz. Aggregated power signal sampled per minute is utilized from the pecan street, database for this algorithm development and load disaggregation. The single-appliance plug in wall socket meter used to acquire data is a WattsUp" meter. The device under test plugs into the WattsUp. The WattsUp records the samples once every minute for the day(2 MBytes of internal memory). Data are downloaded as CSV file via computer from the WattsUp. Composite data and individual appliance data used to design this algorithm are real power signals (watt) sampled at 1/60 Hz of sampling rate using wattmeter.Appliances whose data are used in algorithm are-

- Power Signature of Air-Conditioner (AC)
- Power Signature of Washing Machine
- Power Signature of Dish Washer
- EV Charging Load
- Power Signature of Oven
- Power Signature of Refrigerator
- Power Signature of Water Heater

Composite Signal Power Signature of whole house aggregated signal i.e. sum of all the aboveappliance.

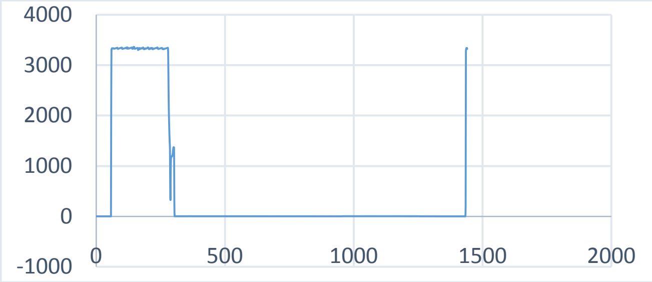

Fig. 2. Power signature of EV

From the known appliance database it can be concluded that the EV real power waveform is close to a square wave and the amplitude of EV charging waveform is always greater than 3kW. While the other appliance real power waveform is different and their amplitude is also low in some watts only Air Conditioner has high amplitude which can interfere in the disaggregating identification of EV.

VI.ALGORITHM

Step 1 : Remove baseline noise

There is always some unwanted noise will be present in the signal that will affect the algorithm working and if the baseline noise will be very large then it will make the present threshold value not suitable. So the first step is to remove the baseline noise from the signal.

$$\mathrm{Mf}(x) = \min \sum_{n=1}^{\infty} \text{composite signal} - \text{minimum value} \quad (3)$$

Step 2 : Threshlonding the signal to get the rough estimation of EV

In the data analysis it was found that EV charging load amplitude is always greater than 3 kW, so a threshold of 2.5 kW is applied to get the second filtered composite signal which gives the rough estimation of EV charging load.

$$\mathrm{X1}(t) = \begin{Bmatrix} x(t) & x(t) \geq Tlow \\ x(t) & x(t) \leq Tlow \end{Bmatrix} \quad (4)$$

Step 3 : Segment Information

After thresholding the next is to know the no. of segments present in the signal and the starting point and end point of individual segment.

Step 4 : Segment filter

A filter is designed that will remove the segment basically coming from AC,dryer and other individual appliance except EV. This filter works on segment width dynamics and removes the segment by doing backward and forward search of the signal, it first find the segments with width less than or equal to minduration and then from this segment search forward for the segment nearest to this segment and check the width from preceding segment with the increment percentage of 1 similarly it searches backward also to prevent from eliminating largewidth that can be from EV max_duration is set to filter. But not all width less than max_duration will be eliminated as it can be an EV also only those segments will be eliminated if their width does not increase pointedlyin comparison to their relative location.

Step 5 : Removing surplus noise

This noise refers to the amalgam of errors from fluctuation of power signal with location information of each segment acquired in the previous steps, the amplitude of this noise can be approximated around each segment.

Step 6 : Segment type Identification

Identifying the type of filtered segment and the amplitude at which the segment waveform has significant changes due to other appliance operating at the same time.

Step 7 : Height information and segment width information of each segment

For each segment effective height and effective width is determined and compared with the known database. Competent Width is determined as the width of a segment at the bottom. Competent height is determined as the height at which the segment width becomes 70% of the bottom.

Step 8 : Final EV waveform estimation

With the study of known EV database and Considering EV waveform has very stable and constant amplitude throughout the day, the EV power signature can be disaggregated with a height estimate at another time of the same day or another day and by segment height evaluation. Therefore an EV square wave is regenerated using the height and the calculated competent width Information.

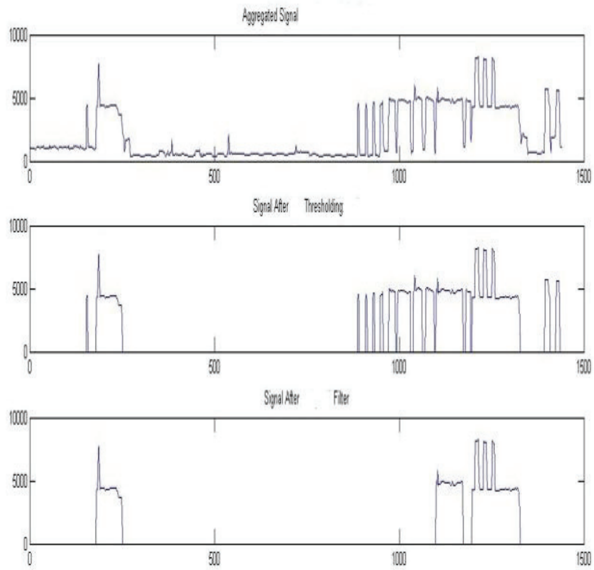

Fig. 3. Signature disaggregating at various steps of code run.

VI. RESULTS

The proposed algorithm uses the input data and values acquired from the known data to disaggregate the EV charging load signals. In the result graphs are plotted to show the actual meter composite data, EV charging load ground truth and the algorithm disaggregated EV charging load.Some of the output results are shown here-

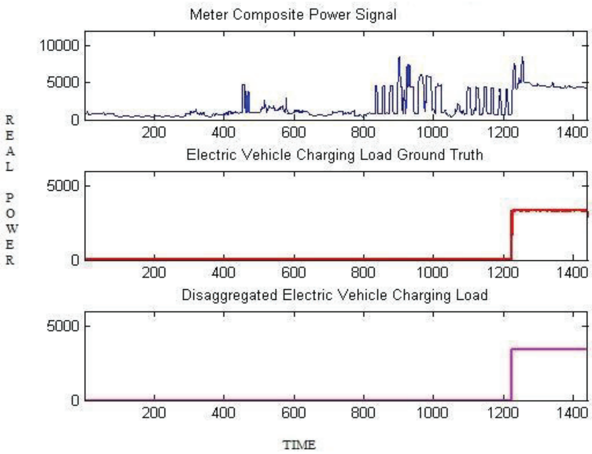

Fig. 4. Ground truth of EV charging Showing EV charging started early night and algorithm also detects the same.

Result: Energy Accuracy: 97.4% |Composite signal (kWh): 45.0678|Difference in estimation EV(kWh): -0.3 | Percentage of EV: 26.96% | Truth: 12.1494 (kWh); Estimated: 12.4669 (kWh).

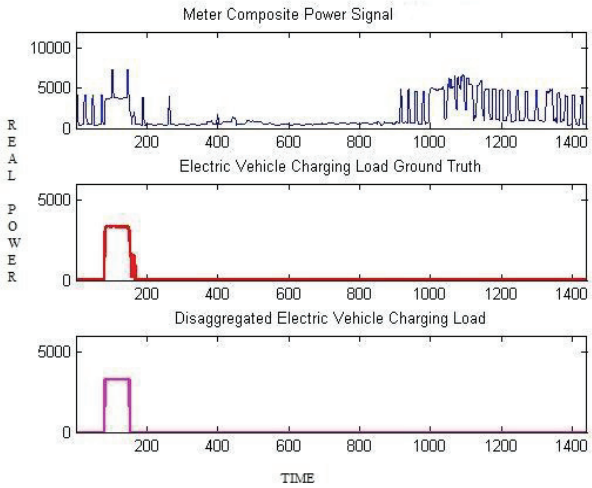

Fig. 5. Ground truth of EV charging Showing EV charging Started late night after 12 and algorithm also detects the same.

Result: Energy Accuracy: 89.6% |Composite signal (kWh): 39.5632|Difference in estimation EV(kWh): 0.4 | Percentage of EV: 10.65% | Truth: 4.21298 (kWh); Estimated: 3.77599 (kWh).

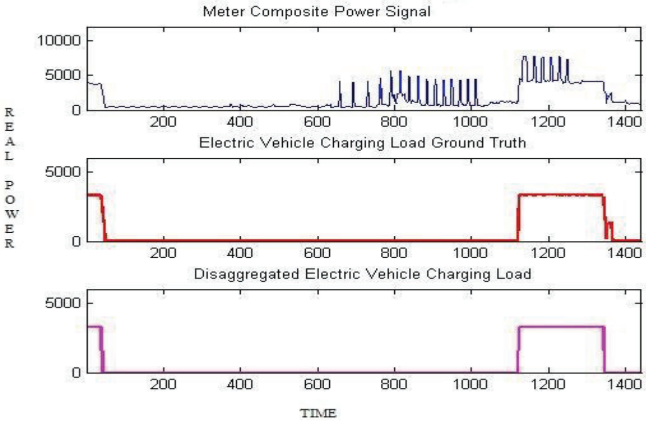

Fig. 6. Ground truth of EV charging Showing EV charging done twice once in midnight and in evening also and algorithm also detects the same.

Result: Energy Accuracy: 94.2% |Composite signal (kWh): 38.1646|Difference in estimation EV(kWh): 0.9 | Percentage of EV: 39.64% | Truth: 15.1278 (kWh); Estimated: 14.2462 (kWh).

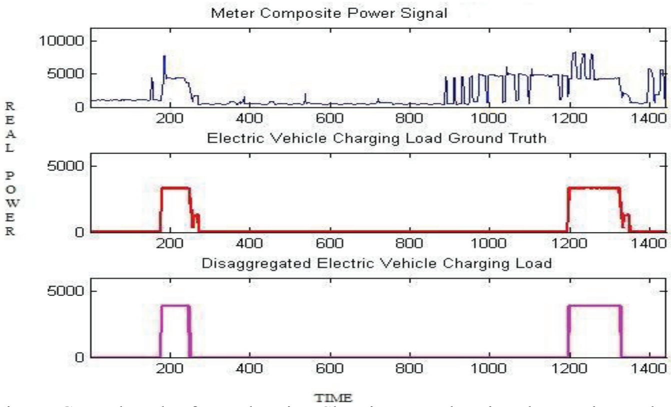

Fig. 7. Ground truth of EV charging Showing EV charging done twice early morning and evening time and algorithm also detects the same.

Result: Energy Accuracy: 92.5% |Composite signal (kWh): 47.8765|Difference in estimation EV(kWh): -0.9 | Percentage of EV: 25.00% | Truth: 11.9701 (kWh); Estimated: 12.8642 (kWh).

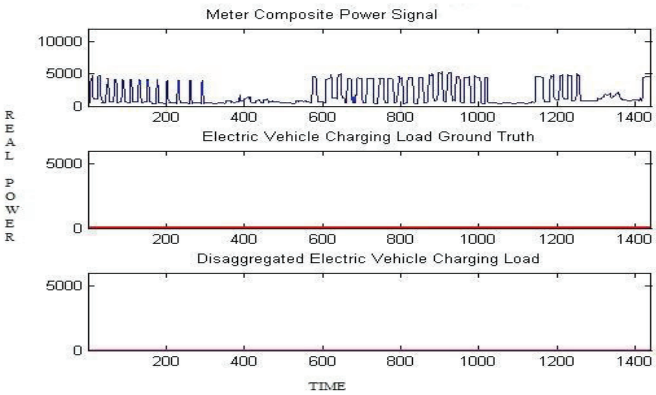

Fig. 8. Ground truth of EV charging Showing NO EV charging is done on that day and algorithm also detects the same.

Result: Energy Accuracy: 100% |Composite signal(kWh): 40.858|Difference in estimation EV(kWh): 0 | Percentage of EV: 0% | Truth: 0 (kWh); Estimated: 0 (kWh).

VIII. CONCLUSION

An algorithm is developed for nonintrusive energy disaggregation of charging load due to electric vehicle charging by feeding a real aggregated power signal sampled at the rate of 1/60 Hz. The algorithm delivers a high estimation rate of more than 90% accuracy. Detects EV charging load even in the existence of other high wattage appliances like AC. The algorithm gives the individual kWh energy consumed by EV charging load as well as total kWh consumed by all the appliances. It gives the percentage of EV charging load out of total composite load. As our current power distribution infrastructure and transformer ratings are not designed for the upcoming EV charging load. So this algorithm will help in knowing the power loading pattern of each EV charging home and will help in monitoring the loading of the transformer as well. By knowing the EV charging pattern and time of each home customers who charging EV in peak hours can be monitored and encouraged to charge EV in off peak hours. Thus avoiding overloading of transformer.

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