On Electrical Load Disaggregation Using Factor Graphs

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***Abstract*—The problem of source separation in general and electrical load disaggregation in particular, is an important component within the context of cyber-physical systems. Electric load disaggregation aims to bring in a number of benefits for different stake holders from end consumer to utilities and grid companies. In this paper, we illustrate the use the frame work of Factor graphs (FGs) to solve the problem of electrical load disaggregation, for a home scenario. We map the load disaggregation problem into a factor graph framework under some assumptions and demonstrate the applicability and elegance of the framework on an experimental set up as well as on an open data set. Additional pointers towards applying the FG-based techniques in realistic situations suitable for actual deployment are also discussed.**

Keywords—Electrical Load Disaggregation; Non Intrusive Load Monitoring; Factor Graphs; Message Passing.

I. INTRODUCTION

Electricity is one of the most common and important commodities we use everyday [1]. The ability to recognize individual appliances from a composite load signal measured at the meter or a few convenient points can enhance the value of electricity by knowing more on how it is used [1]. The process of identifying the individual appliances and their usage patterns from the composite load is referred to as load disaggregation.

It is possible to insert an intermediate monitoring device between the socket and the appliance and then record its operation. This approach is generally called "intrusive" monitoring [1]. This method is inconvenient and expensive for large-scale deployment [1]. Nonintrusive load monitoring (NILM), which can determine the operating schedule of electrical loads in a target system from measurements made at a centralized location, such as the electric utility service entry, is an attractive alternative [2],[1].

Even though the idea of NILM is around since 1980's in terms of different strategies and techniques, it is getting an increased attention till today due to a renewed emphasis on managing energy consumption due to both economic and environmental pressures [3],[4]. More than 70% of the US energy consumption is by buildings of which about 30% is wasted [5]. Also research has shown that users are willing to reduce consumption if given appropriate feedback and incentives [6]. A number of recent researches focusing on various aspects of NILM, viz., methods, algorithms, hardware updates etc.

It is useful to note that the electrical load disaggregation is one instance of the Source Separation (SS) problems which also has received considerable attention over the last two decades. But it has become more relevant today due to the increasing involvement of sensors in our daily activities. However, like many inverse problems, SS is also ill-posed and there is no single solution applicable for different domains and scenarios. And even within a single domain, say, electric load disaggregation, specific scenarios demand different techniques.

In case of NILM, in order to identify individual appliances and their usage patterns from a smart meter reading, it is essential to have a signature of each appliance. The signature can be any or the combination of: active and reactive power levels, power factor, harmonic distortions, transient characteristics, etc. Essentially, the signature corresponds to a feature vector which assists in identifying the appliance. The signatures can be obtained from the prior experimentation (using annotated ground truth data) and the knowledge about the appliance. The other approach is to learn the signatures from the unlabeled data in an unsupervised or semi-supervised manner; which is briefly discussed in our other work [7]. In this paper on the other hand, we assume the availability of explicit feature vectors. In this scenario, many of the existing disaggregation algorithms are based on either (i) optimization-based approach, for e.g., based on integer quadratic programming or (ii) pattern-recognition based approach, for e.g., based on Artificial Neural Networks (ANNs), including radial basis function networks, kernel Support Vector Machines, etc. (see [1], [3], [6], [8] and the references therein). Further, both these approaches can be adopted towards arriving at a committee decision mechanism for improved accuracy of disaggregation.

In this paper, we consider Factor Graph (FG) based algorithms to arrive at the inferences on the individual appliances. An FG is a graphical model that represents a factorization of a function of several variables. In other words, it represents factorizations of arbitrary multivariate functions and dependencies among variables. The pivotal issue in factor graphs is eliminating the variables or in other words computing the marginals of the function [9]. This can be achieved by the sum-product algorithm that arrives at the marginals by passing the messages on the factor graph. The factor graphs were introduced in the late 1990s as a way to capture structure in statistical inference problems [9],[10]. They form an attractive alternative to Bayesian belief networks and Markov random fields [9],[10].

The factor graph offers a language for signal and system modeling [9], [10]. This is helpful for the development of complex and practical detection and estimation algorithms. Since the factor graphs have a modular structure, they facilitate comprehending, changing, and extending the models themselves as well as the algorithms derived based on them [9], [10], [11]. In [10], a factor graph approach to model-based signal separation has been suggested with a focus on electromyographic (EMG) signal analysis. The measured EMG signals, which are made up of superimposed motor action potential (MUAP) trains from several sources, are decomposed into their constituent trains. The approach facilitates the integration of action potential shape information, firing statistics, multiple channels, and other properties of EMG signals very naturally into the same model.

The usage of FG in [10] was one of the motivations for us to consider it to solve the electric load disaggregation problem [12], based on which the present paper is written. Further, in this paper we have restricted to the case where appliance signature is just active power or a combination of active and reactive powers. This is not too restrictive since most of the smart meters provide only these measurements and the scenario appears to stay for some more years. In fact, having one or two features in a feature vector poses more challenge in separating the appliances compared to many features as signature. Based on our study using the simulated (not discussed in this paper) as well the experimental data, FG appears to be a useful framework when the appliances' ratings are available and sufficiently distinct.

The paper is organized as follows. In Section III, we map the problem of electrical load disaggregation on to FGs and briefly touch upon the message-passing algorithms required to deduce the confidence measures at a given disaggregation instant. Section IV presents some results and relevant discussions. Conclusions are provided in Section V. To start with (in Section II), we provide various steps involved in the data analytics, of which disaggregation task is one module.

II. MODULES OF DATA ANALYTICS

The process of data analytics can be split into different modules as shown in Fig.1 (following [1]). As shown in Fig. 2, the output confidence measures shall be fed to a rule-based engine to visualize the disaggregated results in a meaningful way, like, displaying the top 5 power-consuming appliances, advisory services to the consumers. Additionally, the disaggregation algorithm can take feedback from users as well as inputs from other sources towards making better decisions.

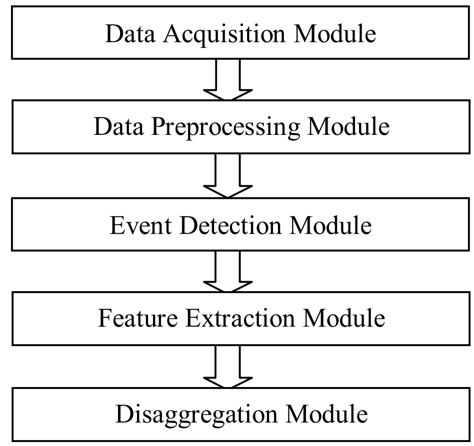

Fig. 1: Modules of Data Analytics

One of the key aspect of the analytics module is the feature extraction, which in our problem translates to event detection. There are different ways one can carry out event detection. One simple strategy is the method of differences, where, the difference between the (active or reactive power) readings at instants t and $t-1$ is calculated and if the result is greater than a chosen threshold, then event occurrence is declared. The event detection can also be carried out using wavelet analysis or using Teager-Kaiser energy operator see [12] and the references therein.

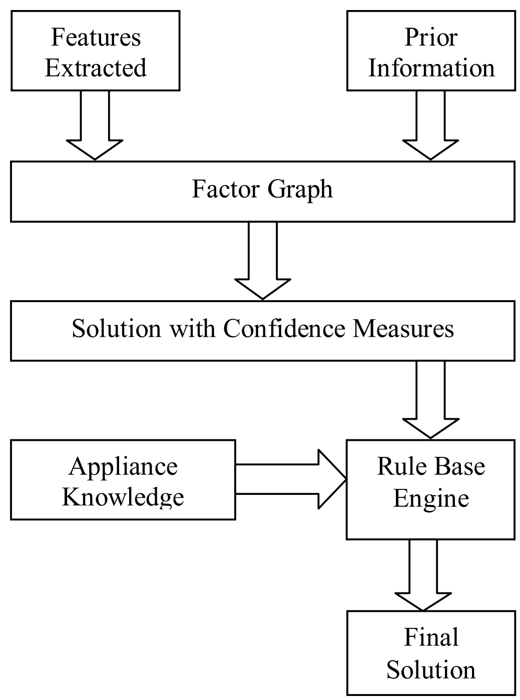

Fig. 2: Modules of Electrical Load Disaggregation using FG

III. Disaggregation Using Factor Graphs

A. Factor Graphs and Message-Passing

FGs are a way of graphically representing the factorization of a function [11]. A detailed account of FGs is available in [11] [9] and [10], here we only present some main points, closely following [11]. In the literature two different types of FGs are used: a conventional type and normal factor graphs (introduced by Forney). A normal factor graph is created as follows [11]: create an edge for every variable and a vertex (a node) for every factor in the factorization. Connect an edge to a node if and only if the corresponding variable appears as an argument in the corresponding factor. Variables that appear in more than two factors require a special equality node. An example is the function of four variables with three factors

$$f(x_1,x_2,x_3,x_4,x_5)=f_1(x_1,x_2)\,f_2(x_2,x_3,x_5)\,f_3(x_4)\,f_4(x_4,x_5) \tag{1}$$

The corresponding normal factor graph is depicted in Fig.3, where the equality node is also present. The case of interest to us is where the function of N variables $f(x_1,x_2,\cdots,x_N)$ represents a joint probability density function and we are interested in computing the marginals, which readily facilitate solving statistical inference problems. The classical definition of marginal of any variable (say x_n) is

$$g_{X_n}(x_n)=\sum_{\sim x_n} f(x_1,x_2,\cdots,x_N) \tag{2}$$

and hence involves summation over all possible values of all variables except x_n (the notation $\sim x_n$ stands for this). The cumbersome computation of (2) can be avoided by using factorization and passing messages over the edges of the factor graph, leading to efficient computation of marginals. Two popular message-passing algorithms being Sum Product Algorithm (SPA) and the max-sum algorithms (see [11] for more details). Following the notation of [11], we denote the message from node f_k over edge X_m by $\mu_{f_k\to X_m}(X_m)$; messages are the functions of the corresponding variables. As summarized in [11], in the SPA nodes accept incoming messages and compute outgoing messages. The algorithm starts from the leaf nodes and half-edges in the graph. The message-computation rule relating incoming messages $\mu_{X_n\to f_k}(X_n)$ to an outgoing message $\mu_{f_k\to X_m}(X_m)$ is given by (see pp.74-75 of [11] for more clarity):

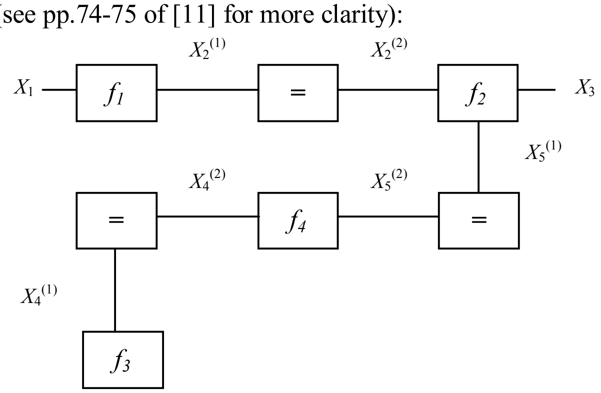

Fig. 3: Normal Factor Graph representation of the function f

$$\mu_{f_k\to X_m}(x_m)=\sum_{\sim\{x_m\}} f_k\left(\{X_n=x_n\}_{X_n\in \mathrm{N}(f_k)}\right)\prod_{X_n\in \mathrm{N}(f_k)\setminus\{X_m\}}\mu_{X_n\to f_k}(x_n) \tag{3}$$

In (3), $\mathrm{N}(f_k)$ stands for the neighborhood of f_k and corresponds to the variables that appear in f_k. (3) also justify the name SPA due to presence of the summation and product. Further, (3) also suggests that while computing an outgoing message on an edge the incoming message on that edge is not considered in the computation as captured by the exclusion symbols $\sim$ and $\setminus$. After computing all the messages, the marginal of the variable (say, X_n) can be found by point wise multiplication of the two messages over the corresponding edge:

$$g_{X_n}(x_n)=\mu_{f_k\to X_n}(x_n)\,\mu_{X_n\to f_k}(x_n) \tag{4}$$

In the case of Max-Sum algorithm, the message computation rule of (3) gets modified to (pp.72-73 of [11]):

$$\mu_{f_k\to X_m}(x_m)=\max_{\sim\{x_m\}}\left\{f_k\left(\{X_n=x_n\}_{X_n\in \mathrm{N}(f_k)}\right)+\sum_{X_n\in \mathrm{N}(f_k)\setminus\{X_m\}}\mu_{X_n\to f_k}(x_n)\right\} \tag{5}$$

B. Electrical Load Disaggregation Using Factor Graphs

Now, we are equipped to map the electrical load disaggregation problem onto the FG framework. Consider N appliances or load $L_1,L_2,\cdots,L_N$, which can also be grouped together into load vector $\boldsymbol{L}=[L_1 \quad L_2 \quad \cdots \quad L_N]$. Each of the L_i's can take a value 1 or 0 corresponding to the load being ON or OFF. Let us also consider that we have observed or measured real power W and reactive power R (say, by a smart meter). The electrical load disaggregation problem can be cast as a Maximum A Posteriori (MAP) estimation in the probabilistic framework as follows:

$$\boldsymbol{L}_{ON}=\arg\max\, p(L_1,L_2,\cdots,L_N \mid W,R) \tag{6}$$

which can be written as

$$\boldsymbol{L}_{ON}=\arg\max \frac{p(\boldsymbol{L},W,R)}{p(W,R)} \propto \arg\max p(\boldsymbol{L},W,R) \tag{7}$$

The joint probability function $p(\boldsymbol{L},W,R)$ can be factored into the product of likelihood function and a priori probabilities:

$$p(\boldsymbol{L},W,R)=p(W,R\mid \boldsymbol{L})\,p(\boldsymbol{L}) \tag{8}$$

If the loads are operating independently, then (8) can be written as

$$p(\boldsymbol{L},W,R)=p(W,R\mid \boldsymbol{L})\{p(L_1)\cdot p(L_2)\cdots p(L_N)\} \tag{9}$$

The FG framework allows us to represent the factors above as nodes. For example, for the case of 3 loads independently operating, the FG is as shown in Fig.3; note that in this example we have considered only active power measurement W. It is immediately evident now that by suitably applying SPA, we can obtain the marginal probabilities $p(L_1), p(L_2),\cdots, p(L_N)$ efficiently. These probabilities provide the confidence measures of each of the appliances being ON

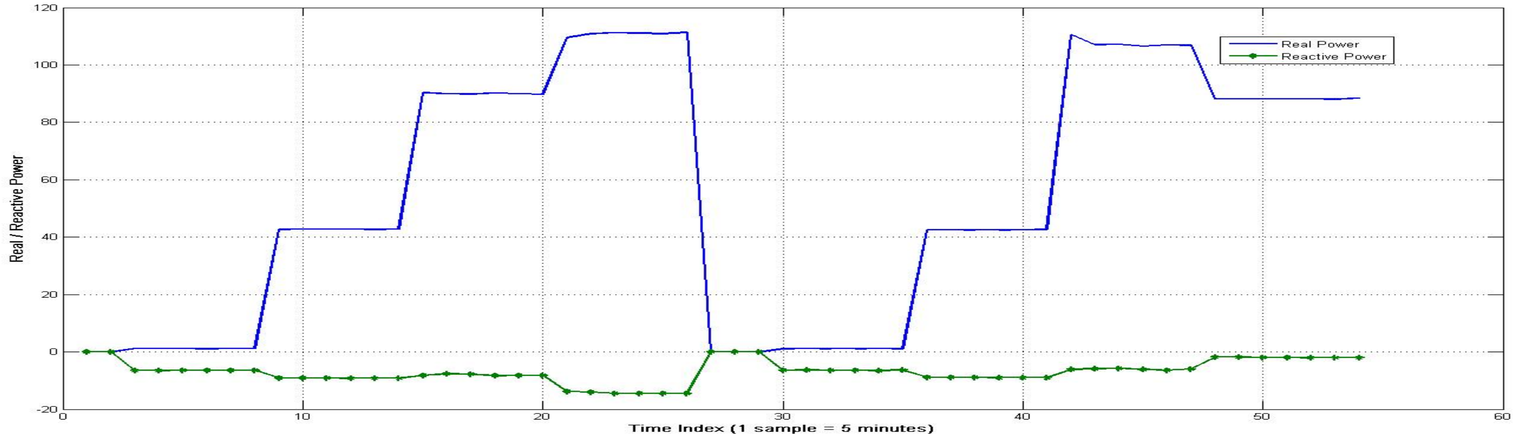

Fig. 4. Real / Reactive Data collected from meter

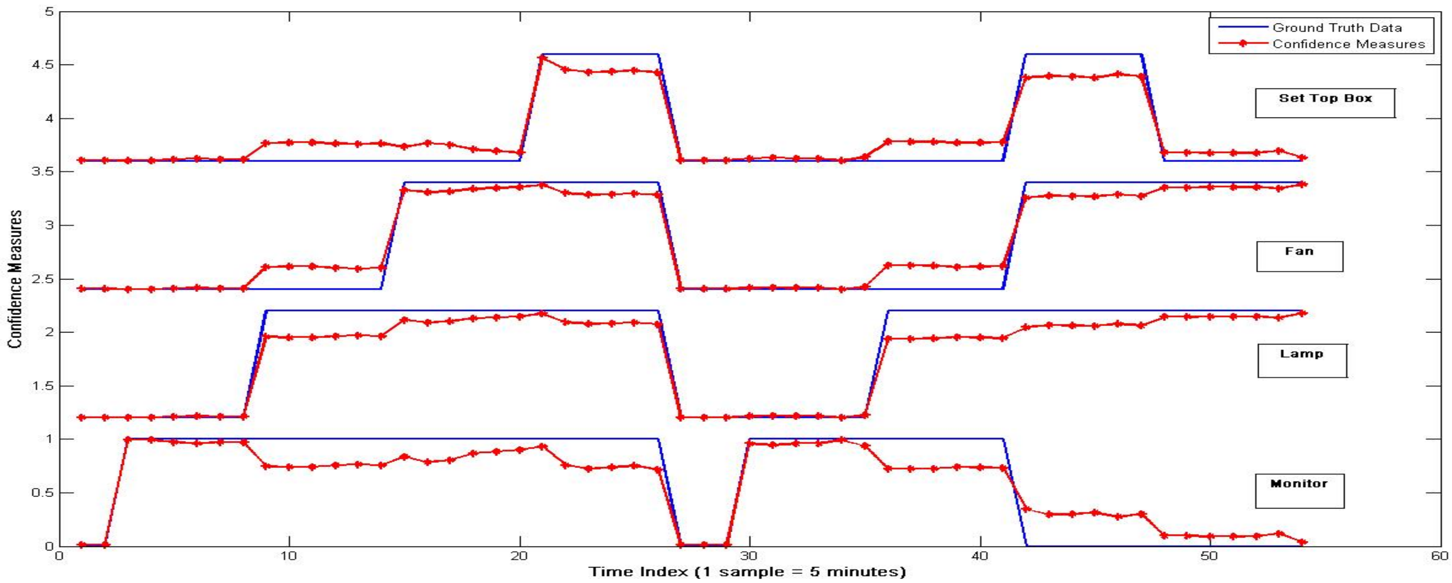

Fig. 5. Comparison of Ground Truth vs Confidence Measures

for given measurements. These outputs can be further used in decision making as shown in Fig.2. Of course, we can appropriately employ max-sum algorithm to estimate the entire load sequence $\boldsymbol{L}$ that are ON together with the confidence measure of the entire sequence.

In order the execute SPA, we need to pass messages as discussed earlier. To compute these messages, we need a priori probabilities and likelihood values. The a priori probabilities can absorb some (prior) knowledge like the geyser in a household is more likely to be ON during the morning time, etc.

The likelihood computation shall be addressed in multiple ways. In the algorithm proposed, the likelihood of a load combination ($p\left(W,R\middle|\,\boldsymbol{L}\right)$) is to be computed based on the observed power. In the algorithm, the approach used is the inverse of norm of difference between the observed power and the power of the load combination. The latter is available since we assume that the ratings of the appliances are available. The results presented in the paper use a 1-norm, whereas it is also feasible to use the Euclidean norm. When both real and reactive powers are considered, we can treat them as one complex number and evaluate the likelihoods as in the one-norm case. Once the *a priori* probabilities and the likelihoods are known computing the marginals consists of only simple operations.

In realistic situations where the loads will be in large numbers, computing the likelihood needs to be appropriately organized. For instance, if the measured power is W then we can safely avoid all load combinations a certain threshold above and below W from likelihood computation. In the derivation above, the loads are assumed to be independent. However, FG offers a way to capture dependence between appliances by opening/closing the nodes. A typical dependency can be a cloths dryer is used after cloths washer. In the same way, grouping appliances in a specific room can also be handled, providing a hierarchical modeling.

FG can also handle cases of non-NILM scenarios. For instance, a vibration sensor on a washing machine can indicate its operation, and this can be captured as a dependency node for the washing machine in the FG. Similarly, if some appliance plug-level data is available, this can be used to modify the a priori probability of the concerned appliance.

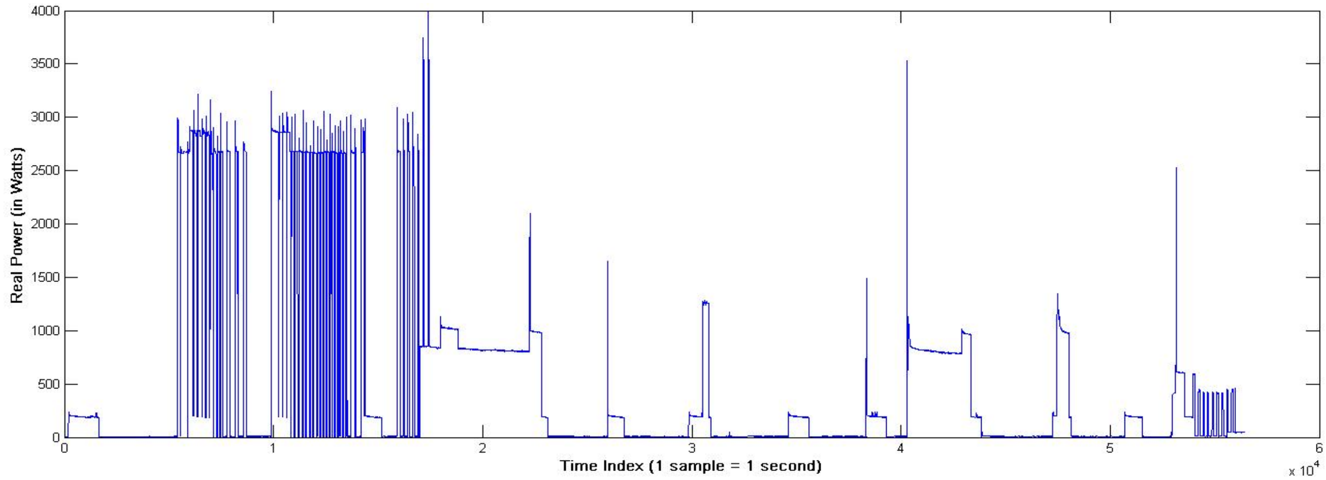

Fig. 6. Active Power Data

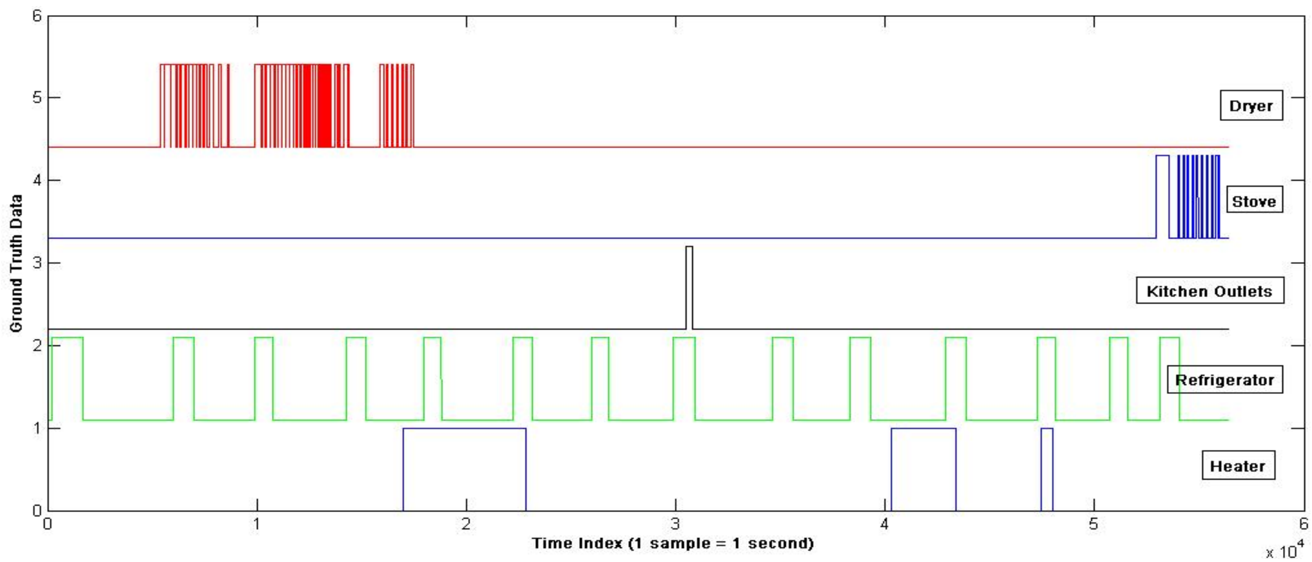

Fig. 7. Appliance Ground Truth (ON/OFF) based on Plugs

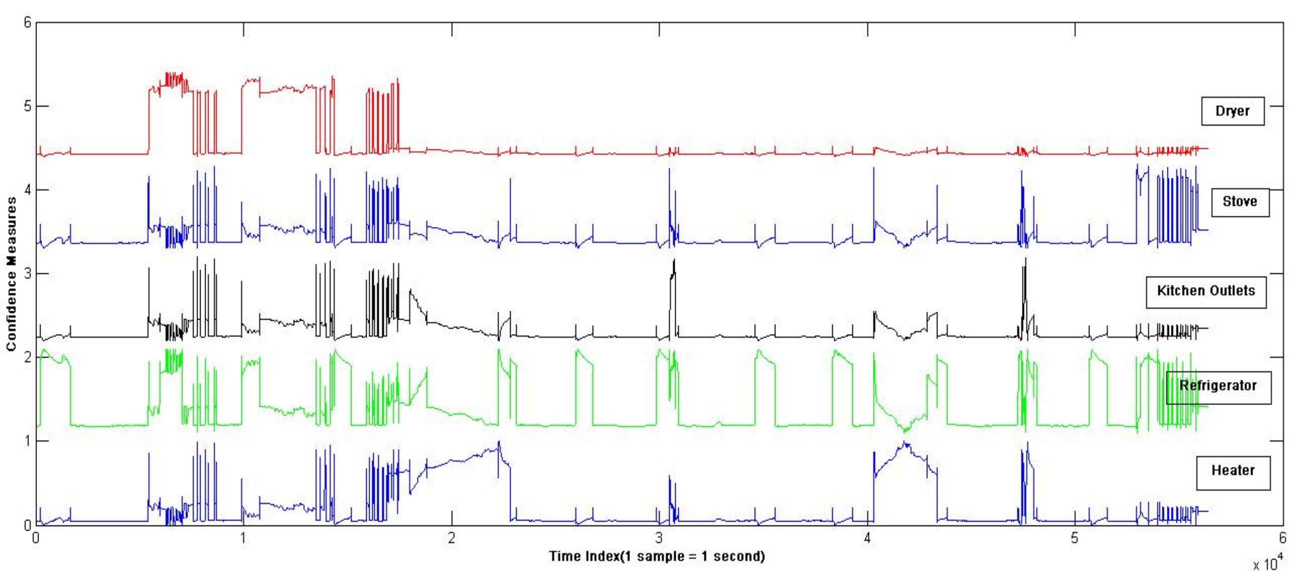

Fig. 8. Confidence Measures for the Appliances (stacked)

IV. RESULTS AND DISCUSSION

We discuss the results of the load disaggregation problem using two data sets. First is a small experimental set up, a Home Energy Monitoring System (HEMS), with 4 low power appliances, viz., Monitor, Lamp, Table Fan and the Set-top box. The set up can provide the (i) real power in watts (ii) kWh consumed (iii) frequency (iv) RMS voltage (v) RMS current (vi) reactive power (vii) VARh consumed and the (viii) phase angle at a sampling rate of one sample at every 5 min. In the results discussed, we use only the active and the reactive power from the HEMS set up. The Fig. 4 shows the measured active and reactive power. In Fig.5 the confidence measures are plotted against the ground truth data indicating the ON/OFF of the appliance. In this experiment, prior probabilities of each appliance are considered equal.

We also illustrate the result of the FG approach based on the open REDD data set [13], which is an open data set of plug and meter data from house holds. Since the meter data from the REDD data set contains unknown appliances, we have prepared the active power data as a sum of data from different appliance plugs, namely, Dryer, Refrigerator, Heater, Stove, Kitchen outlets. The active power input is shown in Fig. 6. The ground truth ON/OFF indication for each appliance is shown in Fig. 7 and the confidence measures obtained from the algorithm are given in Fig. 8. In the Fig.7 and Fig. 8 the probability of ON/OFF ([0,1]) for appliances are stacked one above the other for ease of visualization.

It is observed that as long as the appliances have ratings that are distinct, the algorithm can identify the ON/OFF of appliance with a good accuracy.

We used one form of FG mapping for electric load disaggregation in our paper. Another type of mapping shall also be considered motivated by the approach in [10]. The assumption in this approach is that the measurement features are additive or can be represented in a form that they are additive (e.g. active/reactive powers/harmonics are additive, however power factor can be additive in rectangular form). With this assumption, each feature of every appliance can be represented as a tap of a Finite Impulse Response (FIR) filter (see [12] for illustration). The filter is excited by a source *X*, which can take a value of a series of 0s and 1s representing the presence or absence of the appliance. Now the sum of all the feature vectors can be compared with the feature vector of the measurement and using the MAP optimization, we can arrive at the best possible combination of appliances.

V. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper we presented our first results on considering the Factor Graphs (FGs) for solving the electric load disaggregation problem in the home scenario under some assumptions. The FG framework can be of great value if appropriately used, since apart from providing confidence measures of appliances being ON, can elegantly take care of *a priori* information and hierarchical problem solving, which are essential in electric load disaggregation. Further, once the problem is set up, the subsequent computations are simple to execute, a useful feature in many circumstances. In realistic situations with constraints on the sampling rate, non availability of the appliance ratings and appliances with closely spaced power ratings, FG based inference can still be useful together with an appropriate learning module. Even though we have touched upon only home scenario, we envision its utility in the enterprise electrical load disaggregation or in other source separation problems like water flow disaggregation.

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