Incorporating Appliance Usage Patterns for Non-Intrusive Load Monitoring and Load Forecasting

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***Abstract*—This paper proposes a novel non-intrusive load monitoring (NILM) method which incorporates appliance usage patterns (AUPs) to improve performance of active load identification and forecasting. In the first stage, the AUPs of a given residence were learned using a spectral decomposition based standard NILM algorithm. Then, learnt AUPs were utilized to bias the priori probabilities of the appliances through a specifically constructed fuzzy system. The AUPs contain likelihood measures for each appliance to be active at the present instant based on the recent activity/inactivity of appliances and the time of day. Hence, the priori probabilities determined through the AUPs increase the active load identification accuracy of the NILM algorithm. The proposed method was successfully tested for two standard databases containing real household measurements in USA and Germany. The proposed method demonstrates an improvement in active load estimation when applied to the aforementioned databases as the proposed method augments the smart meter readings with the behavioral trends obtained from AUPs. Furthermore, a residential power consumption forecasting mechanism, which can predict the total active power demand of an aggregated set of houses, 5 min ahead of real time, was successfully formulated and implemented utilizing the proposed AUP based technique.**

***Index Terms*—Non-intrusive load monitoring (NILM), fuzzy systems, usage patterns, smart grid, demand side management (DSM), direct load control (DLC), demand response (DR).**

I. Introduction

IN THE recent years, Demand Side Management (DSM) has become an essential element of the rapidly developing smart grid; mainly as a result of increasing penetration of intermittent and variable renewable energy sources such as solar photovoltaic (PV) and wind. Due to the unpredictable nature of the generation, maintaining the second-by-second balance between demand and generation has become a challenging task, if an expensive reserve service is not maintained. As reserve services are mainly provided by operating certain power plants below their rating, this not only underutilizes its own capacity but also results in them being operated inefficiently. As a viable solution to this problem, DSM is considered. DSM tries to reduce/increase the demand either by shifting or reducing the consumption so that the available generation can be utilized efficiently while maintaining a minimum reserve.

Direct Load Control (DLC) is one attractive option for DSM which helps the utility to shape the customer energy consumption profile by remotely controlling customers pre-agreed set of controllable appliances such as, heat, ventilation, air-conditioning and smart (HVACS) systems. Even though a smart meter connected at the consumer premises could make these HVACS loads flexible, unless the grid operator knows the amount of flexible load that is available at a given time, the utilities continue to maintain a large reserve by deloading generators.

This paper proposes a solution to this problem in the form of a Load Monitoring (LM) method that can predict the amount of flexible load available at consumer premises. Using LM, the set of appliances that are currently turned ON and their individual energy contributions at a customer premise is predicted. Even though LM could be achieved by attaching sensors for each appliance, due to the implementation cost and the complexity, it is not a feasible solution. In contrast, Non-Intrusive Load Monitoring (NILM) approaches, in which only the total power at the entry point to the consumer premise is monitored to find the load activities [1], involve lower implementation cost and complexity. Due to these advantages, NILM methods are gaining popularity.

A. Related Work

Throughout literature, a number of different NILM methods have been proposed. In general, those NILM methods can be categorized based on the type of measurements utilized, as steady state methods and transient state methods.

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Among steady state measurement based NILM methods, information of active power [2]–[5], reactive power [6], harmonic content [7], [8], and voltage-current trajectory [9], [10] are commonly utilized. In transient state measurement based NILM methods, voltage and current [11]–[13], power [8] as well as harmonic information [7], [14] have been utilized.

NILM methods based on steady state measurements have the common difficulty of identifying non resistive appliances [1], [15], [16] and appliances which cause non-discrete changes in power [17]. Transient measurement based NILM methods have the common drawback of requiring measurements with higher sampling rates in kilohertz range [18]–[20]. Such methods require high communication bandwidths and processing power. Moreover, some of the aforementioned techniques require more than one electrical measurement, resulting in the need for costly, multi-functional smart meters. Considering all these factors, for a scalable NILM solution, such commercial costs and implementation complexities should be mitigated.

In more recent works, this NILM problem has been further studied along several different major avenues. In [21] and [22], several multi-label classification techniques based on wavelet-domain and time-domain feature sets have been evaluated to address the NILM problem. In parallel, Graph Signal Processing based techniques have been utilized in [23]–[25] for the same purpose. In [26]–[28], event detection and clustering avenue have also been explored to address the same NILM problem, based on Subtractive Clustering, Bayesian-Viterbi Clustering and Dynamic Time Warping techniques respectively. Further, Sparse Coding (SC) and Hidden Markov Model (HMM) based techniques are also two emerging avenues in the same research. NILM methods proposed in [29]–[31] are based on learning a basis for each individual appliance through sparse coding and dictionary learning. These methods use Deep-SC, 'Powerlet' Learning and Descriptive-SC techniques respectively. In [5] and [32]–[38], number of different HMM-based NILM techniques have been discussed. Furthermore, a more detailed overview on various such recent NILM methods have been presented in [21] and [39]–[41].

Even though there are many such diverse NILM approaches suggested in [1]–[25] and [29]–[42] almost all the NILM methods estimate the present turned ON appliance combination based on the recently collected set of measurements. For example, the NILM strategy proposed in [3] decides the currently turned ON appliance combination based on ten most recent set of total active power measurements. Most of the proposed NILM methods completely rely on smart meter measurements without incorporating any of the activity that happened in the recent past in terms of load activity and inactivity. Due to this reason, a single erroneous or unlearned measurement has the potential to mislead the NILM algorithm.

B. Contributions

As a remedy to the above mentioned common shortcoming of NILM methods, this paper proposes a NILM method which adapts itself to the user behavioral patterns rather than being rigidly dependent on collected measurements or on the learning period. This proposed NILM method uses the NILM technique in [2] and improves upon it to gain this added adaptability. Hence, in this proposed novel approach, individual appliance usage patterns (AUPs) are used to augment the direct smart meter measurements to identify the currently turned ON appliance combination.

In this approach, the priori probabilities of individual appliances at the current time instant are calculated using a developed fuzzy system. This fuzzy system utilize the pre-observed historical individual AUPs containing historical activity of each appliance as pertaining to the time of day and turned ON/OFF duration likelihoods.

Further, to calculate the individual appliance priori probabilities, the developed fuzzy system also uses the information of the turned ON appliance combinations identified in the recent past.

The individual appliance priori probability is the probability of that appliance being in the turned ON state at the current time instant. This key information is appropriately biased for each appliance depending on the current behavior trends and then considered in the proposed NILM method to find the most probable currently turned ON appliance combination.

Hence the proposed NILM method does not solely depend on collected measurements. To decide the NILM solution at a certain time instant, apart from collected active power measurements, it also considers the priori probability values (given by pre-observed AUPs) of each appliance combination. As a result of this novel approach, it delivers more accurate NILM results when compared to very recent NILM methods.

Further, this paper proposes a novel load forecasting technique which uses the learned usage patterns of appliances together with the present NILM result to predict the load profile of an aggregated set of houses a few minutes ahead of current time. Since this proposed total load forecasting technique incorporates both the AUPs as well as the current NILM solution, it clearly demonstrates the viability of applying the proposed NILM method and its incorporated AUPs in a DSM application such as in DLC.

Furthermore, in this paper, implementation and scalability aspects of the proposed complete NILM solution (with forecasting) have been explored. This is a clear contribution of this paper as none of the NILM methods existing in the literature have not extensively demonstrated such applicability and practicality of NILM in DSM.

In the proceeding sections, first, the underlying NILM technique is summarized under Section II. Then, the improvement of the NILM algorithm by studying appliance usage pattern is examined in Section III. Finally, the proposed total power profile forecasting mechanism is introduced in Section IV.

II. Underlying NILM Method Used

A. Overview of the NILM Algorithm

The overall flow of the proposed NILM algorithm is described in Fig. 1. The main steps are,

1) Feature extraction from individual appliance power profiles (in Reading Set 1 - RS1) by the Karhunen Loève Expansion (KLE) based technique described in [3].

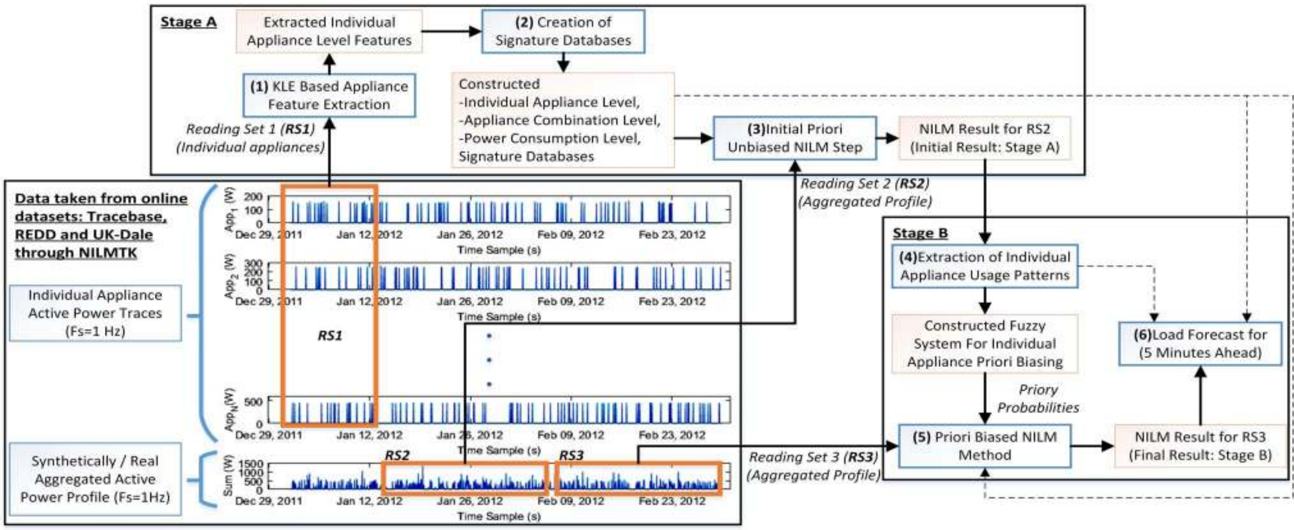

Fig. 1. Overall Flow of the Proposed NILM Algorithm.

2) Creation of Appliance/Combination/Power consumption level signature databases using extracted features.
3) Turned ON appliance combination identification using initial priori unbiased NILM step (for Reading Set 2 - RS2).
4) Appliance Usage Pattern (AUP) extraction using the obtained initial result (of RS2).
5) Evaluation of priori biased NILM method using constructed AUP based fuzzily priori biasing technique (for Reading Set 3 - RS3).
6) Aggregated residential power profile forecasting method (using the priori biased NILM result and usage patterns).

For the ease of explanation, steps 1-3 are referred to as "Stage A" of the proposed NILM method. This section describes the processes involved in Stage A. An in-depth analysis about this stage can be found in [2]. The final three steps are referred to as "Stage B" and it is introduced in Sections III and IV.

Individual appliance power profiles taken from two publicly available datasets containing real measurements collected from U.S. and German households were considered for this study. They are *Tracebase Database* [43] and *Reference Energy Disaggregation Dataset (REDD)* [34]. A publicly available toolkit named *NILM Toolkit (NILMTK)* [44] was utilized for dataset conversion and data pre-processing.

B. KLE Based Appliance Feature Extraction

If $\mathbf{X} = [X_{(n)}\ X_{(n-1)}\ \ldots\ X_{(n-i+1)}\ \ldots\ X_{(n-N+1)}]^T$ is a sliding window (SW) of an individual appliance active power trace (taken from RS1, at time instant n), its KLE is given by,

$$\mathbf{X} = Q\bar{x} = \sum_{i=1}^{\bar{N}} q_i^T \mathbf{X} q_i \tag{1}$$

where, $q_1, q_2, \ldots, q_{\bar{N}}$ are the eigenvectors and Q is the eigenvector matrix of the Autocorrelation Matrix (ACM) of $\mathbf{X}$. Further, $\bar{x}$ is the Karhunen Loève Transform of $\mathbf{X}$.

According to (1), signal $\mathbf{X}$ was decomposed into $\bar{N}$ number of mutually uncorrelated spectral components which are also known as Subspace Components (SCs) of $\mathbf{X}$, named hereafter as, $x_1, x_2, \ldots, x_{\bar{N}}$ where $x_i = q_i^T \mathbf{X} q_i$. Here, q_i can be thought of as a narrow band eigen-filter whose output is sinusoidal with a center freq of f_{ci} and phase angle of θ_i. Thereafter, the average amplitude of SC, which is incidentally the eigenvalue λ_i, and the phase angle θ_i formed the complex features for each SC. This is converted to rectangular form via relations, $Re_i = \lambda_i cos(\theta_i)$ and $Im_i = \lambda_i sin(\theta_i)$. With that, for each SW of length N there are $\bar{N}$ number of SCs denoted by x_i and each of these SCs have three features, namely f_{ci}, Re_i and Im_i. In order to establish the stationarity within the SW, parameters N and $\bar{N}$ has been chosen as ten and five respectively.

C. Signature Database Construction

Using the feature data obtained from each SW of training data (i.e., the RS1) for an appliance, 2D histograms were formulated for each center frequency f_c. Once these histograms are normalized, they yield the probability of having a feature; for instance, (Re_1, Im_1) at $f_c = 0.2$ Hz for the learned appliance (say A_1). This is denoted simply as an appliance level Probability Mass Function (PMF) $P_{(A_1, f_c=0.2Hz)}(Re_1, Im_1)$. Utilizing each of these constructed appliance specific PMFs, a set of appliance combination specific PMFs for each f_c for each possible appliance combination were constructed through mathematical convolution operation between corresponding appliance specific PMFs [3]. This gives the probability of obtaining a feature when that appliance combination is currently turned ON.

These generated sets of appliance specific PMFs and appliance combination specific PMFs form the appliance level signature database (ALSD) and the combination level signature databases (CLSD) respectively [45]. Furthermore, in order to perform the power level disaggregation according to [46] after the active appliance combination is identified, the power consumption levels of each and every appliance were studied

Algorithm 1 Work Flow of Appliance Combination Identification in Initial Priori Unbiased NILM Step (for RS2)

for each SW in RS2 **do**
  Extract features from the SW; *#5 SCs:* Z_i; $i = 1, 2, ..., 5$;
  Set $i = 1$; *#Iteration or SC Number*
  Set *execution* $= 1$; *#Matching Incomplete Yet*
  Set $S_0 = \{C_j : j = 2^{N_{apps}}\}$ *#Set of All Combinations*
  Apply the PES to S_0 and obtain S_1;
  while *execution* **do** *#Iterative SC Matching*
    Consider the i^{th} dominant SC : Z_i;
    Apply the FES to S_1 or S_3 and obtain S_2;
    Apply the SES to S_2 and obtain S_3;
    Apply the MAP criteria to S_3 and obtain S_4; *#Get* $\gamma_{C_{j,i}}$
    if $\gamma_{C_{j,i}} > 0.99$ **then** *#Matching of* C_j *upto* i^{th} *SC*
      Output: Turned ON Appliance Combination $= C_j$;
      Set *execution* $= 0$; *#Matching Complete*
    else if $(i == 5) \cup (S_4 \in \emptyset)$ **then**
      Output: Most Probable Solution: $argmax(\gamma_{C_{j,i}}, C_j)$;
      Set *execution* $= 0$; *#Matching Complete*
    else
      $i = i + 1$ *#Go to Next SC Matching*
    end if
  end while
end for

and a power consumption level signature database (PCLSD) was constructed [46].

D. Initial Priori Unbiased NILM Step

The next step of the proposed NILM method is to evaluate the initial priori unbiased NILM step for the aggregated power profile of RS2. In this step, every appliance combination was considered to have an equal priori probability value to be the currently active appliance combination. Thus, it is called the priori unbiased NILM step in this paper.

First, as in [3], sliding windows of 10 samples taken from the aggregated power profile in RS2 were considered sequentially. Such a sliding window is referred to as an observation sliding window (OSW). Then for each OSW, its corresponding set of features were extracted in the same way as described in Section II-B. After that, these extracted features (i.e., the five SCs) were used to find the matching turned ON appliance combination corresponding to that particular OSW. The constructed CLSD was utilized for this matching purpose, where the possible features corresponding to every viable appliance combination had been stored. This identification process is summarized in Algorithm 1.

Initially, all the possible appliance combinations were considered as viable solutions and then appliance combinations were rapidly reduced based on a "pre-elimination stage" (PES), a "first elimination stage" (FES), and a "second elimination stage" (SES). Finally, a Maximum a Posteriori (MAP) criteria was applied to evaluate the most likely solution.

At PES, the static level of the OSW (i.e., the first SC) is compared with the minimum static levels obtained for every possible appliance combination. Then every appliance combination with a minimum static level larger than the measured active power signals static level (i.e., within the OSW in concern) was eliminated. At FES, average power level of each SC was used to eliminate the appliance combinations which showed lower maximum possible average SC power levels [2]. After that, at the SES, for every remaining appliance combination, probability of generating the current SC of the OSW was calculated using the PMFs stored in the CLSD. These values were denoted by $P(Z_i/C_j)$ where Z_i is the features of i^{th} SC of an OSW and C_j is the j^{th} appliance combination. If this likelihood value is not larger than 0.1, those combinations were also eliminated.

Then at the MAP criteria, probabilities obtained after the SES were utilized to calculate the most probable appliance combination which matched all OSW SCs up to the current iteration. This MAP criteria value is given by,

$$\gamma_{C_{j,i}} = \frac{P\big(C_j/Z_{1,\ldots,i}\big)}{\sum\limits_{\forall j} P\big(C_j/Z_{1,\ldots,i}\big)}, \tag{2}$$

where,

$$P\left(\frac{C_j}{Z_{1,\ldots,i}}\right) = \prod_{k=1}^{i} P\left(\frac{C_j}{Z_k}\right) = \prod_{k=1}^{i} \frac{P\left(\frac{Z_k}{C_j}\right)P\big(C_j\big)}{\sum\limits_{\forall j} P\left(\frac{Z_k}{C_j}\right)P\big(C_j\big)}. \tag{3}$$

Here, $P(Z_k/C_j)$ values are taken from the pre-constructed CLSD and $P(C_j)$ denotes the priori probability of the appliance combination C_j. In this step, since every appliance combination was assumed to have an equal priori probability value, (3) was simplified further by assuming,

$$\forall j,\ \forall OSWs : P\big(C_j\big) = constant. \tag{4}$$

If the calculated $\gamma_{C_{j,i}}$ value in (2) is larger than 0.99 for a certain appliance combination C_j, in a certain iteration i, then that combination was taken as the identified initial NILM solution (i.e., the active set of appliances) for that OSW [2].

Finally, after evaluating Algorithm 1 for the RS2, through the obtained results at the end of Stage A, each Appliance Usage Pattern (AUP) was observed.

Next section describes how the proposed NILM method in this paper utilized these observed AUPs to use the full MAP criteria definition given in (3) without assuming (4).

III. STUDY OF APPLIANCE USAGE PATTERNS (AUPs)

In the NILM method proposed in [2], which was also used in stage A, the turned ON appliance combination at a particular time instant was found by considering the most recent few samples of measurements (i.e., by using the OSW). This direct dependence between NILM result and the sensor measurements hinders the accuracy levels. Therefore, as a remedy, historical AUPs were used to enhance the accuracy of the NILM method.

For example, due to an anomaly in measurements such as, sensor measurement noises, interferences or unlearned behavior of appliances and residential voltage level fluctuations, correctly identified appliance combination given by a NILM method may get altered by yielding an incorrect appliance combination for a small duration of time. However, it is understandable that a sudden changes in the turned ON appliance combination within a residential building is unlikely.

In the proposed NILM method, an avenue was created to utilize the observed AUPs from the results of Stage A, in order to obtain the priori probability values for each appliance combination for each OSW in Stage B. This section describes the extracted AUPs, the technique used to calculate the priori probabilities and the method which utilized the calculated priori probabilities referred to as the "priori biased NILM method".

A. Extracted Different Appliance Usage Pattern Profiles

Vital information was revealed when analyzing the AUPs obtained from Stage A (See Fig. 1) of the proposed NILM method. First, by exploring the individual appliance usage profiles given by the results of Stage A (for the RS2), it was found that most of the appliances show certain ON durations followed by certain OFF durations more often. For example, appliances like Refrigerators, Freezers and Water Fountains show specific ON and OFF duration occurrences more frequently. Further, it was noticed that, some appliances are in the ON state more commonly during a particular time period of the day. For example, certain Lamps are more likely to be in the ON state during the night and in the early morning. Therefore, in order to interpret AUPs, these three parameters ON Duration (OnDu), OFF Duration (OFFDu) and Time of Day (TOD) were used.

In Stage B, results from Stage A were utilized to extract the ON and OFF durations characteristics of each appliance. Then the appliance specific histograms for ON and OFF durations were constructed and converted to corresponding Complementary Cumulative Mass Functions (CCMFs) as respectively given by,

$$P_{ONDu,A_k}(t) = P(ONDu \geq t), \tag{5}$$

and,

$$P_{OFFDu,A_k}(t) = P(OFFDu \geq t). \tag{6}$$

Here, (5) gives the probability of the k^{th} appliance A_k being used for a duration of time more than t seconds. For example, ON duration histogram and respective CCMF curve obtained ($P_{ONDu}(t)$) for the Freezer (FR) is given in Fig. 2(a). According to that histogram, ON duration of the FR takes a bimodal behavior where it is most likely to show an ON duration of 5 or 10 minutes. Also FR is less likely to show an ON duration more than 12 minutes or less than 4 minutes.

Similarly, (6) describes the probability of appliance A_k being in switched OFF state for a duration of time more than t seconds. As an example, OFF Duration histogram and the obtained $P_{OFFDu}(t)$ curve for the FR is shown in Fig. 2(b). Note that CCMF curves in Fig. 2 should be read using the right hand side y-axis.

Then, the first CCMF in (5) was converted into a conditional Probability Mass Function (PMF) using,

$$P_{ON,A_k}(t) = P\left(\frac{OnDu > t}{OnDu > (t-1)}\right) = \frac{P_{ONDu,A_k}(t)}{P_{ONDu,A_k}(t-1)}, \tag{7}$$

which gave the probability of the appliance A_k being in the turned ON state in the current time instant, given that it has been in the turned ON state for a duration of time t seconds up till now. Similarly, the probability of appliance A_k being

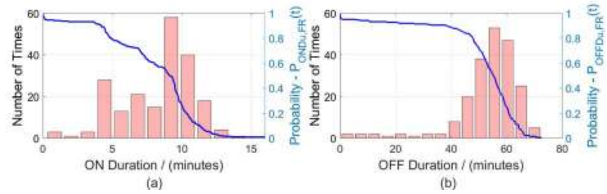

Fig. 2. (a) $P_{ONDu}(t)$ and (b) $P_{OFFDu}(t)$ for FR.

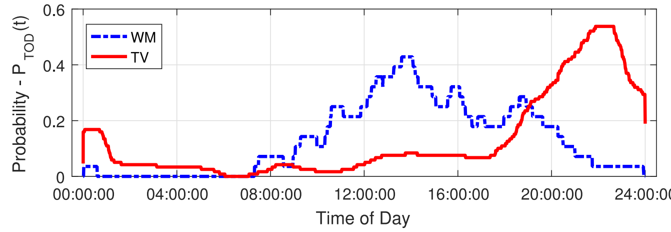

Fig. 3. $P_{TOD}(t)$ for WM and TV.

switched ON in the current time instant after being in the OFF state for a duration of time t seconds up to now is,

$$P_{OFF,A_k}(t) = 1 - \frac{P_{OFFDu,A_k}(t)}{P_{OFFDu,A_k}(t-1)}. \tag{8}$$

Finally, through tracking the time of day on which the appliance A_k has been mostly used, a likelihood function was constructed as $P_{TOD,A_k}(t)$ which gave the likelihood of an appliance being used at a given time in a day. Fig. 3 shows the constructed $P_{TOD}(t)$ for the Television (TV) and washing machine (WM). Following this technique, AUPs were characterized in terms of three appliance specific likelihood functions: $P_{ON,A_k}(t)$, $P_{OFF,A_k}(t)$ and $P_{TOD,A_k}(t)$.

B. Fuzzy Based Priori Probability (PP) Calculating Strategy

As the step after the AUP extraction described in Section III-A, through the constructed likelihood functions, a fuzzy logic based priori probability (PP) calculating technique was used to obtain the appliance combination specific PP values $P(C_j)$. Those PP values were used to generalize the evaluation of MAP criteria in (3) without assuming the constraint in (4).

For an appliance combination $C_j = \{A_1, A_2, \ldots, A_n\}$ where $n \in \{1, 2, \ldots, N_A\}$; N_A = number of appliances; and $j \in \{1, 2, \ldots, 2^{N_A}\}$; its priori probability at the time instant $t = t_0$ was obtained from under the assumption that all appliances are independent as,

$$P(C_j)|_{t=t_0} = \prod_{k=1}^{n} P_{PP,A_k}(t_0). \tag{9}$$

Here, $P_{PP,A_k}(t_0)$ denotes the PP value of the appliance A_k at time instant $t = t_0$. In order to get this value, first, the history of the given appliance state (ON or OFF) was used to obtain the corresponding time duration that the appliance remained in that state. While executing the proposed NILM method for each appliance, the state history and the corresponding time durations were updated and stored. Now, through the constructed likelihood functions in (7) or (8), either $P_{ON,Ak}(t_0)$

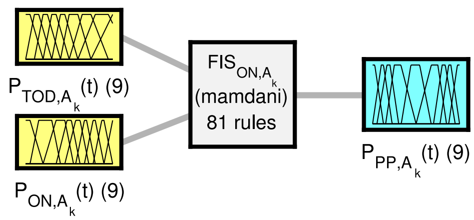

Fig. 4. FIS used to get the PP when A_k is ON : (FIS_{ON,A_k}).

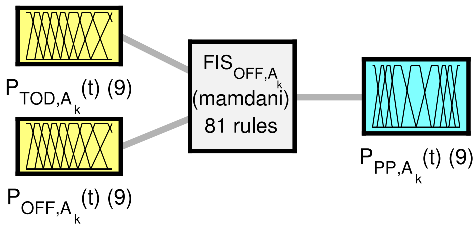

Fig. 5. FIS used to get the PP when A_k is OFF : (FIS_{OFF,A_k}).

or $P_{OFF,A_k}(t_0)$ was found for each appliance A_k depending on its ON/OFF state. Further, a time of day based likelihood value for the appliance A_k was also evaluated based on the constructed likelihood function P_{TOD,A_k}. Based on the most recent state of the appliance A_k, one of constructed Fuzzy Inference Systems (FISs) out of FIS_{ON,A_k} in Fig. 4 or FIS_{OFF,A_k} in Fig. 5 was used to get the $P_{PP,A_k}(t_0)$ value appropriately.

For the FISs, as shown in Fig. 4 and Fig. 5, piecewise linear membership functions (MFs) were used. Since the appliance A_k has the $P_{ON,A_k}(t)$ values biased towards 1, these MFs were also automatically shifted towards that region in order to get a better input sensitivity [47], [48]. Similarly, other input MFs (3 per each appliance) were also decided based on that automated logic. All output MFs of FISs (2 FISs per appliance) have the same MF arrangement where MFs have been shifted outward from 0.5 towards both 0 and 1. This was done in order to have a more information rich output rather than having a result similar to $P_{PP,A_k} = 0.5$ where the information content is less [49].

Furthermore, for each appliance, same two different Fuzzy Rule Bases (FRBs) have been used for respective two appliance specific FISs. These two FRBs were designed in such a way that they can eliminate NILM solutions which indicates sudden appliance state changes that occur at unusual time of day. This fact is illustrated by the FIS Output Surfaces shown in Fig. 6. There, since in such incidents P_{TOD,A_k} value is near 0, while the P_{ON,A_k} or the P_{OFF,A_k} value is near 1, FRB has been designed to have a low priori probability value output for such inputs. Thus, it increases the stability and the robustness of the NILM solution.

The proposed priori biasing technique in this Section depends on extracted common appliance usage behaviors. However, as a result of randomness in the human behavior, actual appliance usages might occasionally deviate from these pre-constructed appliance usage patterns. Therefore, the usage patterns may not solely be able to decide the turned ON appliance combination. As a remedy to this scenario, the overall priori biased NILM technique uses the usage patterns

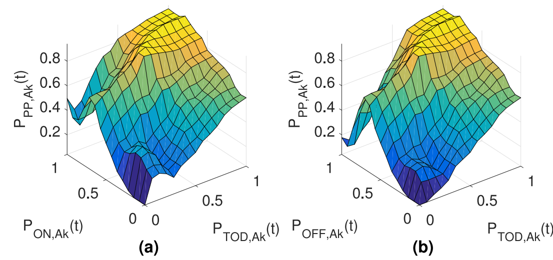

Fig. 6. Output Surfaces for (a) FIS_{ON,A_k} and (b) FIS_{OFF,A_k}.

only for priori probability biasing. Thus it is not the sole criteria for determining the turned ON appliance combination. Therefore, even under random behaviors, this priori biased NILM algorithm works accurately.

C. The Priori Biased NILM Method

Using the AUP based PP calculation technique discussed in Sections III-A & B, PP values required to evaluate the MAP criteria given in (3) were found. To incorporate this priori biasing approach into the priori unbiased NILM method described in Section II, two additional stages were incorporated into the Algorithm 1.

First, each appliance state and its present ON or OFF duration was updated before the PES (in Algorithm 1: line 6) using the NILM solution in the previous time instant. Then, in the first iteration ($i = 1$), after the SES (in Algorithm 1: line 10), PP values of all remaining possible appliance combinations were calculated using (9), by utilizing the constructed appliance specific FISs: FIS_{ON,A_k} and FIS_{OFF,A_k}.

With these modifications, the NILM algorithm with the priori biasing technique as shown in Algorithm 2 was deployed as step 5 of the proposed NILM algorithm to carry out the load combination identification for the aggregated power profile: RS3. Here, from the obtained results, an improvement in the NILM accuracy levels was observed with the introduction of the AUP based priori biasing technique for NILM.

IV. Total Power Demand Forecasting Method

Total power demand forecasting is considered as one key application of NILM for DSM [1]. However, to the best of authors knowledge, there are no known cases of NILM or even AUP based approaches been utilized to tackle this problem of demand forecasting reported in literature. As a viable solution, this paper proposes a NILM and AUP based approach to forecast the total demand of a number of houses, 5 minutes ahead of current time instant. This information enables a DSM aggregator to inform the Transmission System Operator the amount of DSM available in case of a system emergency.

In the proposed NILM technique, identified ON and OFF sets of appliances as well as their respective ON or OFF durations are available for a given time instant. Since pre-calculated ON or OFF duration based CCMFs given in (5) and (6) are also available, for each appliance, most probable ON or OFF durations into the future were calculated for a constant confidence level value, α, for each time instant. For illustrative purposes, confidence levels have been chosen as 0.9 and 0.5.

Algorithm 2 Work Flow of Appliance Combination Identification in Priori Biased NILM Step (for RS3)

for each SW in RS2 **do**
  Extract features from the SW; *#5 SCs:* Z_i; $i = 1, 2, ..., 5$;
  Set $i = 1$; *#Iteration or SC Number*
  Set $execution = 1$; *#Matching Incomplete Yet*
  Set $S_0 = \{C_j : j = 2^{N_{apps}}\}$ *#Set of All Combinations*
  Update ON and OFF durations of each appliance;
  Apply the PES to S_0 and obtain S_1;
  while *execution* **do** *#Iterative SC Matching*
    Consider the i^{th} dominant SC : Z_i;
    Apply the FES to S_1 or S_3 and obtain S_2;
    Apply the SES to S_2 and obtain S_3;
    if $i == 1$ **then** *#only in 1^{st} iteration*
      Calculate priori probabilities for every appliance combination in S_3 using (9) and constructed FISs;
    end if
    Apply the MAP criteria to S_3 and obtain S_4; *#Get* $\gamma_{C_{j,i}}$
    if $\gamma_{C_{j,i}} > 0.99$ **then** *#Matching of* C_j *upto* i^{th} *SC*
      Output: Turned ON Appliance Combination $= C_j$;
      Set $execution = 0$; *#Matching Complete*
    else if $(i == 5) \cup (S_4 \in \emptyset)$ **then**
      Output: Most Probable Solution: $argmax(\gamma_{C_{j,i}}, C_j)$;
      Set $execution = 0$; *#Matching Complete*
    else
      $i = i + 1$ *#Go to Next SC Matching*
    end if
  end while
end for

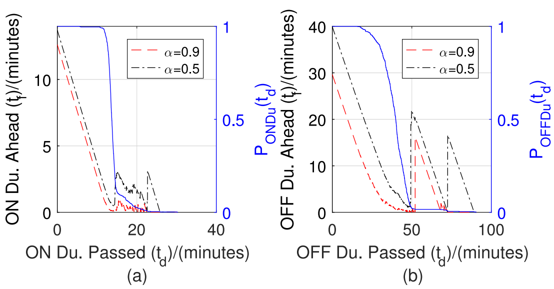

Fig. 7. t_f vs t_d Profiles of RF for (a) ON and (b) OFF States.

These confidence levels are adjustable and the two values were specifically selected to highlight the impact of this parameter.

For example, if the NILM method detected that, appliance A_k has been in the ON state for a duration of t_d up till the current instant, then, using the CCMF given in (5) the turned ON duration t_f into the future for that appliance with a confidence level of α was found using the conditional probability given by,

$$\alpha = P\left(\frac{ONDu > (t_d + t_f)}{ONDu > t_d}\right) = \frac{P_{ONDu,A_k}(t_d + t_f)}{P_{ONDu,A_k}(t_d)}. \quad (10)$$

Further, to reduce the execution time, for each appliance A_k and for each possible ON duration t_d, corresponding t_f values were pre-stored for few confidence levels such as $\alpha = 0.3,\ 0.5,\ 0.7,\ 0.8,\ 0.9,\ \&\ 0.95$, during AUP extraction step. Due to this pre-storing techniques, forecasts with different confidence levels can be achieved. Same procedure was repeated to predict the likelihood of the OFF state t_f into the future for a given confidence level. Fig. 7 shows such pre-stored curves for the Refrigerator (RF).

Now, these pre-constructed sets of profiles were used along with the proposed NILM method's present solution and the power level disaggregation solution [46], to predict the individual appliance power profiles ahead from the current time. Through aggregation of these results for appliances in a number of houses, the proposed total power demand forecasting technique was successfully validated.

V. Case Study

Two case studies were carried out to evaluate the proposed NILM method and the demand forecasting technique.

A. Performance Metrics

The case study utilized the following performance metrics.

1) Appliance Combination Identification Accuracy (A_{ci}): To asses the overall performance of the NILM method, A_{ci} value was calculated as the percentage of OSWs where the turned ON appliance combination was found correctly [2].

2) F-Measure (F_m): The F-measure (F_m) [50] was used to evaluate the accuracy of identifying the states of combination (C_j), and is given by,

$$F_{m,C_j} = 2TP/(2TP + FN + FP), \quad (11)$$

where TP, FN and FP, for each identified turned on appliance combination, are the True Positives, False Negatives and False Positives. The average F_{m,C_j} over $\forall C_j$ in a given aggregated active power signal is denoted as A_{fm}.

3) Total Power Correctly Assigned (A_{pa}): To evaluate the performance of the power disaggregation, the "Total Power Correctly Assigned" (A_{pa}) metric described in [1] and [34] was used. Metric A_{pa} is formally defined as follows [34]:

$$A_{pa,C_j} = \left[1 - \left(\sum_{t=1}^{T}\sum_{i=1}^{n} |\hat{y}_t^{(i)} - y_t^i| / \left(2\sum_{t=1}^{T}\bar{y}_t\right)\right)\right] \times 100\%, \quad (12)$$

where $\hat{y}_t^{(i)}$ denotes the calculated mean power level of the proposed method for i^{th} appliance at the t^{th} OSW while y_t^i denotes the measured mean power level for i^{th} appliance at the t^{th} OSW in a given aggregated signal. Moreover, $\bar{y} = \sum_{i=1}^{n} y_t^i$. The average A_{pa,C_j} over $\forall C_j$ in a given aggregated active power signal is denoted as A_{pd}. Further, the metric A_{pa} for estimation of power demand forecasting is denoted as A_{pf}.

4) Average Execution Time (A_{et}): All algorithms in this paper were executed on a workstation with Intel Core i5 processor and 16 GB RAM running at 2.3 GHz, with Windows 10 OS. In order to demonstrate the speed of the solution, the metric Average Execution Time (AET) taken to process an OSW to generate the NILM result was used.

B. Case Study 1

This case study was carried out to evaluate the NILM accuracy improvement achieved by AUP based fuzzily priori biasing. Here, seven tests were carried out by deploying the proposed NILM method exactly as illustrated in Fig. 1 for the real data taken from *Tracebase* and *REDD* datasets.

TABLE I
PERFORMANCE METRICS COMPARISON BETWEEN BASIC NILM (PUN) VS AUP BASED ENRICHED NILM (PBN)

House Name	A_{ci} (%)		A_{fm} (%)		A_{pa} (%)		A_{et} (ms)	
	PUN	PBN	PUN	PBN	PUN	PBN	PUN	PBN
HouseT	84.2	93.2	82.2	91.6	87.0	90.0	420	640
House1	84.1	93.0	83.1	90.2	85.2	89.8	501	820
House2	83.4	93.7	81.4	91.7	86.2	85.7	315	515
House3	82.4	89.0	81.0	87.2	79.1	82.7	418	627
House4	76.6	86.1	76.5	85.2	76.2	80.2	369	658
House5	76.2	86.3	75.8	84.1	74.6	79.2	357	562
House6	79.1	87.7	78.2	85.7	78.6	80.2	302	501

TABLE II
COMPARISON OF OBTAINED F-MEASURE VALUES

NILM Method	A_{fm} /(%)	Remarks
Proposed Method:PBN	**88.5**	**Using all appliances in all six houses.**
Basic NILM (PUN) [2]	79.7	
Supervised GSP [26]	64.0	Using only 5 most performing appliances in Houses 2 & 6.
Unsupervised GSP [27]	72.2	
Unsupervised HMM [5]	62.0	Using only 7 most performing appliances.
Additive FHMM [37]	71.3	
Supervised DT [30]	76.4	Using only 9 most performing appliances.
Unsupervised DTW [30]	68.6	
Multi-Label KNN [23]	59.1	Using only 9 arbitary selected appliances.
Bayesian Classifier [29]	83.0	
Viterbi Algorithm [29]	88.1	

1) Procedure: The *Tracebase* dataset contains 22 different individual appliance power profiles collected at 1 samples per second from German households and office spaces. For the first test, 12 residentially used appliances were purposively selected from this dataset such that, selected set of appliances contained 2 or more number of appliances from each appliance category [2]: "single-state" (SS), "multi-state" (MS), and "continuously varying" (CV). From the selected set of appliances by manually aggregating the appliance power profiles a house was created (HouseT) which had individual and aggregated power profiles for 52 days. As higher number of different types of appliances have been used in the case study, real-world complex conditions have been emulated in the constructed HouseT.

First ten days of individual appliance power data (RS1) were used in feature extraction and creation of signature databases. Then, next 21 days of the aggregated power signal (RS2) were evaluated by Stage A of Figure 1 to study the AUPs. Then from the remaining aggregated power profile data (RS3), priori biased NILM method was evaluated. Finally, for performance comparison purposes, priori unbiased NILM method was also evaluated for RS3.

The *REDD* dataset contains real measured active power signals taken from 6 real households in USA, with whole home, appliance/circuit level data at 1/3 samples per second. These data from the 6 *REDD* houses (House1-6) were used for the evaluation of the proposed NILM method as the next six tests. For each house, reading sets RS1, RS2 and RS3 were selected in a similar manner to the previous case (HouseT). Since these houses consists of different types of loads and even some unknown loads, viability of the proposed NILM algorithm under real measurements was validated through this real world scenario.

2) Results and Discussion: Appliance combination identification accuracy (A_{ci}, A_{fm}), power disaggregation accuracy (A_{pa}) and the Average Execution Time (AET-A_{et}) obtained for described test cases are given in Table I. From these results, it was observed that, with the proposed priori biased NILM method (denoted by PBN), for each house tested, turned on appliance combinations were identified with more than 86% accuracy in-terms of A_{ci} and more than 84% accuracy in-terms of A_{fm}. However, with the priori unbiased NILM method (denoted by PUN), these two values were 76% and 75% respectively. So, the improvement due to the introduction of AUP based priori biasing technique is substantial.

It should be noted that accuracy of the power level disaggregation has also been increased by around two percentage points from using this strategy. Since both priori unbiased and biased NILM algorithms had used the same power breakdown technique in [46], this slight improvement should be due to the increased appliance combination identification accuracy achieved by the proposed NILM method. Although AET has been increased by around 30% due to the introduced priori biasing step in the proposed NILM method, still the AET is well inside 1s or 3s sampling periods. Thus, real-time implementation of this strategy is clearly viable.

Furthermore, *REDD* houses 3-6 contains several unknown appliances and plug sockets. So, activation of such appliances should decrease the NILM accuracy levels significantly. The proposed NILM method was able to produce an accuracy improvement even under such a challenging scenario. Also, it should be noted that, in the absence of such unknown appliances, the proposed method generates NILM results with accuracy levels higher than 93%. In addition, most NILM solutions in the literature have actually not used the *REDD* houses in concern (4, 5 and 6) due to the presence of the unknown appliances. Even compared to the few that have used these houses [5], [51], the accuracy level of the method proposed in this paper is significantly higher [41], [42].

3) Comparison With State of the Art: In order to demonstrate the strength of the proposed NILM method, obtained F-Measure values (A_{fm}) and power disaggregation accuracy (A_{pa}) values were compared among other state of the art NILM methods. In this comparison, all considered algorithms have utilized the data taken from publicly available *REDD* dataset [34]. Moreover, use of common accuracy metrics such as A_{fm} and A_{pa} suggested in [34] and [50] enabled this direct comparison.

Table II summaries the overall average F-measure values achieved by different state of the art NILM methods including the proposed method in this paper. Here, for the completeness of the comparison, fundamentally diverse set of recent and benchmark NILM methods were used. These approaches have been summarized in the following paragraph.

In [24] and [25], supervised and unsupervised Graph Signal Processing (GSP) based two NILM methods have been discussed. Two benchmark NILM algorithms based on Hidden Markov Models (HMMs) have been introduced in [5] and [35]. There, [5] uses an unsupervised HMM algorithm while [35]

TABLE III
COMPARISON OF OBTAINED POWER DISAGGREGATION ACCURACY VALUES

NILM Method	A_{pa} /(%)	Remarks
Proposed Method:PBN	**84.0**	**For all six houses**
Basic NILM (PUN) [2]	81.0	
Greedy Deep SC [31]	62.6	Using only Houses 1, 2, 3, 4 & 6 [31].
Exact Deep SC [31]	66.1	
General SC [33]	56.4	
Discriminating SC [33]	59.3	
Powerlets-PED [32]	46.5	
Temporal ML [24]	53.3	
Factorial HMM [36]	47.7	
F-HDP-HSMM [35]	84.8	Using only 5 appliances in the Houses 2 [27].
F-HDP-HMM [35]	70.7	
EM-FHMM [35]	50.8	
With Int. FHMM [38]	66.5	Using only 7 appliances in the House 2 [27].
Without Int. FHMM [38]	65.5	
Unsupervised GSP [27]	77.2	
Subtractive Clustering [28]	86.0	Using only 6 selected appliances [28].

uses an additive factorial-HMM to identify the turned ON appliance combination. Further, NILM via event (i.e., ON/OFF transition) classification is also an emerging technique in the research. In [28] two such methods have been introduced based on supervised Decision Tree (DT) classifier and a Dynamic Time Warping (DTW) based classier. Similarly, [27] define Bayesian classifier and a Viterbi algorithm to address same even classification task. Furthermore, [21] explores multi label classification (ML-KNN) based NILM methods based on both time domain and wavelet domain feature sets.

As reported in [5], [21], [25], [27], [28], and [39], it should be noted that, the F-measure value of each aforementioned NILM method has been evaluated considering only certain set of appliances. In most cases, this specific set is selected based on the identification accuracy level of each appliance under the considered NILM method. Further, as mentioned before, some of these NILM methods do not consider *REDD* houses such as House 4, 5 and 6 due to the presence of unknown appliances. In contrast, the proposed NILM method have been evaluated for all houses of the *REDD* dataset considering all appliances in each household. Therefore the proposed NILM algorithm have considered in essence a more challenging dataset. Despite this challenging nature of the used data, according to the results shown in Table II, proposed NILM method have also outperformed all the other NILM methods in terms of appliance identification accuracy.

Another comparison was carried out to compare the achieved individual appliance power level disaggregation accuracies (A_{pa}) by different state of the art NILM methods including the proposed NILM method in this paper. Results of this comparison are summarized in Table III. Here also, for the comparison, a fundamentally diverse set of recent and benchmark NILM methods have been used. These approaches are summarized as follows.

In [29], two load disaggregation schemes named as the Greedy Solution and the Exact Solution have been proposed based on Deep Sparse Coding (SC). In the work [31] another two NILM methods, named General SC and Discriminative SC have been proposed. For the load disaggregation task, another three avenues have been explored in [22], [30], and [34] which uses 'Powerlets' Learning (PED), Temporal Multi-Label Classification (ML) and Factorial HMM (FHMM) respectively. Moreover, three HMM based techniques, named Factorial-Hierarchical Dirichlet Process HMM (F-HDP-HMM), F-HDP Hidden Semi-Markov Model (F-HDP-HSMM) and Expectation Maximization FHMM (EM-FHMM) have been proposed in [33]. Furthermore, in [26], Subtractive Clustering technique have been evaluated.

From the comparison of the results it is clear that, F-HDP-HSMM method proposed in [33] and Subtractive Clustering method proposed in [26] have slightly outperformed the proposed NILM method. However, it should be noted that, these two methods only have been evaluated for a limited number of appliances considering only a single household, as reported in [25], [26], [29], and [33]. In contrast, the proposed NILM method was evaluated on all six houses. Also, in each house, power profiles were disaggregated for the seven highest power consuming appliances in each household.

From both comparisons, it can be concluded that, both appliance identification accuracy and the power level disaggregation accuracy of the proposed NILM method are comparable or superior compared to existing state of the art NILM methods.

C. Case Study 2

This case study was carried out to validate the proposed total power demand forecasting technique described in Section IV.

1) Procedure: Real household data taken from *REDD* Houses 1, 2 & 3 were used for this study. For each of these chosen houses, signature databases, and extracted AUPs had already been constructed (using respective RS1, RS2 data in the Stage A of the proposed NILM method) for the previous case study. So, for each house, only the priori biased NILM method was evaluated (i.e., the step 5) while generating load forecasts for five minutes ahead of the current time instant. So, for each house, using its RS2 data, the 5th and 6th steps of the proposed NILM method were re-evaluated.

Next, for the chosen three houses, data corresponding to 21 different days were selected from their whole house power profiles (from RS2 of each house). Then these 21 residential power data profiles (each of length of 24 hours) were considered as data which belongs to 21 different houses for one complete day. This was done to demonstrate the viability of the prediction technique for a large area.

Finally, using appliance level power demand predictions of each of the 21 constructed houses (during a day), the total aggregated power demand forecast was estimated with confidence levels (i.e., α) of 50%, 70%, 90% and 95%.

2) Results and Discussion: Actual and predicted total power profiles of the 21 houses are presented in Fig. 8. For demonstration purposes, Fig. 8 displays the prediction result of a 15-minute window out of the power profile which was actually predicted for one complete day with a confidence level of 90%. The accuracy of the total aggregated power prediction of all 21 houses for each 3 hour period from 06:00 to 24:00 is presented in Table IV. Further, sensitivity of the forecasting accuracy was studied by varying the confidence level parameter α and those results are also shown in Table IV.

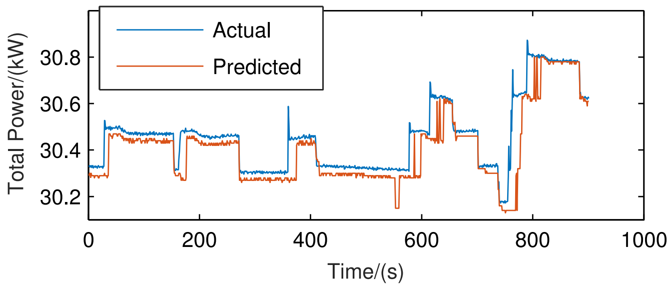

Fig. 8. Actual Vs Predicted Total Power Profiles.

TABLE IV
TOTAL POWER DEMAND PREDICTION ACCURACIES VS CONFIDENCE LEVEL (α) WHEN TIME STEP AHEAD = 5 MINUTES

Prediction Accu. A_{pa} (%)	Time of Day (09:00 - 24:00) Hrs					
	6-9	9-12	12-15	15-18	18-21	21-24
α = 0.30	74.2	75.7	71.9	76.2	72.9	74.3
α = 0.50	78.8	76.3	73.6	79.3	77.0	78.3
α = 0.70	78.6	76.5	74.9	79.4	78.1	79.1
α = 0.90	79.6	77.2	78.9	78.7	80.2	81.2
α = 0.95	72.6	75.7	70.6	70.4	72.1	73.2

According to the actual and predicted total power profiles (See Fig. 8), the proposed NILM algorithm has the ability to identify downward steps in the total power demand more efficiently when compared to identifying the upward trends. Here, for many appliances as shown in Fig. 2 and in Fig. 7, observed ON durations would be shorter compared to their OFF durations. As a result, it improves the predictability of instants where appliances are turning OFF compared to the instants where appliances are turned ON. Thus, prediction of downward trends in the total power demand by the proposed NILM method is more efficient compared to forecasting upward steps.

In general, according to the results in Fig. 8 and Table IV, it is clear that the proposed NILM method identifies the turned on appliance combinations and predicts the total power consumption of number of houses five minutes into the future with reasonable accuracy.

Furthermore, since the predicted breakdown is available at the appliance level in each house, it enables a power system aggregator to predict both the non-critical appliances that could be turned off and the amount of Demand Response achievable, ahead of an event that could create a possible system emergency. A proper architecture to implement such a mechanism in large scale is shown in Fig. 10 and discussed in Section V-D.

3) Inferences From Sensitivity Analysis: From the sensitivity analysis, a trade off between the used confidence level α and the prediction accuracy was observed. Observations in Table IV revealed that in order to forecast the total power demand of 21 houses 5 minutes ahead, using a 90% confidence level is more accurate than using a 95% or 70% confidence levels.

In order to further investigate this dependence between accuracy level, confidence level and the forecasting time step ahead, same experiment was carried out to forecast the total power demand of 21 houses, both 10 minutes and

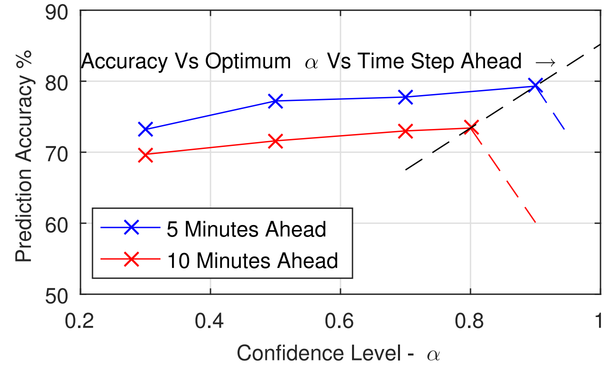

Fig. 9. Prediction Accuracy Vs Confidence Level.

15 minutes ahead. For such time steps, optimum prediction accuracy levels were achieved when the confidence level is selected as 80% and 50% consecutively. Results of this investigation is illustrated in Fig. 9.

According to the obtained results, predictions with increased time step durations ahead are achieved through lowering the used confidence level. This will slightly decrease the prediction accuracy as shown in Fig. 9. On the other hand, more accurate predictions for the near future can be obtained via increasing the used confidence level. This is a logical observation as in any case, with higher levels of confidence, it is not possible to predict the behavior far beyond the near future and vice versa. So, the introduced parameter α enabled changing the prediction duration further into the future.

D. Some Aspects of Installation and Scalability

Several key aspects have been discussed in this chapter on the installation and scalability of the proposed NILM method.

1) Installation: The architecture and operation of its hardware installation is illustrated in Fig. 10.

Here, for each household, only a dedicated processor unit with a communication channel is required apart from the smart meter. Once this residential NILM processor unit is installed and connected to the smart meter, individual appliance signature learning and signature database construction phases (i.e., steps 1 & 2 in Fig. 1) are initiated as described in Sections II-B and II-C. Since most of the appliance models are commonly used in many households, for a large scale implementation, signatures for such appliance models can be taken from global databases. Apart from that, unique appliances for the considered house should be learned individually by turning each of them ON and observing their power profile for a duration of few hours. At the end of this signature learning stage, House specific set of signature databases will be stored in the processor unit.

After that, steps 3 & 4 (See Fig. 1) of the proposed NILM method will be automatically completed in the residentially installed processor unit. There, first, priori unbiased NILM method as described in Section II-D will evaluate the appliance usages. This method have been verified by the authors, both in simulations [2] as well as in real-time implementation [45]. Next, using the obtained results, in step 4, appliance usage

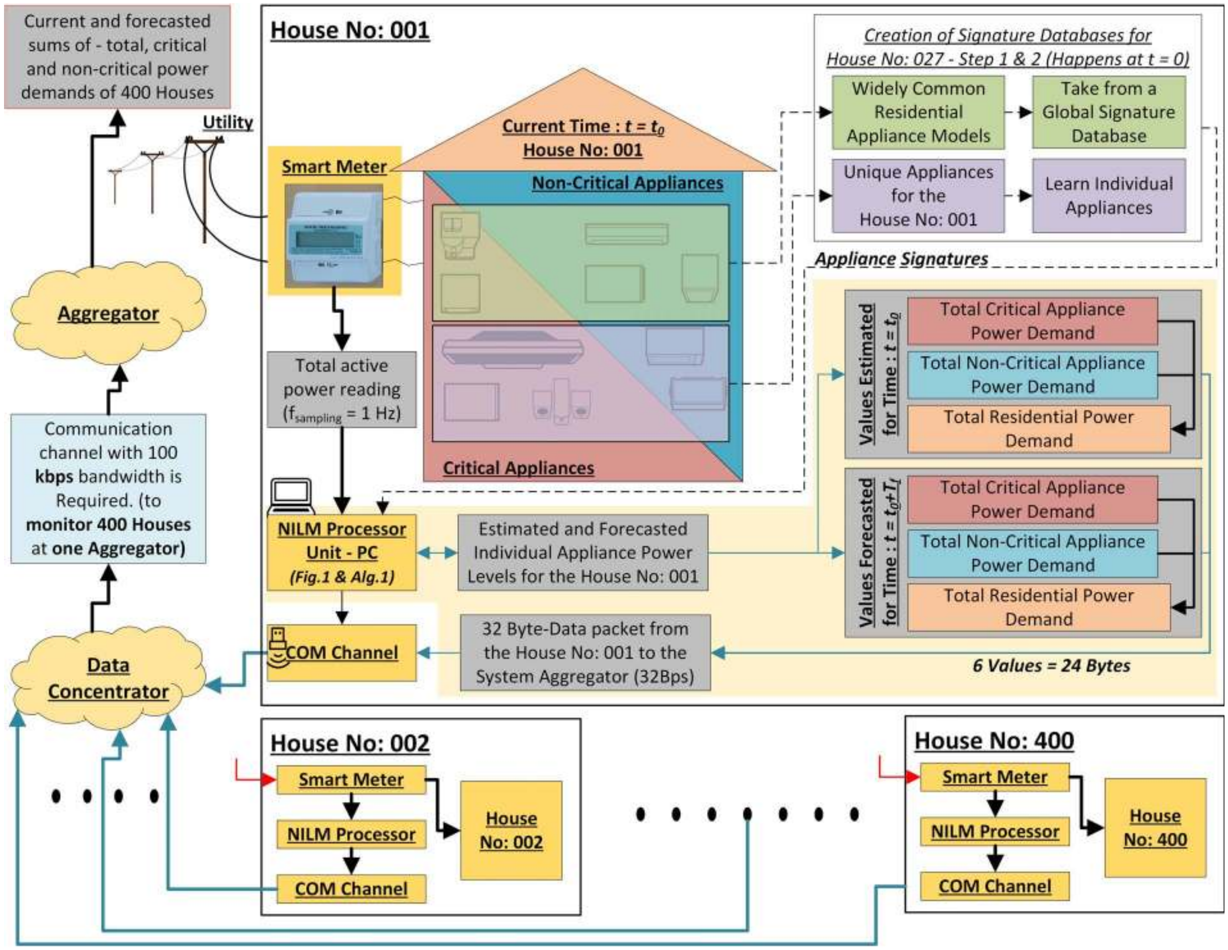

Fig. 10. Proposing Overall Hardware Architecture.

patterns of the installed household are extracted and, priori biasing technique is formulated in the corresponding NILM processor as described in Sections III-A and III-B.

There onwards, step 5 & 6 (See Fig. 1) are continuously evaluated in the residentially installed processing unit. Here, the novel priori biased NILM technique described in Section III-C will evaluate the currently turned ON appliance combination as well as the appliance power level disaggregation. Further, as described in Section IV, power level forecast for five minutes ahead of current time value can also be evaluated for each appliance in the considering household.

2) Increasing Number of Appliances Per House: In the proposed NILM method, all the house specific signature databases are kept pre-stored in the residentially installed processor unit. There, in constructing the appliance combination level signature database (CLSD) as described in Section II-C, all possible appliance combinations for the given set of residential appliances are considered. So, it was observed that the size of this CLSD tends to grow exponentially with the increase of number of appliances in the household.

Table V was obtained by constructing CLSDs for different number of residential appliances. For this task, real measurements obtained from a laboratory setup was utilized. From the obtained CLSD sizes and data reading times shown in Table V, it is clear that even for higher number of appliances, database sizes will not go beyond the sizes of conventional data storage device.

TABLE V
MEMORY REQUIREMENT FOR DATABASES

No. of Appliances	10	14	18	20	25
Database Size (MB)	1.750	28.51	450.4	1701	49875
Reading Time (ms)	2.781	3.945	5.012	6.753	15.23

Furthermore, when identifying the currently turned ON appliance combination for an observed sliding window (OSW), the proposed NILM method (i.e., the Algorithm 2) first starts by considering all possible appliance combinations as viable solutions for that OSW. Then onwards, this solution space is continuously reduced using one pre elimination stage (PES) and two iterative first and second elimination stages (FES & SES) as described in the Section II-D & Algorithm 2.

In order to illustrate the strength of these elimination stages, first, a house was synthetically created with 15 different appliances taken from *REDD* dataset. Then, corresponding CLSD of that house was constructed as described in II-C. Then, for that CLSD, for all possible static levels of an OSW, the number of appliance combinations left in the solution space after each elimination stage in the 1st iteration was observed. This result is illustrated using a logarithmic plot in Fig. 11 (a). From this result, an exponential drop in the solution space was observed for every possible static level of an OSW.

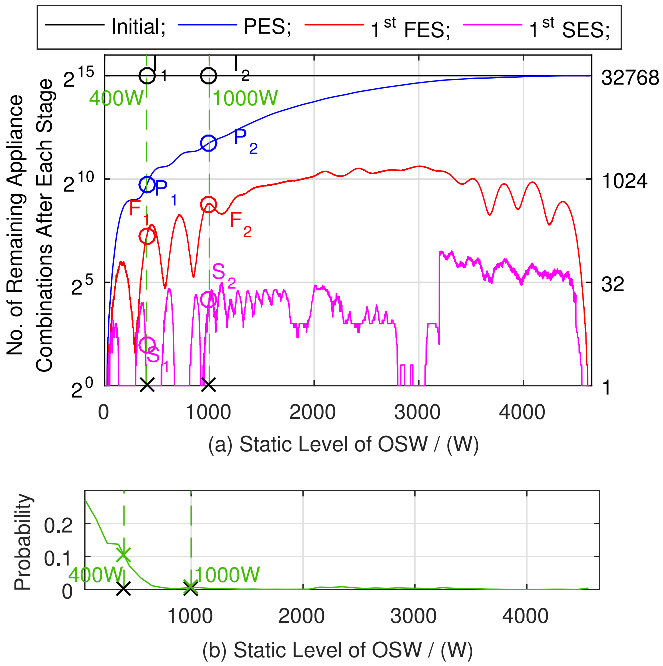

Fig. 11. (a) Remaining no. of appliance combinations after each elimination stage of the first iteration of Algorithm 2 and (b) Likelihood Vs different possible OSW static levels.

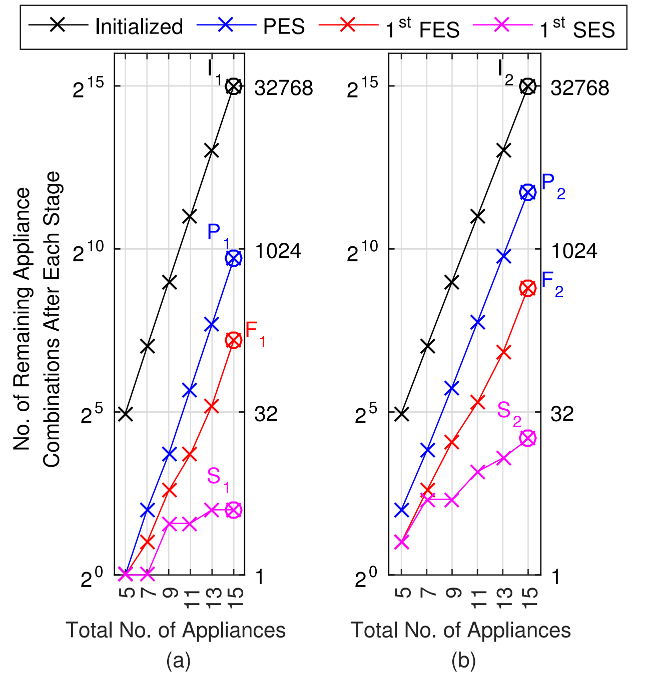

Fig. 12. No. of appliance combinations remaining after each elimination stage of the first iteration of Algorithm 2 Vs Total no. of appliances in the household when the Static Level of OSW is (a) 400W and (b) 1000W.

Further, considering the actual total power profile of the created household, a likelihood function was created for the OSW-Static Level. This is shown in Fig. 11 (b). This behavior conveys the fact that for an actual household, static levels of observed sliding windows, taken from the total power profile are more likely to have lower values. For this particular case, most likely OSW static levels are in the range 0 W - 1000 W (Fig. 11 (b)). From this range, to further study the strength of elimination stages, 400 W and 1000 W static levels were arbitrarily chosen.

Then, same experiment was carried out while changing the number of appliances in the household. After that, for the selected OSW static levels of 400 W and 1000 W, the number of remaining appliance combinations in the solution space after each elimination stage was observed. This is shown in Fig. 12.

These observations conveys that, even though the number of possible appliance combinations grow exponentially with the number of appliances present in the house, the used elimination stages are capable of eliminating appliance combinations in the solution space in an exponential manner so that final solution is achieved within few iterations.

3) Increasing Number of Houses Per Aggregator: Once the residential appliances have been classified into critical and non critical categories [52], [53], using the appliance level breakdown of the current and forecast power consumptions, the values of total / critical / non critical power demands can be calculated for the household as shown in Fig. 10. Then, only these six values are to be transmitted from each household to the concentrator per every 1 s interval.

For this purpose, required communication bandwidth between a house and the concentrator is estimated as 256 bps (i.e., 32Bps). Further, monthly consumed data amount is calculated to be 80 MB per house. From the data concentrators point of view, in order to monitor 400 houses by one aggregator [54], a communication bandwidth of 100 kbps is required between the aggregator and the concentrator. Furthermore, inside the data aggregator, in order to carryout the data acquisition, manipulation and storing for 400 households for 1 s sampling interval, the average execution time was evaluated to be 0.1225 s for the processor mentioned in Section V-A4.

All estimated parameter values confirms the ability to deploy the proposed NILM technique using normal processor units and conventional communication methods. This proves the scalability as well as the feasibility of the proposed NILM technique in a large scale setup.

VI. Conclusion

This paper proposes a novel NILM method with enriched capabilities to not only identify turned-on appliances and their power consumption levels, but also to adapt itself according to AUPs. Since this NILM solution does not depend solely on collected measurements, it produces more accurate and robust results compared to existing NILM techniques. The ability to use AUPs in NILM allowed this method to be used to predict the total power consumption of a number of houses a few minutes ahead of the present time instant (i.e., real-time). This has an important practical interest as utilities are reluctant to utilize DLC for DR due to difficulty of estimating amount of load available for DR ahead of the real time.

The method utilizes the KL expansion to separate uncorrelated spectral information in active power profiles and construct signature databases. Further, it incorporates AUPs via a fuzzy logic based priori biasing technique. Since the algorithm performs with high accuracy even on power profiles sampled at low rates, expensive hardware is unnecessary. Furthermore, from the execution speeds achieved, this is a viable algorithm for a real-time implementation.

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