Household Load Forecasting based on a pre-processing Non-Intrusive Load Monitoring Techniques

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***Abstract*—the new vision for moving the power system to a smart grid enables a variety of smart applications at different power system infrastructure's levels. Households represent a massive section of the grid infrastructure which could not be considered as a smart grid without smart households integrated into it. Short Term Load Forecasting (STLF) is the essential tool needed in the management and control techniques required for households to be smart. STLF at this level of the grid is very challenging due to the high percentage of uncertainty in the load demand, influenced by customer behavior, which is too stochastic to predict. In this paper, a new approach for STLF of household load demand is employed based on artificial neural network (ANN) and a pre-processing stage of a Non-Intrusive Load Monitoring (NILM) techniques. The NILM techniques extract the individual load pattern from the available historical aggregated load demand. These new features increase the training data window for the ANN forecaster and achieve a significant enhancement for its prediction performance. By comparing the new approach with the state of the art techniques in household load forecasting, the proposed method outperforms feed-forward artificial neural network (FFANN) regarding RMSE. Two techniques of NILM were used to emphasize the correlation between the NILM disaggregation accuracy performance and the load forecasting enhancement performance.**

Keywords— Short-Term Load Forecasting (STLF), Non-Intrusive Load Monitoring (NILM), Household Load Forecasting, Artificial Neural Network (ANN).

I. Introduction

THE contemporary power system is moving forward towards a smart grid, whereas several innovations at different power system infrastructure's levels occur. Furthermore, the unprecedented penetration increase of renewable energy, time-varying load demand, and Electric Vehicle (EV) in the distribution grid, add an extra burden on the grid regarding the complexity and uncertainty. Therefore, the stability of the grid is experiencing extraordinary challenges due to the intermittency of renewable generations, the complexity of utility-customer interaction, and dynamic behaviors. A considerable section of this complex distribution network represented on Households which are responsible for a significant portion of electrical energy consumption.

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Enable the active participation of households' demand-side response (DSR) instead of considering it as a passive load will have a positive impact on the power system stability.

In this case, forecasting household load consumption is essential for residential DSR program. Accurate short-term load forecasting (STLF) on the household level can significantly facilitate the power system operations. STLF refers to the expectation of the power demand in the next hour, next day, or up to a week. STLF is the essential tool needed in the management and control techniques required for households to be smart. STLF at this level of the grid is very challenging due to the high percentage of uncertainty and volatility in the load demand, influenced by customer behavior, which is too stochastic to predict.

Based on the state of the arts in the field of load forecasting, the prediction methods have been used include time-series analysis such as exponential smoothing and autoregressive regressive integrated moving average (ARIMA) and machine learning approaches such as artificial neural networks (ANN) and support vector machine (SVM). In [1] adopted autoregressive integrated moving average model for a day ahead load forecasting was presented. In which the prediction mechanism is based on grouping the targeted day with the similar meteorological days in the historical data. In [2] Radial basis function (RBF) neural network had been used to address the STLF. In [3] a combination between RBF neural network and the adaptive neural fuzzy inference system (ANFIS) was presented to adjust the prediction by taking into consideration the real-time electricity price. In [4] it is proposed a neural network based predictor for very short-term load forecasting.

It takes only the load values of the current and previous time steps as the Input to predict the load value at the subsequent time step. In [5] an ensemble of extreme learning machines (ELMs) to learn and forecast the total load of the Australian national energy market was used. In [6] a dedicated input selection scheme to work with the hybrid forecasting framework using wavelet transformation and the Bayesian neural network was presented. Based on the previous literature, the techniques used for load forecasting can be concluded in three categories. The first is avoid the uncertainty by Clustering/classification techniques which group similar customers, days or weather in the hope of reducing the variance of uncertainty within each cluster[7]. However, the performance is heavily dependent on the data. The second is

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trying to cancel out the uncertainty by using aggregated smart metering data so that the aggregated load exhibits mostly regular patterns and more easier to predict, yet the prediction is visible only at an aggregated level. The third is trying to separate the regular pattern from the other component of load profile such as uncertainty and noise by pre-processing techniques, mostly spectral analysis such as empirical mode decomposition (EMD) [8], Fourier transforms[9], and wavelet analysis[10]. This method can be ruled out in household load forecasting due to the high uncertainty proportion of the load pattern.

All these previous work for load forecasting techniques are suitable for the aggregated level such as system or community level. There is a little work on the literature regarding load forecasting at the household level. For example, the first two trails to address load forecasting at household level in [11], [12]. In which, a functional time series forecasting approach was proposed. However, it used daily median absolute errors (DMAE) which is not the commonly used metric. In that way, it is improper to assist as a benchmark for experimental assessments. The standard metric used to assess the forecaster performance is mean absolute percentage error (MAPE). Recently, some work is done in the area of load forecasting using the deep artificial neural network (DANN). In [11], the accuracy of load forecasting for industrial customers is improved by using DANN. It was the first attempt to use a factored conditional restricted Boltzmann machine, for household load forecasting. However, it outperforms regarding the performance than artificial neural network and support vector machine. In [13], another deep neural network (DNN) approach called long short-term memory (LSTM) is used. Although deep learning has received high expectation in forecasting community, the state of the arts indicates that deep learning is more prone to over-fitting compared with artificial neural networks[14]. The problem is expected due to the existence of more parameters and relatively fewer data. For that reason, another work based on a pooling-based deep recurrent neural network (PDRNN) is proposed in [15] to tackle the overfitting issue. However, the methodology was tried to avoid the over-fitting problem by increasing the data dimension which is the historical data of the neighbors to the neural networks. The main drawback here that this method is pooling the data of the neighboring household to increase the data set. Which most probably not available in another place for privacy policy.

In this paper, a new approach for STLF of household load demand is employed based on artificial neural network (ANN) and a pre-processing stage of a Non-Intrusive Load Monitoring (NILM) techniques. The NILM techniques extract the individual load pattern from the available historical aggregated load demand. These new features increase the training data window for the ANN forecaster and achieve a significant enhancement for its prediction performance. By comparing the new approach with the state of the art techniques in household load forecasting, the proposed method outperforms ARIMA, SVR, and ANN regarding root mean square error RMSE. We use two different disaggregation algorithms called Factorial Hidden Markov Model (FHMM) and Combinatorial Optimization (CO) to extract the power demand profile for individual appliances from the main aggregated Household smart meter. Two techniques of NILM were used to emphasize the correlation between the NILM disaggregation accuracy performance and the load forecasting enhancement performance. Fig.1 Shows the block diagram of the whole proposed system. This paper is organized as follows: in Section II description for the Non-Intrusive Load Monitoring system and its implementation are given. In Section III, a description of the proposed Short-Term Load Forecasting approach are mentioned. In Section IV, simulation results are presented and investigated to validate the developed forecaster. Finally, in Section V, some of the conclusions that can be deducted from this paper are listed.

II. NILM: NON-INTRUSIVE LOAD MONITORING

Non-intrusive load monitoring or energy disaggregation is a computational approach for estimating the individual appliances power consumption from a single meter which measures the aggregated power consumption of multiple appliances. This research started with the vital work of George Hart [16], [17] in the mid-1980s. His earliest work described a signature taxonomy of feature. However, his focus was on extracting only transitions between steady-states. Following Hart's lead, many NILM algorithms designed for low-frequency data (1 Hz or slower). But only extract a small number of features. Regarding the high frequency (sampling at kHz or even MHz), there are several examples of manually engineering feature extractors discussed in the literature [18], [19]. Humans can learn to detect appliances in aggregate data by eye, especially appliances with feature-rich signatures. Hand-engineering feature extractors could be considered for analyzing profiles with rich features. But this would be time-consuming, and the resulting feature detectors may not be robust to noise and artifacts. Hand-engineer feature extractors such as scale-invariant feature transform [20] (SIFT) and difference of Gaussians (DoG) was the dominant approach to extract features for image classification prior 2012. But, in 2012, during the competition of ImageNet Large Scale Visual Recognition, different algorithms achieved an excellent performance and did not use hand-engineered feature detectors. Instead, they used different disaggregation algorithm which automatically learned to extract a hierarchy of features from the raw image. Using the same approach in this paper, we will use various disaggregation algorithms called Factorial Hidden Markov Model (FHMM) and Combinatorial Optimization (CO) to extract the power demand profile for individual appliances from the main aggregated Household smart meter. The detailed illustration of these algorithms introduced later in this section.

A. Dataset and Non-Intrusive Load Monitoring Tool Kit (NILMTK)

There are numerous problems in energy sector need to be tackled. A lot of them need prediction tasks and data analysis, areas where techniques such machine learning and data mining

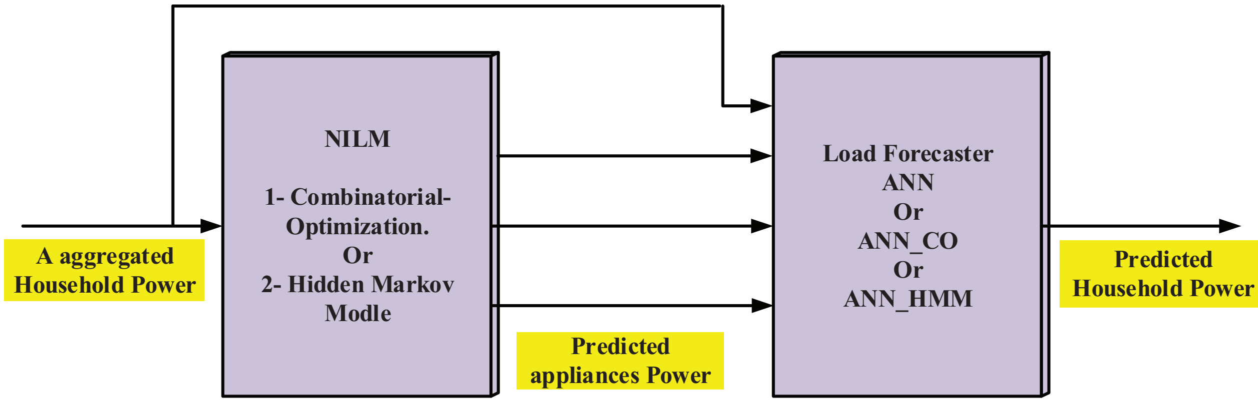

Fig. 1. Block diagram for the proposed household load forecasting approach.

can prove invaluable. As is the case in this paper, to use the NILM to enhance the household forecasting performance, the energy consumption of each household has to be available. For this reason, the data from the Reference Energy Disaggregation Data Set (REDD) released in 2011[21]is used. The first publicly available dataset collected mainly to assist the research of NILM. The dataset comprises of whole-home and device/circuit specific electricity consumption for some real houses over several months' time. For each house, the whole home electricity signal is recorded. The measurement placed as follows: a voltage monitor on one phase and current monitors on both phases of power. All these recorded at a high frequency (15kHz). Furthermore, there are 24 individual circuits in the home, which labeled with its category of appliances, recorded at 0.5 Hz. Also, there are 20 plug-monitors in the home, recorded at 1 Hz, with a focus on plugged electronics devices where multiple devices are grouped into a single recorded point circuit. It is considered the most popular dataset for evaluating energy disaggregation algorithms.The implementation of the two disaggregation algorithms as mentioned above is done based on the NILMTK [22] to implement the disaggregation process. This NILMTK implemented based on Python which

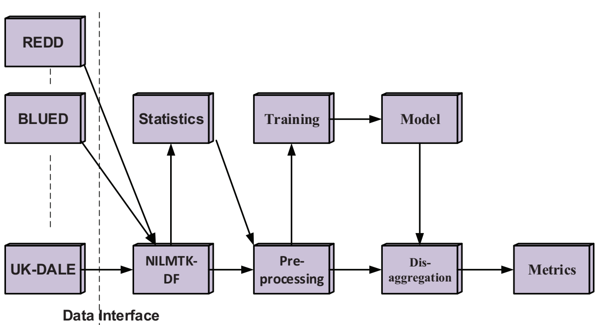

Fig. 2. NILMTK's process block diagram

provides a massive set of libraries supporting both machine learning and NILM algorithms. Furthermore, Python permits easy implementation in diverse environments including academic settings and is increasingly being used for data science. Fig. 2. presents the NILMTK's process block diagram from the import of the datasets to the estimation of different disaggregation algorithms over multiple metrics [22].

B. Combinatorial Optimization (Optimization Methods)

Optimization approaches require the existence of appliance signature libraries with all possible combinations of power demands of the appliances it is needed to disaggregate. If we include the combinations of all the installed appliances in a household, then this optimization approach is called brute-force. However, as was stated in [23] due to memory limitations, brute-force methods are impossible to be applied in an embedded system. Thus the load identification requires the definition of an objective function and its minimization.

Considering the aggregate data $\bar{x}$ and an appliance set $= [x_1, \dots\dots\dots\dots, x_N]$, the problem is formulated as [23]:

$$\min_{1 \le n \le N} \parallel \bar{x} - \sum_{n=1}^{N} x_n \parallel \quad (1)$$

The most critical algorithm in this domain is the Combinatorial Optimization which minimizes the difference between the sum of the measure aggregate power and predicted appliance power [24]. This method was also used by Hart in [25]. The computational complexity is $o\ (K^N T)$, where K is the number of appliance states, N the number of appliances and T the number of times slices used in the implementation. The problem complexity increases as the number of different loads in the aggregated signal increases, since the algorithm should take into account all possible combinations of appliances contained into the training set. The problems with this approach are[24]:

1. The presence of new loads in the aggregated signal.
2. The sequential dependencies among the appliances are neglected.
3. Appliances with similar consumption are difficult to distinguish

Thus optimization methods address mainly disaggregation for the most power-hungry devices and a limited number. In [26] it is discussed the two commonly cited disadvantages of this approach which are the decreasing of accuracy with the number of appliances and level of noise.

Factorial Hidden Markov Model belongs to the category of Temporal Graphical Models which is a class of probabilistic models. Such models have been applied previously to many real-world problems like speech recognition. The most straightforward representation of sequence data is through the use of a Markov chain which is a sequence of discrete variables. State transitions of devices are handled by the hidden Markov model (HMMs) which is a statistical tool. Each variable is described by its real power consumption in addition to other useful information such as duration of the on and off periods and time of use during the day/week. Thereby, at an instant of time t of a period T, t ∈ T, the aggregate consumption is $\bar{x}(t)$ and needs to be broken down to number of appliances z_t^n, where t ∈ T and n ∈ N with N the number of appliances. The value of each device z_t^n at any time corresponds to one of the K states of the trained model of the appliances[23]. The mathematical representation of the a HMM represented through Eq 2-6 [23].The behavior of a HMM can be completely defined and inferred by three parameters. First the probability of each state of the hidden variable at the time t can be represented by the vector π such that

$$\pi_K = \rho(z_t = k) \tag{2}$$

Second, the transition probabilities from state i at t to state j at t + 1 can be represented by the matrix A such that,

$$A_{i,j} = \rho(z_{t+1} = j | z_t = i) \tag{3}$$

Third, the emission probabilities for x are described by a statistical function with parameter $\emptyset$ which is commonly assumed to be Gaussian distributed such that,

$$x_t \mid z_t, \emptyset \sim \mathcal{N}(\mu_{z_t}, \tau_{z_t}) \tag{4}$$

Where $\emptyset = \{\mu, \tau\}$, and μ_{z_t}, τ_{z_t} are the mean and precision of a state's Gaussian distribution. Finally, Equations 2, 3, 4 can be used to compute the joint likelihood of a HMM:

$$\rho(x, z|\theta) = \rho(z_t|\pi) \prod_{t=2}^{T} \rho(z_{t+1}|z_t, A) \prod_{t=1}^{T} \rho(x_t|z_t, \emptyset) \tag{5}$$

Where the set of all model parameters which must be found for each appliance during the training phase is represented by $\theta = \pi, A, \emptyset$.

Therefore, when applying an HMM for Energy Disaggregation, it is needed to tune the θ parameters for each appliance during the training phase and afterwards, given a sequence of power signal $\bar{x}$ to find the optimal sequence of discrete states z. Their ability to handle daily operation consumption and the information about state transition of devices makes them a suitable solution for the problem. The complexity of the disaggregation using HMMs is $O\ (K^2T)$, where K is the number of states of all the appliances and T is the number of the time slices, i.e. ,who many times the algorithm is required to be applied [23]. As it is shown the complexity is exponential with regard to the number of appliances while re-training is needed when a new group of appliances is added [27]. In [28], the HMMs were used for appliance load recognition, and it was also shown that they are useful in the field of NILM. Finally, Oliver Parson in [26] is using HMMs to disaggregate an energy signal using generalized appliance model, and as a result, it was possible to extract consumption of individual devices without any manual labeling. But he used low-frequency Smart Meter data because of lack of high-frequency data and smart metering infrastructure supporting such high rates. Although the HMM is a powerful technique, the method for the inference of hidden states is often affected by local minima[29]. To overcome this limitation, variants of HMMs are used like the Factorial HMM (FHMM). The concept is that the output is an additive function of all the hidden states. In the model, each observation is dependent upon multiple unknown variables [30]. The graphical model is given in Fig. 4. [23] Similarly, the joint likelihood of an FHMM as stated in [31] is computed by,

$$\rho(x^{(1:N)}, z|\theta) = \prod_{n=1}^{N} \rho\left(z_t^{(n)}|\pi\right) \prod_{t=2}^{T} \prod_{n=1}^{N} \rho\left(z_{t+1}^{(n)} \middle| z_t^{(n)}, A\right) \prod_{t=1}^{T} \rho\left(x_t \middle| z_t^{(1:N)}, \emptyset\right) \tag{6}$$

Where 1: N symbolizes a sequence of appliances 1,..., N. However, the computational complexity of both learning and disaggregating is greater for FHMMs compared to HMMs. This is due to the conditional dependence of the Markov chains.

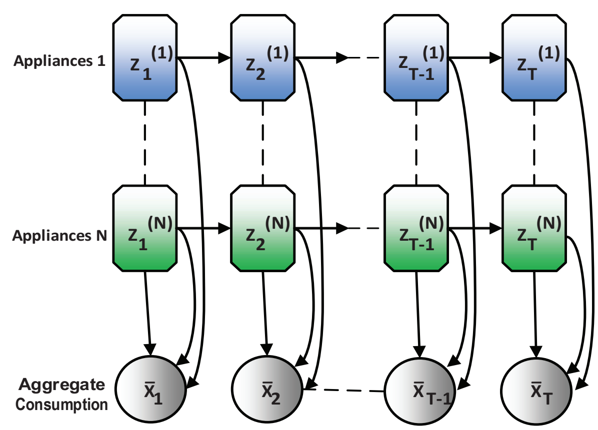

Fig. 3. Illustration of a Factorial Hidden Markov Model.

C. Load disaggregation

In this part, the performance of the NILM algorithms is presented. For preparing the appliances power profiles for load forecasting stage, the data are reformed to be hourly power demand as in Fig.4. And Fig.5. Where fig.4. Represent the aggregated data and the disaggregated data by using FHMM

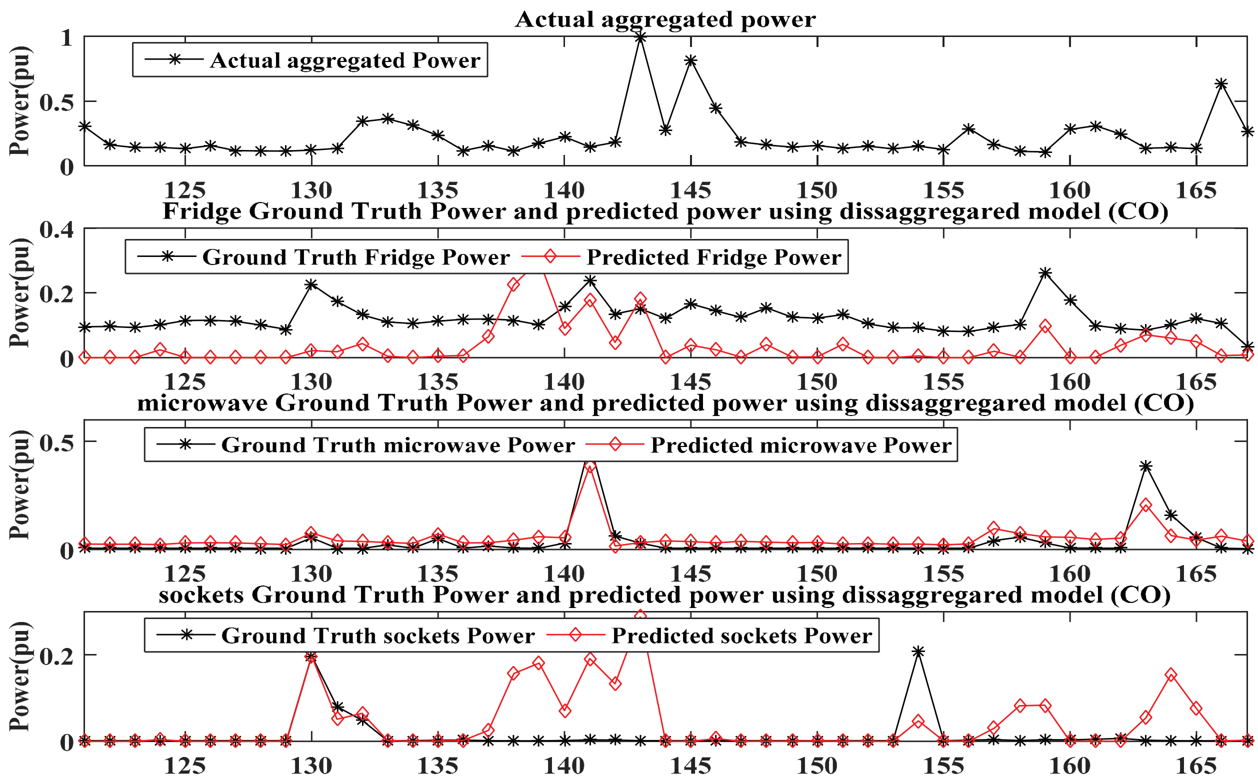

Fig. 4. Aggregated power for Home (b). Comparison between predicted and ground truth fridge power. (c) Comparison between predicted and ground truth microwave power. (b) Comparison between predicted and ground truth Kitchen Sockets power by using FHMM algorithm for disaggregation..

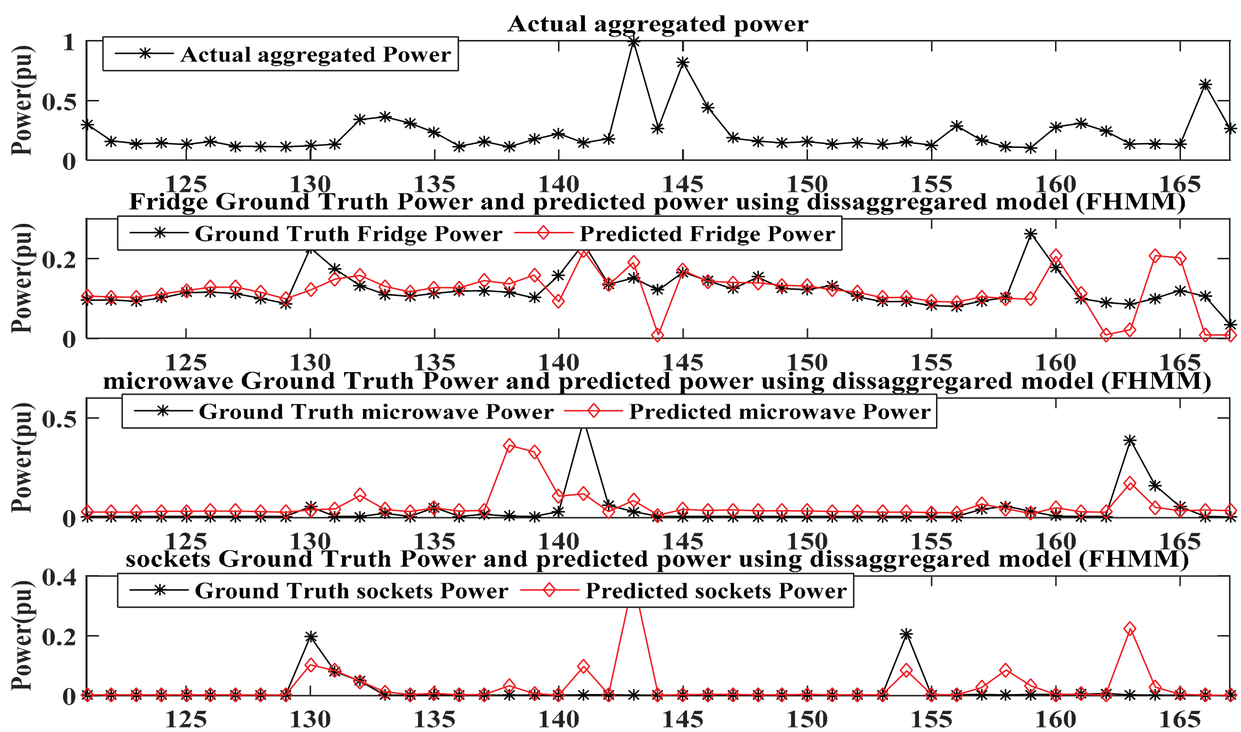

Fig. 5 (a). Aggregated power for Home (b). Comparison between predicted and ground truth fridge power. (c) Comparison between predicted and ground truth microwave power. (b) Comparison between predicted and ground truth Kitchen Sockets power by using CO algorithm for disaggregation.

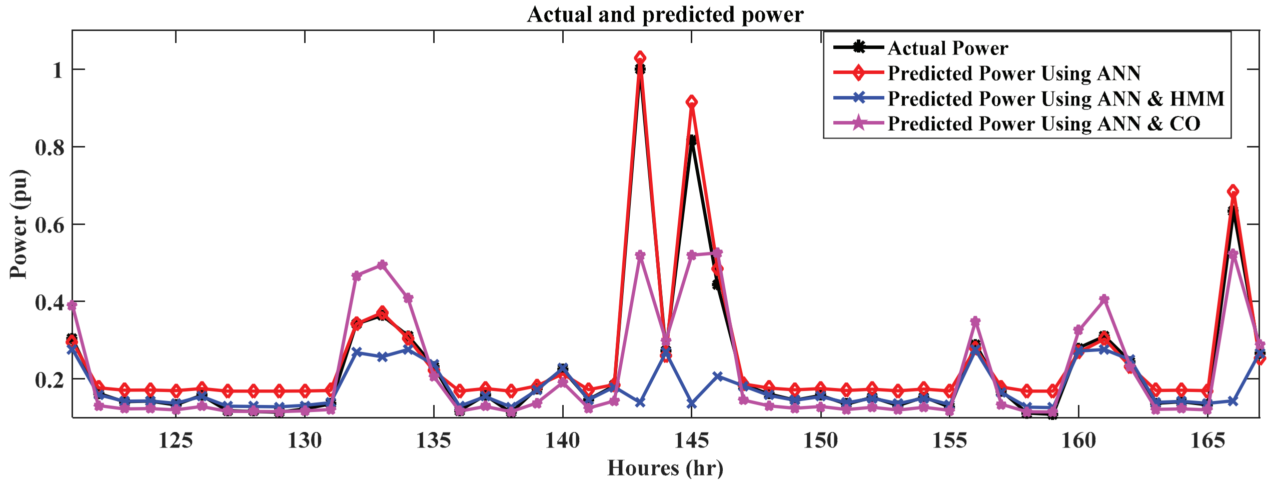

Fig. 6. Comparison between the actual and predicted power demand with three different algorithms FFANN, FFANN combined with FHMM, and FFANN

algorithm. However, fig.5. Represent the aggregated data and the disaggregated data by using CO algorithm.

III. The implemented Short-Term Load Forecasting

A feed-forward Neural Network of the same design as used in [32] is employed.which is with nine input nodes and one output nodes. One input for the current hour power demand, one for an hour before, one for two hours before, one for a day before, one for the 23 hours before, one for 22 hours before, and three inputs for the three predicted appliances from the current power profile. The output node for the expected hour ahead. The loads used were taken from 2 weeks April 2011. In many ways, this test network presents a challenging forecasting case these are all drawn from the real USA. Forecasts with all models are made at midnight every day for subsequent 47 hourly increments. Load forecasts across all 123 premises on the network are aggregated together and compared to the actual aggregate load.

IV. Simulation Result

Fig. 6. Shows the comparison between the actual and predicted load for the home with different prediction algorithm technique one using FFANN, the second using FFANN with the extracted predicted appliances from FHMM, and FFANN with the extracted predicted appliances from CO. Fig.7. Shows the difference Error between the expected power developed by ANN or ANN_HMM or ANN_CO and the actual power. It can be noticed from Fig.7 that the orange graph represent the least error condition. Table 1, shows the estimated RMSE and NRMSE at different predictor approached used in household load forecasting through this work.

TABLE 1
Comparison of the RMSE and NRMSE with the three predictors approach

	ANN	ANN_HNN	ANN_CO
RMSE	0.088693502	0.034189461	0.110849268
NRMSE	0.065156642	0.033566291	0.700878406

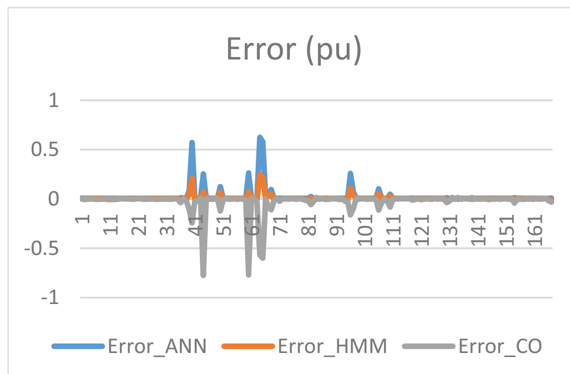

Fig. 7. Show the difference Error point by point.

It can be inferred that the approach has the least RMSE and the least NRMSE is the one used the ANN with combined with pre-processing NILM technique (HMM).

V. Conclusion

This paper for the first time explores the potential of employing the state-of-art NILM techniques combined with ANN for household STLF under high uncertainty and volatility. The proposed mechanism provides the possibility to forecast the energy consumption conditions and to predict the home energy requirements at different times of the day or on different days of the week. The proposed approach is suitable for smart grid applications for effective demand-side management, as it can rely on matching present generation values with demand by controlling the energy consumption of appliances and optimizing their operation at the user side.

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