EMD and Gradient Boosting Regression for NILM at Residential Houses

Christos Timplalexis, Stelios Krinidis, Dimosthenis Ioannidis, Dimitrios Tzovaras
Information Technologies Institue/ The Centre for Research and Technology Hellas
Thessaloniki, Greece
{ctimplalexis, krinidis, djoannid, Dimitrios.Tzovaras}@iti.gr

***Abstract*— In this paper a novel appliance load estimation in a non-intrusive way is presented. The proposed algorithm includes signal processing techniques such as filtering and Empirical Mode Decomposition (EMD) which is used to decompose random noise from the power consumption data collected from the smart meter. Lag features that capture the variance of the data across time are utilized. Experimental results which showcase the effectiveness of the suggested method are also presented.**

Non intrusive load monitoring (NILM) was initially introduced in the early 1980s [1] and describes the process of distinguishing the individual energy consumption profile of each appliance, utilizing as input the total energy consumption of a residential or commercial building. Using a single point sensor, this technique disaggregates the total energy consumption, without interrupting the occupants' privacy. Most of the applications that derive from the implementation of NILM are mainly focused on [2]: 1) energy efficiency, since individual devices energy monitoring may motivate the occupants towards energy awareness and 2) Ambient Assisted Living as information obtained from NILM can be used to infer activities within a home.

Many of the approaches found in the literature about NILM problem consider Hidden Markov Model - based methods that imply discrete states for the appliances. The current study proposes a supervised energy disaggregation method following a regression approach based on an ensemble of decision tree models, gradient boosting regression. Emphasis is given on the feature extraction process where the temporal change of the selected electrical attributes (current, active/ reactive/ apparent power) is taken into account. Median filtering is utilized for denoising (spikes smoothing) of the time-series consumption data. The non-linearity and non-stationarity of the power and current signals produced from the devices, allows the implementation of EMD, a concept which is not unprecedented in the field of NILM [3]. EMD is used in order to decompose the initial signal into a number of Intrinsic Mode Functions that act as a naturally derived set of basis functions for the signal. As shown in figure 1, the algorithm uses a set of available data creating pre-trained models that can be re-trained if appliance-level data are provided. A set of parameters such as data sampling frequency and device selection may be adjusted by the user.

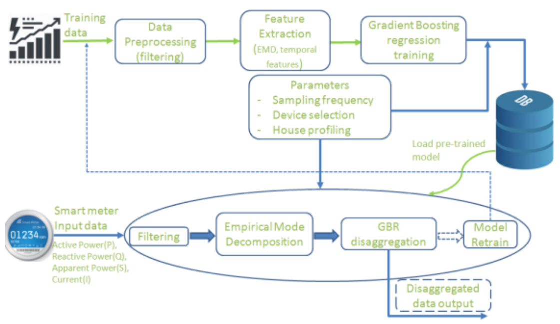

Figure 1 Disaggregation algorithm architecture

The proposed algorithm workflow is implemented on two different cases. The first one (figure 2) is AMPds dataset [4] that provides electric measurements of a residential user for two years, with a sampling rate of 1 minute. In the second case, data were collected from ITI/ CERTH's smart home infrastructure [5]. The data sampling rate was also 1 minute. Disaggregated power consumption of the most energy consuming appliances is presented against ground truth data available from smart plugs.

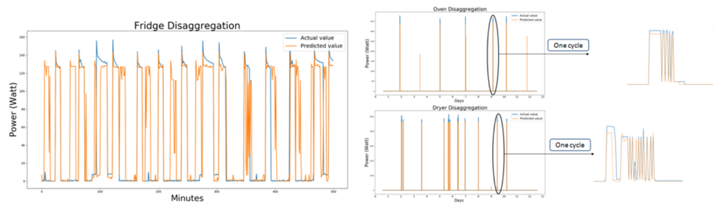

Figure 2 AMPds dataset disaggregation

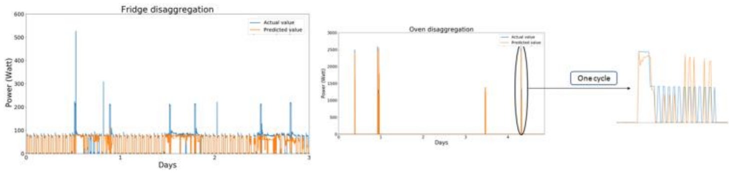

Figure 3 CERTH smart home disaggregation

Table 1 Disaggregation algorithm evaluation metrics

	AMPds dataset			*CERTH smarthome*	
	Fridge	*Oven*	*Dryer*	*Fridge*	*Oven*
RMSE	74.1	84.1	67.8	30.9	135.9
MAE	31.4	3.78	4.2	15.1	15.6

The results showcase a considerable accuracy in terms of detection of on/off events as a small number of false positive and false negative occurencies are graphically observed. Moreover, according to Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values, the predicted disaggregated power values for each cycle of the appliances, may provide to the user information regarding the amount of energy that an appliance has consumed during an "on" event, keeping in mind that MAE and RMSE depend on the appliances' nominal power values and frequency of occurrence of "on" events.

The proposed method could be incorporated by appliance manufacturers as a disaggregation service, for specific appliance models whose power signature and nominal values are already known.

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