Energy Disaggregation using Ensemble of Classifiers

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***Abstract*— We study an approach towards energy disaggregation using ensemble of classifiers, a supervised machine learning method. Specifically we identify different appliance loads from the aggregated power usage data. Experimental results on a public data sets show the accuracy of ensemble of classifiers using diverse features in identifying appliance loads.**

I. Introduction

Energy disaggregation refers to process of decomposing the whole-home energy signal into its component appliances. In energy disaggregation, one of the approaches is to identify appliance loads from the aggregated signal. A number of approaches are observed in the literature [1], [2] that can be broadly classified into intrusive and non-intrusive. Non-Intrusive Load Monitoring (NILM) is the most popular approach among them. NILM is the process of analyzing the aggregate power data and deducing what appliances are used in the house without associating meters with individual appliances. For clarity, we assume NILM approach towards energy disaggregation in this paper.

Machine learning approaches like classification are used quite often in this field [3], [4], [5]. The NILM process using supervised classification framework is presented in Fig.1. A number of statistical features are extracted from the composite power signal and combined into a feature vector. During classifier training process, each feature vector is labeled with a class label. A class label encodes the component appliances. While testing, the feature vector is supplied to the trained classifier that produces the class label i.e. the list of composite appliances.

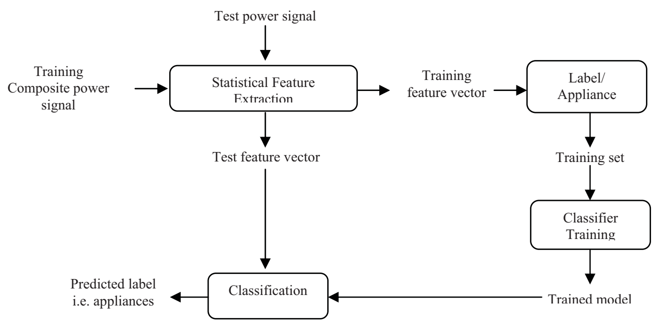

Fig. 1. NILM using classifiers

A careful review of the existing literature reveals that a number of unique classifiers are used for the purpose of NILM. The list includes neural network, support vector machine (SVM), decision tree and bayesian network [2]. However the performance of a combination of classifiers is yet to be explored on this problem.

The machine learning literature uses the term ensemble classifier to refer to a collection of individual classifiers. A set of base classifiers are trained on a problem in a cooperative fashion so that their collective performance is better than their individual performance. The decisions produced by the base classifiers are combined into a single decision using a fusion method. Ensemble classifiers defer in terms of their generation process and fusion method.

The research presented in this paper is motivated by the above findings and aims to (i) investigate the performance of ensemble classifiers using different features and (ii) study the characteristics of different appliance load identification using ensemble of classifiers.

This paper is organized as follows. In section II, we briefly review some ensemble of classifiers and context feature extraction techniques. Experimental results are presented in Section III. Finally, we conclude in Section IV.

II. Methods

In this section, we discuss ensemble of classifiers [6] and context features for NILM approach.

A. Ensemble of Classifiers

Bootstrap aggregating or bagging [7] is one of the earliest ensemble classifier generation methods. In bagging, the base classifiers are trained on different subsets of the training data. The subsets are randomly drawn (with replacement) from the training set. The base classifiers are homogeneous in nature. The decisions of the individual classifiers are fused using majority voting i.e. the class chosen by most base classifiers is the final verdict of the ensemble classifier. A variant to bagging approach is random forest [8].

Boosting [9] creates data subsets for base classifier training by re-sampling the training examples, however, by providing the most informative training example for each consecutive classifier. Each of the training examples is assigned a weight that determines how well the instance was classified in the previous iteration. The subset of the training data that is badly classified is included in the training set for the next iteration. This way the different base classifier errors are made uncorrelated.

AdaBoost [10] is a more generalized version of boosting. In this paper we present the performance of bagging, boosting, and random committee method [11] on NILM problem

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and compare with individual classifiers. The random committee ensemble classifier is a diverse ensemble of random tree classifiers. The random committee algorithm produces predictions by averaging probability estimates over these classification trees [11].

B. Context Features

In ensemble of classifiers, we consider two types of features: power feature and context features. By power feature, we take real power usage of the appliances. We show an example of power usage of dishwasher in Fig.2.

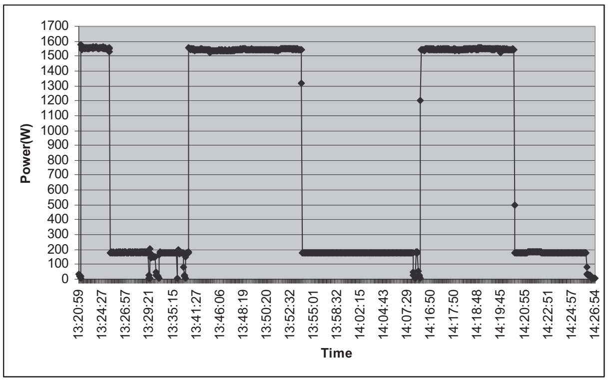

Fig. 2. Power usage signature of dishwasher

Context features are derived from temporal information of the appliances and also from available sensors (e.g. motion sensors). We denote context feature values using 0 (context absent) or 1 (context present). We extract four types of context features based on the Smart* data sets [12].

- *Time of the day* and *days of the week*. In this case, we consider the appliance dishwasher usage.
- *Ordering of the appliances*. We consider washing machine and dryer usage for this case.
- *Activity*. We consider motion sensor data in two rooms with air-conditioners (ACs) to infer whether ACs are switched on.

We show an example of context feature *Ordering of the appliances* in Fig.3. In the figure, dryer is run after the washing machine.

III. Experimental Results

In this section, we present the experimental results of NILM using different ensemble of classifiers. In the experiment, a subset of data from the Smart* [12] is used for this purpose. We considered the power usage (in Watts) of six household appliances (Fridge-F, Dishwasher-DW, Washing machine-WM, Dryer-DR and two Air Conditioner-AC). We conducted experiments using ensemble of classifiers in WEKA [13] machine learning tool.

We have conducted experiments on the NILM problem with bagging, boosting, random forest and random committee method and compared their performance against power features and context features. Accuracy of appliance loads using power features is given in Table I. In Table II, we

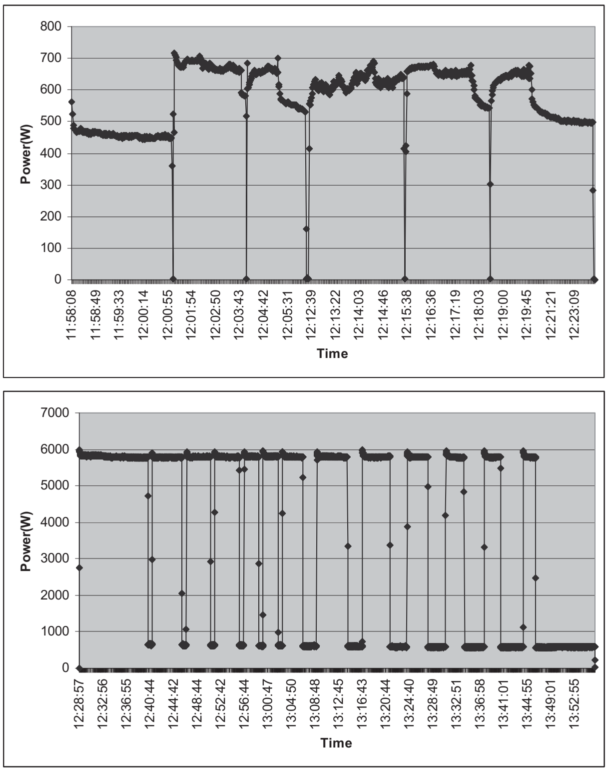

Fig. 3. The dryer is used after the washing machine on 05/05/2012

TABLE I
Accuracy (10-fold cross validation) of ensemble of classifiers for all appliance events using power feature only

Ensemble of classifiers	Accuracy
Random Forest	81.39%
Random committee	81.17%
Bagging	85.34%
LogitBoost	83.97%

present results of accuracy in identifying loads using power feature and context features. We find that accuracy is higher for ensemble of classifiers when using context features with power feature. We get the highest accuracy 96.54% using bagging technique.

We now present the confusion matrix of identifying different appliance loads using ensemble of classifiers. In Figures 4,5, 6 and 7, the confusing matrices of random forest, random committee, bagging and LogitBoost using power feature and context features are shown respectively. The confusion matrix shows how different features help in improving accuracy of load identification using ensemble of classifiers.

IV. Conclusion

We studied the application of ensemble of classifiers for non-intrusive load identification towards energy disaggregation problem. We consider power usage data and context features in ensemble of classifiers. Experimental results validate the implementation in terms of accuracy improvements. In future, we plan to extend our approach of using ensemble

TABLE II

ACCURACY (10-FOLD CROSS VALIDATION) OF ENSEMBLE OF CLASSIFIERS FOR ALL APPLIANCE EVENTS USING POWER AND ALL CONTEXT FEATURES

Ensemble of classifiers	Accuracy
Random Forest	95.81%
Random committee	95.78%
Bagging	96.53%
LogitBoost	95.72%

a	b	c	d	e	f	g	h	i	j	<--classified as
1511	104	6	0	6	6	0	4	0	0	a = DW
128	263	6	0	1	4	1	3	8	1	b = DW_F
5	8	202	0	4	1	0	1	0	2	c = F
0	0	0	11	22	1	0	19	9	0	d = WM_F
5	4	3	17	1119	362	65	105	212	2	e = WM
10	4	2	0	366	7249	144	0	31	3	f = DR
0	0	0	0	78	144	369	0	0	10	g = DR_F
2	3	1	20	107	0	0	354	202	1	h = Ac_b
0	12	0	6	217	24	0	186	627	0	i = Ac_m
0	1	1	0	3	2	14	2	1	202	j = Ac_m_Ac_b

(a) Random forest(power feature)

a	b	c	d	e	f	g	h	i	j	<--classified as
1527	110	0	0	0	0	0	0	0	0	a = DW
132	283	0	0	0	0	0	0	0	0	b = DW_F
0	0	217	0	6	0	0	0	0	0	c = F
0	0	0	27	35	0	0	0	0	0	d = WM_F
0	0	8	32	1854	0	0	0	0	0	e = WM
0	0	0	0	0	7664	145	0	0	0	f = DR
0	0	0	0	0	145	456	0	0	0	g = DR_F
0	0	0	0	0	0	0	690	0	0	h = Ac_b
0	0	0	0	0	0	0	0	1072	0	i = Ac_m
0	0	0	0	0	0	0	0	0	226	j = Ac_m_Ac_b

(b) Random forest (power feature and context features)

Fig. 4. Confusion matrix for Random forest

of classifiers for other data sets where context features can be derived.

V. ACKNOWLEDGEMENT

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a	b	c	d	e	f	g	h	i	j	<--classified as
1508	107	6	0	6	6	0	4	0	0	a = DW
127	263	7	0	1	4	1	3	8	1	b = DW_F
5	8	201	0	4	2	0	1	0	2	c = F
0	0	0	12	21	1	0	20	8	0	d = WM_F
4	3	4	18	1105	370	66	109	213	2	e = WM
10	4	2	0	376	7236	148	0	30	3	f = DR
0	0	0	0	79	145	367	0	0	10	g = DR_F
2	3	1	20	103	0	0	352	208	1	h = Ac_b
0	10	0	7	213	25	0	189	628	0	i = Ac_m
0	1	1	0	3	3	13	2	1	202	j = Ac_m_Ac_b

(a) Random committee (Power feature)

a	b	c	d	e	f	g	h	i	j	<--classified as
1524	113	0	0	0	0	0	0	0	0	a = DW
131	284	0	0	0	0	0	0	0	0	b = DW_F
0	0	217	0	6	0	0	0	0	0	c = F
0	0	0	28	34	0	0	0	0	0	d = WM_F
0	0	6	32	1856	0	0	0	0	0	e = WM
0	0	0	0	0	7660	149	0	0	0	f = DR
0	0	0	0	0	146	455	0	0	0	g = DR_F
0	0	0	0	0	0	0	690	0	0	h = Ac_b
0	0	0	0	0	0	0	0	1072	0	i = Ac_m
0	0	0	0	0	0	0	0	0	226	j = Ac_m_Ac_b

(b) Random committee (Power feature and context features)

Fig. 5. Confusion matrix for Random committee

A	b	c	d	e	f	g	h	I	j	←classified as
1593	33	6	0	1	1	0	3	0	0	a = DW
155	242	11	0	1	1	1	2	1	1	b = DW_F
5	4	209	0	2	0	0	1	0	2	c = F
0	0	0	8	19	1	0	30	4	0	d = WM_F
8	4	1	13	1160	327	74	90	217	0	e = WM
10	5	1	0	211	7423	138	0	18	3	f = DR
0	0	0	0	46	94	458	0	0	3	g = DR_F
4	4	0	8	84	0	0	456	134	0	h = Ac_b
0	14	0	1	123	30	0	171	733	0	I = Ac_m
0	0	0	0	2	1	18	1	2	202	j = Ac_m_Ac_b

(a) Bagging (Power feature)

a	b	c	d	e	f	g	h	i	j	<--classified as
1591	46	0	0	0	0	0	0	0	0	a = DW
150	265	0	0	0	0	0	0	0	0	b = DW_F
0	0	215	0	8	0	0	0	0	0	c = F
0	0	0	18	44	0	0	0	0	0	d = WM_F
0	0	9	13	1872	0	0	0	0	0	e = WM
0	0	0	0	0	7668	141	0	0	0	f = DR
0	0	0	0	0	96	505	0	0	0	g = DR_F
0	0	0	0	0	0	0	690	0	0	h = Ac_b
0	0	0	0	0	0	0	0	1072	0	i = Ac_m
0	0	0	0	0	0	0	0	0	226	j = Ac_m_Ac_b

(b) Bagging (Power feature and context features)

Fig. 6. Confusion matrix for Bagging

A	b	c	d	e	f	g	h	I	j	←classified as
1580	27	29	0	0	1	0	0	0	0	a = DW
179	217	12	0	1	2	1	2	1	0	b = DW_F
5	4	210	0	2	0	0	0	0	2	c = F
0	0	0	8	0	1	0	39	14	0	d = WM_F
13	5	2	8	886	367	82	205	326	0	e = WM
9	4	4	0	136	7563	82	0	9	2	f = DR
0	0	0	0	32	180	384	0	0	5	g = DR_F
3	5	3	5	10	0	0	522	142	0	h = Ac_b
0	14	0	2	4	38	0	304	710	0	I = Ac_m
0	0	0	0	1	1	17	2	1	204	j = Ac_m_Ac_b

(a) LogitBoost (Power feature)

a	b	c	d	e	f	g	h	i	j	<--classified as
1614	23	0	0	0	0	0	0	0	0	a = DW
189	226	0	0	0	0	0	0	0	0	b = DW_F
0	0	213	0	10	0	0	0	0	0	c = F
0	0	0	0	62	0	0	0	0	0	d = WM_F
0	0	4	0	1890	0	0	0	0	0	e = WM
0	0	0	0	0	7783	26	0	0	0	f = DR
0	0	0	0	0	312	289	0	0	0	g = DR_F
0	0	0	0	0	0	0	690	0	0	h = Ac_b
0	0	0	0	0	0	0	0	1072	0	i = Ac_m
0	0	0	0	0	0	0	0	0	226	j = Ac_m_Ac_b

(b) LogitBoost (Power feature and context features)

Fig. 7. Confusion matrix for LogitBoost

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