ANN-based Appliance Recognition from Low-frequency Energy Monitoring Data

Francesca Paradiso, Federica Paganelli
CNIT University of Florence
{francesca.paradiso, federica.paganelli}@unifi.it

Antonio Luchetta, Dino Giuli
Dep. of Information Engineering
University of Florence
Italy
{luchetta, dino.giuli}@unifi.it

Pino Castrogiovanni
Innovation & Industry Relations – Research & Prototyping
Telecom Italia, Turin Italy
pino.castrogiovanni@telecomitalia.it

Abstract— **The rational use and management of energy is a key objective for the evolution towards the smart grid. In particular in the private home domain the adoption of wide-scale energy consumption monitoring techniques can help end users in optimizing energy consumption behaviors. While most existing approaches for load disaggregation and classification requires high-frequency monitoring data, in this paper we propose an approach for detecting and identifying the appliances in use by analysing low-frequency monitoring data gathered by meters (i.e. smart plugs) distributed in the home. Our approach implements a supervised classification algorithm with artificial neural networks and has been tested with a dataset of power traces collected in real-world home settings.**

Keywords: energy; smart grid; home gateway; home energy management system; metering; artificial neural network

I. INTRODUCTION

In the last decades the rational use and management of energy has become a relevant challenge for national governments and energy distribution operators, due to two main issues: i) the scarcity of energy resources and ii) the constantly growing energy consumption.

The fast-paced technological progress is expected to produce a remarkable reduction in energy consumption in both industrial and private home domains.

In this context, the concept of Home Energy Management System [1] refers to a home environment enhanced with sensors, smart appliances and application logic for managing and optimizing the energy consumption and properly interacting with the end user to this purpose.

The wide-scale adoption of energy consumption monitoring techniques in the consumer home domain can bring several advantages. First of all, consumers can be made aware of the household energy consumption and its associated costs. Energy consumption monitoring techniques can be properly configured to detect the load profile of specific appliances and their usage profiles. Consequently, customers can be kept informed of how much the usage of a specific device influences the curve of total energy consumption and decide whether to replace it with a more efficient one or just shift its usage in a time interval characterized by a less expensive pricing rate. Moreover, the analysis of an appliance load can also help in recognizing a possible malfunction or anomaly and resolving or mitigating it before the appliance status further deteriorates.

Efficient and wide-scale energy consumption monitoring is also a priority for electric companies. Analysis and predictions on energy consumption of a typical household or blocks of buildings can provide information that is useful for defining and enforcing policies for demand response optimization and efficient energy distribution [2].

Most widely adopted home energy monitoring techniques typically provide information on the whole energy consumption profile, which, however, provides poor information for recognizing and predicting user habits and proposing possible suggestions. Several load disaggregation and classification algorithms have been proposed in the literature [3], but they rely on medium or high frequency monitoring data (at least 1 Hz). In real world scenarios, this assumption may be resource demanding.

In this paper we propose an approach for detecting and identifying the appliances in use in a home environment by analysing low-frequency monitoring data (1 sample each two minutes) gathered by meters (i.e. smart plugs) distributed in the home. Our approach implements a supervised classification algorithm with artificial neural networks.

This paper is structured as follows. In Section II we discuss Related Work. Section III describes our appliance classification approach and our reference Home Energy Management System. In Section IV we describe the dataset of consumption traces collected in real homes and in Section V we show results obtained by applying our classification approach to this dataset. Section VI concludes the paper with some insights on future work.

II. RELATED WORK

Energy consumption management refers to the continuous monitoring of electricity consumption in a smart home context and the consequent analysis of measured data to provide end-users with information and suggestions for improving their consumption behaviour.

Several methods for energy consumption monitoring in private buildings have been proposed [3]. Berges et al. distinguished three main approaches [4]:

Whole house continuous monitoring - This approach involves the use of a metering device (i.e., meter) attached to the main electric panel of a building to measure the instantaneous power draw of the whole house.

Non-Intrusive Load Monitoring - Non-intrusive Load Monitoring (NILM) [5] is a family of techniques that aim at

978-1-4673-5828-6/13/$31.00 ©2013 IEEE

recognizing the power consumption of a specific device from the whole-house consumption profile.

Hardware-based sub-metering **-** This method consists in attaching a metering hardware module onto each household appliance. In this way, the energy consumption profile of the attached household appliance can be easily collected.

Non-Intrusive Load Monitoring techniques have been theorized since the late 80s when Hart [5] proposed to measure the total power consumption of a household through the use of an electricity meter and disaggregate the result into partial consumptions caused from the various devices in use. The NILM method has been refined over the years. NILM techniques have been proposed based on the use of various methods, such as Artificial Neural Networks [6], K-NN Clustering [7] and Support Vector Machine [7]. A relevant and recently commercialized system using ANN has been presented in [8] with the name of RECAP. An innovative strategy was proposed by Kolter and Jakkola in 2012, based on an evolution of the Hidden Markov Model [9].

The advantage due to the non-intrusiveness of these methods loses value as the devices to be monitored increase in number, because the distinction of devices with similar behavior and/or with a low-consumption profile becomes increasingly difficult. The commercialization of Smart Appliances, which have communication and sensing logic embedded, could help in solving these issues, but their high market price is a barrier for their widespread adoption.

Therefore, we argue that the adoption of a *Hardware-based sub-metering approach* can offer a better compromise between costs and wealth of measured data. A distributed metering systems made by plugs connected to home devices can conveniently be exploited for acquiring data useful for recognizing an appliance's consumption and usage patterns. On this direction, Reinhardt et al. [10] presented a data set of real-world power consumption traces and an evaluation of appliance recognition algorithms applied on those traces.

Our work is similar to the one by Reinhardt et al. [10] in that we adopt a distributed metering system of smart plugs. Our contribution differs in that our algorithm exploits low-frequency metering data (a power consumption each two minutes), while the work in [10] is based on traces with higher temporal resolution (one- and eight-second average real power consumption). Our low-frequency constraint has the aim of minimizing the resources needed for managing and storing measurement data in real-world home settings, as described in the next section.

III. ANN-Based Classification Approach

Our classification approach has been conceived for coping with the requirements of a running trial of a Home Energy Management System (HEMS) promoted by Telecom Italia in collaboration with other companies in the domain of energy distribution and home appliances.

The HEMS is a distributed system based on the architecture proposed by the Energy@home association [11]. It is made of devices connected on a Home Area Network (HAN) and a central gateway hosting the processing and presentation logic to provide end users with Value-Added Services for energy consumption awareness and efficiency (see Fig. 1).

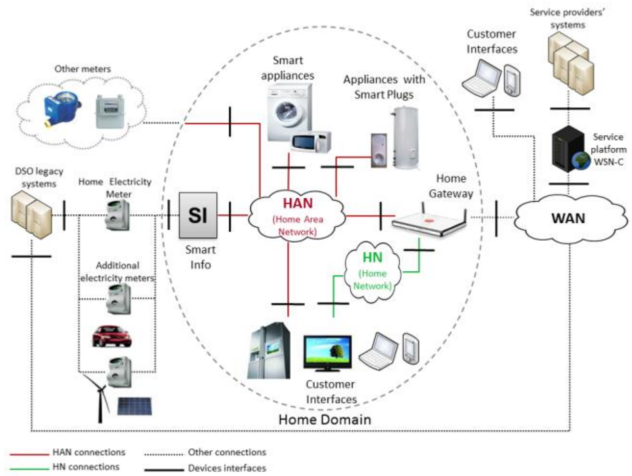

Figure 1. Energy@home system architecture

This HEMS is a highly-configurable platform made of the following components:

- A *Smart Info device* provides end users with the certified information on electricity consumptions managed by the electronic smart meter. It can be plugged in every domestic socket to collect data from the smart meter through powerline communication.
- *Smart Appliances* are white goods (e.g., dishwasher, washing machine) that have local intelligence and networking capabilities. They can provide information on their energy consumption (e.g. used energy, instant power, etc.), respond to remote commands and interact with the user through a GUI.
- *Smart plugs* are able to collect metering data and implement on/off control on simple plugged energy loads, other than Smart Appliances.
- The *Home Gateway* enables local connectivity of home devices and Wide-Area Network (WAN) connectivity with the Public Internet. It is based on a modular and highly configurable OSGI framework (Equinox) and hosts application logic modules. It offers multiple network interfaces, including a HAN interface to communicate with the abovementioned devices (ZigBee), a Home Network (HN) interface to interconnect additional local devices (LAN Ethernet and WiFi) and a WAN interface used to communicate with remote service providers' systems (xDSL connection). It provides general APIs used by local service logics and remote service platform to discover, manage, and communicate with HAN devices.
- *Customer Interfaces* are used by the customer to monitor and configure his/her energy behavior. Typical Customer Interfaces can be exposed by HAN devices (e.g. Smart Appliances and ad-hoc displays), or other devices connected through the HN or the WAN interface (e.g. personal computers, smart phones, PDAs,

This is the author's version of an article that has been presented at the 2013 IEEE 14th Int. Symposium and Workshops on a World of Wireless, Mobile and Multimedia Networks (WoWMoM),. Changes were made to this version by the publisher prior to publication.
The final version is available at http://dx.doi.org/10.1109/WoWMoM.2013.6583496

and entertainment systems). The software application that implements the user interface could be local in the device or remotely hosted in another device (e.g. the Home Gateway) and accessed through web-services.

This HEMS has been deployed in 20 private homes in Italy and experimentation and data collection is currently active. Several types of monitoring approaches (whole house monitoring, real-time monitoring of identified devices through smart appliances, low-frequency monitoring of unidentified devices) are in place, thus allowing the experimentation of different data analysis and service provisioning approaches.

A. Classification System Architecture

The logical architecture of our classification system is shown in Fig. 2. Raw power data are collected by *Smart plugs* installed between each device and the power grid in a living environment, as described above.

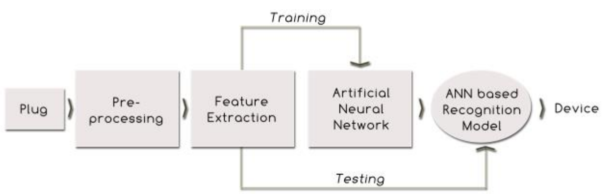

Figure 2. Appliance Classification System architecture

The *Pre-processing block* is responsible for collecting power data samples and for extracting significant power measures to be provided as input to the classification processing chain. As a general rule, we set the algorithm to store 100 power samples from the first nonzero sample different from a stand-by pulse. Therefore devices such as Washing machines or Dishwashers, typically characterized by hourly duration, will often be represented with a full-length load trace; instead devices with a short or strongly variable duration (e.g., Microwave Ovens or Coffee Machines), present a power trace padded with several zeros.

The *Feature Extraction block* process the 100-samples trace provided by the Pre-Processing block to build a vector of features that extract distinguishing characteristics of the power trace (i.e., the shape of the consumption profile, maximum peak, ascending or descending consumption steps, duration). This block extracts the following features:

1) *Maximum power value*
2) *Minimum nonzero power value*
3) *Number of samples equal to zero*
4) *Number of samples less than or equal to 30 W*
5) *Number of samples between 30 and 400 W*
6) *Number of samples between 400 and 1000 W*
7) *Number of samples greater than 1000 W*
8) *Number of transitions greater than 1000 W*
9) *Number of transictions between 10 and 100 W*
10) *Medium value of the nonzero power samples*

These features are provided in input to our ANN-based classification algorithm to train it with a proper knowledge base. Once trained, the *ANN Recognition Model* is ready to classify the new power consumption traces.

An Artificial Neural Networks is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge [12] and, in the specific case of this work, the “Artificial Neural Network” block in Fig. 1 provides a machine learning algorithm with the task of classifying devices. The “Feature Extraction” block is instead the part where the experimental observation is codified (and labelled during the training phase).

The chosen neural paradigm, for this application, is a multilayer perceptron neural network with backpropagation algorithm (commonly called MLBPNN) [12], a well-known supervised model, used because of its simplicity and guaranteed convergence. This kind of network is a universal approximator [13] based on the perceptron elementary neuron, an information-processing unit that takes its origin in the biological counterpart and that can be mathematically described by the following pair of equations:

$$net_k = \sum_{j=1}^{m} w_{kj} x_j$$

$$o_k = \psi(net_k + b_k) \quad k = 1,\ldots,N_{out}$$

where o_k is the output of the kth neuron (if the used neurons are more than one, in the given number N_{out}); $x_1,\ldots, x_m$ are the input signals (with dimension given by m); $w_{k1},\ldots, x_{km}$ are the synaptic weights of the neuron k; net_k is the weighted sum of the input signals, b_k is an external bias and ψ is the “activation function”; in this application the activation function is the bipolar sigmoid:

$$\psi(net_k) = \frac{2}{1 + e^{-\lambda \cdot net_k}} - 1$$

that is chosen because of a couple of main reasons: sigmoid is a nonlinear activation function that allows to quickly perform a classification of non-linearly separable problems when used in multi-layer structures; sigmoid allows, moreover, to use well known always convergent backpropagation algorithm as steepest descent [14] or Levenberg-Marquardt [15] during the learning process. The multi-layer structure is a three-layer network with a number of neurons 10-30-8, respectively in the input-hidden-output layers; the number of neurons in input and output layers is imposed by the nature of the problem, whereas the number of neurons in the hidden layer (30) is coming from an empirical choice, motivated by the best “trial&grow” result, in other words the number of neurons starts from a medium low number (around 10) and it is increased until no further improvement is observed in the results. In order to avoid the generalization drawback, an *early stopping* approach is used [16] during the learning phase.

IV. DATA COLLECTION

The data sets used by the algorithms presented in this paper is based on power consumption traces collected during

This is the author's version of an article that has been presented at the 2013 IEEE 14th Int. Symposium and Workshops on a World of Wireless, Mobile and Multimedia Networks (WoWMoM),. Changes were made to this version by the publisher prior to publication.
The final version is available at http://dx.doi.org/10.1109/WoWMoM.2013.6583496

an initial phase of a trial of the Energy@home system, which started in 2012 with some installations in private houses of friendly customers in Italy. Each installation includes the following devices: i) a Smart Info connected to the home electricity meter; ii) 5 Smart Plugs used to collect consumption data from existing connected loads; and iii) a Smart Appliance, which is a washing machine able to directly provide information on its energy consumption.

The abovementioned devices provide energy consumption data used by the Home Gateway and the Service Platform to implement some use cases aimed at enhancing customer awareness about her/his energy consumption [17]. The structure of consumption data stored by the system have been designed to meet these use cases requirements: energy and instantaneous power data are collected from HAN devices and stored in a service platform database in order to provide customers with historical and statistical information on their energy consumption. Stored data include global in-house consumptions provided by the power meter interface (Smart Info) and single device energy information provided by Smart Appliances and Smart Plugs.

The protocol used for the communication between HAN devices and the Home Gateway is based on ZigBee, which is a very low-cost, low-power-consumption, two-way, wireless communication standard. ZigBee can be used in different application domains (e.g., home automation, healthcare, energy management and telecom services) and some extensions have been designed for the Energy@home system [18] and proposed for the integration in the next release of the ZigBee Alliance Home Automation profile specification.

The Home Gateway uses the reporting mechanisms defined in the ZigBee Cluster Library specification [19] to receive the following consumption data from each device: i) the *summed value of energy* delivered and consumed in the premise (Smart Info) or by a specific device (Smart Plugs and Smart Appliances); ii) the *instantaneous real power* absorbed by the whole house (Smart Info) or by a specific device (Smart Plugs and Smart Appliances).

The reporting parameters configured on each Smart Plug and Smart Appliance provide real time instantaneous power information: every change in instantaneous power that is greater than or equal to 5 W is notified to the Home Gateway with a maximum configured delay of 2 seconds. Instantaneous power data are then processed by the Home Gateway to offer real time consumption information to end users, but all these measures are not directly stored in the platform database. In order to limit the amount of data stored for each device, the Home Gateway filters these measures and stores only a subset of these data. Stored measures are based on the reporting of summed energy values, sent by each device every 2 minutes: for each of these time intervals, the gateway calculates the energy consumption (Wh) of the device and stores this value together with the minimum and maximum instantaneous power values (W) received from the device in the same time interval.

These low-frequency measures are stored in the platform database and have been used to test and validate the appliance identification algorithm described in this paper. An excerpt of the records stored in the platform database is shown in Fig. 3. Fig. 4 show an example of power consumption traces for four monitored appliances.

appl_id	start_time	duration	energy	min_power	min_power_time	max_power	max_power_time
746	1361752107117	120258	0	0	1361752167156	0	1361752167156
746	1361752227375	120733	0	0	1361752287691	0	1361752287691
746	1361752348108	120594	0	1	1361752408367	1	1361752408367
746	1361752468702	120754	0	1	1361752529172	1	1361752529172
746	1361752589456	120698	0	0	1361752649774	0	1361752649774
746	1361752710154	120717	0	0	1361752770566	0	1361752770566
746	1361752830871	120682	1	0	1361752891322	93	1361752933525
746	1361752951553	120743	2	58	1361752951649	72	1361752985833
746	1361753072296	120821	2	70	1361753106463	70	1361753106463
746	1361753193117	120585	3	69	1361753227186	69	1361753227186
746	1361753313702	120764	2	69	1361753347915	69	1361753347915
746	1361753434466	120628	2	69	1361753468611	69	1361753468611
746	1361753555094	120866	1	0	1361753603392	68	1361753589449
746	1361753675960	120658	1	0	1361753724209	0	1361753724209

Figure 3. Excerpt of a refrigerator's records stored in the database

The meaning of each record field is described below:

- *appl_id*: a unique identifier of the monitored device, associated to a specific device category ;
- *start_time*: the start time of the time interval associated to this record, expressed as the difference, measured in milliseconds, between the current time and midnight, January 1, 1970 UTC;
- *duration*: the time interval duration expressed in milliseconds;
- *energy*: the energy consumption (Wh) of the device for the associated time interval;
- *min_power*, *max_power*: the minimum and maximum value of the instantaneous power measures (W) reported by the device during the associated time interval;
- *min_power_time*, *max_power_time*: the time of sampling of the associated power field (same format as *start_time*);

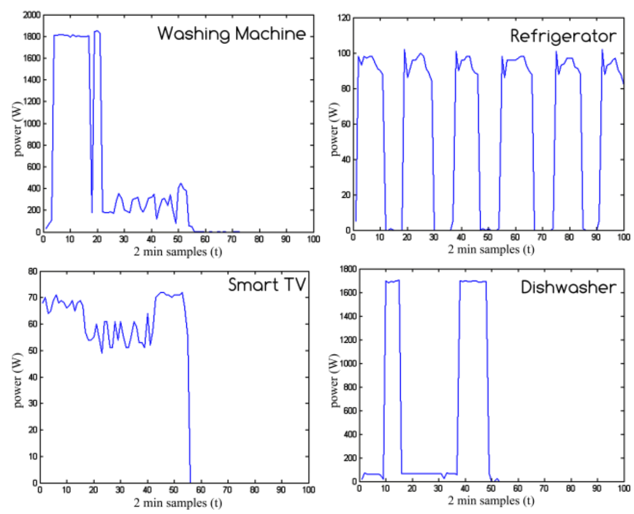

Figure 4. Power consumption traces of four appliances

V. Experimental Results

In this section we present results of few test cases where we applied our classification algorithm to analyse the data set presented in section IV. Testing has been performed using Matlab version R2012a on a machine equipped with an Intel Core2 Duo CPU T7500 at 2.20GHz, 2 GB.

The test data set has been built by selecting eight types of devices and extracting the same number of traces for each type of device from three houses (we extracted 66 example traces for a total number of 528). We selected the subset of devices that were present in all the three houses: washing machine; refrigerator; dishwashing machine; smart TV; iron; microwave oven; lighting stuff; coffee machine.

This data set was divided into three parts; a 70% portion has been allocated to train the ANN, a 15% to validate the training state and to stop the train before an overfitting possible problem. The last 15% has been used to test the classification model. In order to validate the effectiveness of the algorithm we have used the "overall accuracy" index in terms of percentage.

Table I shows the classification results for each device and for five test iterations, where each iteration includes an independent training phase and consequently a different ANN configuration. The final column shows the average accuracy value for each device. The Overall Accuracy row shows the successful recognition percentage of the algorithm for the eight devices.

The relevant fact that emerges from Table I is the high accuracy recognition percentage for each device in particular with regard to the dishwasher, washing machine and coffee machine. Instead, devices such as smart TV, iron and lighting can be misclassified because of their usage duration variability.

A second test case consisted in testing the ANN trained with the previously described test data set (traces from three houses) with power traces collected from a new house. We selected the subset of devices monitored in all the houses: washing machine, refrigerator, dishwasher and microwave oven.

TABLE I. Classification accuracy for each device type and test iteration

Monitored Devices	Single tests and average correct classification percentage (True Positive)					
	Test1	***Test2***	***Test3***	***Test4***	***Test5***	***Total***
Washing Machine	100	100	100	100	98,48	99,70
Refrigerator	92,42	100	100	100	96,96	97,88
Dishwasher	100	100	100	100	100	100
Smart Tv	69,69	84,84	84,84	90,90	81,81	82,42
Iron	90,90	89,39	95,45	90,90	86,36	90,60
Microwave Oven	100	100	100	100	100	100
Lighting	90,90	90,90	93,93	93,93	90,90	92,11
Coffee Machine	98,48	100	100	98,48	100	99,39
Overall Accuracy	92,80	95,64	96,78	96,78	94,31	**95,26**

Table II shows the test results: although these appliances are completely unknown to the Neural Network, the washing machine and the smart TV have been detected, but with medium and low accuracy values. Accuracy values are dramatically low for the recognition of the refrigerator and the dishwasher.

TABLE II. Classification accuracy for previously unknown devices

Device	**Average correct classification percentage (True Positive)**
Washing Machine	56,93
Refrigerator	4,38
Dishwasher	6,32
Microwave Oven	37,47

The result of the second test case has helped us in improving the choice of the features to be extracted. According to the results in Table II, the ten features chosen to characterize the load curve of each device appear to be over-specific. We thus reduced the features number from ten to six by choosing the more general ones (i.e., features 1-2 and 7-10 in section II). Overly specific features, such as the number of samples between a minimum and a maximum value (features 3-6 in section II), could in fact over-describe a power consumption signal.

Table III shows the results obtained by training and testing the ANN Recognition model with the above mentioned six general features and repeating the testing with power traces of previously unknown devices (i.e., devices of a new house). The washing machine and refrigerator have been correctly classified in most cases reaching a medium accuracy percentage respectively of 98,40% and 83,73%. Recognition of the dishwasher and the Microwave Oven is also improved.

TABLE III. Classification accuracy for previously unknown devices (six features)

Monitored Devices	**Average correct classification percentage (True Positive)**
Washing Machine	98,40
Refrigerator	83,73
Dishwasher	16,13
Microwave Oven	44,15

These tests have been performed involving the same number of neurons in the hidden layer of the Neural Network as in the previous ones (30). By increasing the number of neurons from 30 to 50 we obtained better recognition results. In order to compare the results and the generalization characteristics across the different test cases we have shown the results obtained with the 30-neurons configuration.

These test results reveal how the training phase has to be closely linked to the house context and consequently to the specific appliances to be recognized. Although with a subset of features we can improve recognition results even for previously unknown devices, good accuracy values can be achieved by training the ANN with a knowledge base as close as possible to the device characteristics and usage patterns of the target house.

VI. Conclusions

In this work, we have proposed an approach for recognizing appliance loads by exploiting low-frequency measurement data.

This approach has been designed to cope with the requirements of a running trial of a Home Energy Management System in 20 private homes in Italy. In order to optimize the resources usage in the Home Gateway and Service platform, stored measures are based on the reporting of summed energy values, sent by each device every 2 minutes. Our classification algorithm has thus been tested on a set of monitoring data that are significantly sub-sampled with respect to state-of-the art classification and disaggregation approaches discussed in related work. Therefore, accuracy results obtained from testing activities cannot be compared with these approaches.

We are implementing the classification algorithm in the Home Energy Management Systems. In the future, it would be useful to evaluate the use of different neural models characterized by dynamic retraining mechanisms in order to improve the balance between efficiency and complexity [20]. Another direction for future work would be to extend the proposed approach by exploiting information about user habits and daily activity patterns that can be extracted from sensors' observation data through complex event processing techniques [21] [22].

Acknowledgment

This work has been partly supported by the Italian Ministry of Economic Development through the "e-kitchen" collaborative project.

Authors wish also to thank and acknowledge the Energy@home Association [http://www.energy-home.it] that kindly made available the data set and the Home Area Network architecture used in this paper.

A special thank to Fabio Bellifemine and Claudio Borean: they have inspired this work with a lot of helpful advice and suggestions and through their participation to the Energy@home association on behalf of Telecom Italia.

The Authors thank Dr. Samuele Capobianco and Mr. Luca Capannesi for their technical support.

References

[1] D. Niyato, Lu Xiao, Ping Wang, "Machine-to-machine communications for home energy management system in smart grid," IEEE Comm. Magazine, vol.49, no.4, pp.53-59, April 2011.

[2] M. Riveiro, R. Johansson, and A. Karlsson, "Modeling and analysis of energy data: state-of-the-art and practical results from an application scenario," 2011.

[3] A. Zoha, A.Gluhak, M.A. Imran, S.Rajasegarar, "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey", *Sensors* vol. 2012, 12, pp. 16838-16866.

[4] M. Berges, E. Goldman, H. Scott Matthews, L. Soibelman, "Training Load Monitoring Algorithms on Highly Sub-Metered Home Electricity Consumption Data", *Tsinghua Science & Technology*, vol. 13, suppl. 1, October 2008, pp. 406-411.

[5] G. W. Hart, "Non Intrusive Appliance Load Monitoring," Proc. of the IEEE. Dec. 1992, vol. 80, pp. 1870–1891.

[6] H. H. Chang, C. L. Lin, and J. K. Lee, "Load identification in nonintrusive load monitoring using steady-state and turn-on transient energy algorithms," Computer Supported Cooperative Work in Design (CSCWD), Apr. 2010, pp. 27-32.

[7] T. Onoda, G. Rätsch, and K. Müller, "Applying Support Vector Machines and Boosting to a Non-Intrusive Monitoring System for Household Electric Appliance with Inverters," Second International (ICSC) Symp. Neural Computation, 2000.

[8] A.G. Ruzzelli, C. Nicolas, A. Schoofs, and G.M.P. O'Hare, "Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor," IEEE SECON, 2010, pp. 279-287.

[9] J. Z. Kolter, and T. Jaakkola, "Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation," Proc. Track 22, International Conference on Artificial Intelligence and Statistics, 2012, pp. 1472-1482.

[10] A. Reinhardt, D. Burkhardt, M. Zaheer, and R. Steinmetz, "Electric Appliance Classification Based on Distributed High Resolution Current Sensing," Proc. 7th IEEE Int. Workshop on Practical Issues in Building Sensor Network Applications, 2012, pp. 1003-1009.

[11] The Energy@Home Technical Team, (2010). Energy@home: a "User- Centric" Energy Management System, White Paper, 2010. Available at http://www.energy-home.it/

[12] S. Haykin, "Neural Networks: A Comprehensive Foundation," 2nd Ed. Englewood Cliffs: Prentice-Hall, N.J, 1998.

[13] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," Neural Networks, vol. 2(5), 1989, pp. 359–366.

[14] D. E. Rumelhart and J.L. McClelland, "Parallel Distributed Processing: explorations in the microstructure of cognition. Volume 1. Foundations," Cambridge, MA: The MIT Press, 1986.

[15] M. T. Hagan and M. Menhaj, "Training feedforward networks with the Marquardt algorithm," IEEE Trans. Neural Networks, vol. 5, Nov. 1994, pp. 989–993.

[16] R. Gencay, Q. Min, "Pricing and hedging derivative securities with neural networks: Bayesian regularization, early stopping, and bagging", IEEE Trans. on Neural Networks, vol. 12, Apr. 2001, pp. 726–734.

[17] Energy@home Technical Team, "Energy@home Use Case", version 1.2, 2010. Available at http://www.energy-home.it/Documents/Forms/AllItems.aspx (Technical Specifications)

[18] Energy@home Technical Team, "Energy@Home Technical Specification", version 0.95, 2012. Available at http://www.energy-home.it/Documents/Forms/AllItems.aspx (Technical Specifications)

[19] ZigBee Alliance, ZigBee Cluster Library Specification, 2007

[20] A. D. Doulamis, N. D. Doulamis, S. D. Kollias, "On-Line Retrainable Neural Networks: Improving the Performance of Neural Networks in Image Analysis Problems." IEEE Trans. Neural Networks, vol. 11, 2000, pp. 137-155.

[21] I. Zappia, F. Paganelli, D. Parlanti, "A lightweight and extensible Complex Event Processing system for sense and respond applications", Expert Systems with Applications, vol. 39, no. 12, Sept. 2012, pp. 10408-10419.

[22] I. Zappia, D. Parlanti, F. Paganelli, "LiSEP: A Lightweight and Extensible Tool for Complex Event Processing" 2011 IEEE Int. Conf. on Services Computing (SCC), pp.701-708, 4-9 July 2011, Wahington DC, USA.