Forecasting the Usage of Household Appliances Through Power Meter Sensors for Demand Management in the Smart Grid

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***Abstract*—Electricity demand management mechanisms are expected to play a key role in smart grid infrastructures to reduce buildings power demand at peak hours, by means of dynamic pricing strategies. Unfortunately these kinds of mechanisms require the users to manually set a lot of configuration parameters, thereby reducing the usability of these solutions. In this paper we propose a system, developed within the BEE Project, for predicting the usage of household appliances in order to automatically provide inputs to electricity management mechanism, exactly in the same way a user could do. In our architecture we use a wireless power meter sensor network to monitor home appliances consumption. Data provided by sensors are then processed every 24 hours to forecast which devices will be used on the next day, at what time and for how long. This information represents just the input parameters required by load demand management systems, hence avoiding complex manual settings by the user.**

I. Introduction

During the last decade, the electricity distribution market and network started to radically change, with a wide set of decentralized and discontinuous energy suppliers arising, ranging from domestic photovoltaic panels to wind turbines. Furthermore, a communication infrastructure has begun to be deployed alongside of the distribution network, in order to support and improve the efficiency of the electricity net, going from the traditional power grid to the Smart Grid.

In this new grid, many data are available for residential users to adopt energy saving policies, firstly by means of improving their behaviour in using household devices [1]. In order to support users in changing their habits, several electricity demand management mechanisms have recently been proposed with the final goals of automatically and optimally scheduling home devices activities for the next day, starting from both users preferences for the next 24 hours and electricity tariffs. These kinds of mechanism don't just allow user to save energy, but are also useful for improving the efficiency of the Smart Grid itself, reducing the power demand at peak hours. Indeed, peaks impose the electric power grid to be over dimensioned and represent the main causes of power supply failure.

The basic problem of load demand management is that it requires users to provide a lot of setting information (e.g. at what time of the day they prefer to use every home device) thereby reducing the system usability and proliferation in the mass market. For this purpose, forecasting methods are required in order to predict people preferences in using electricity for the next day.

In this paper we present a system for predicting usage of household appliances, developed within the BEE Project. The forecasting process includes two procedures: a mechanism for recording data on home devices usage (i.e power consumption), and a prediction algorithm that allows extracting from all these data some settings of the demand management system that is expected to meet user requirements. In particular, as for the monitoring architecture, we use a Wireless Power meter Sensor Network (WPSN) where each sensor node is responsible for the metering of the appliance it is connected to. Data provided by the WPSN are then processed to forecast users preferences for the next day. The proposed algorithm, in particular, provides three levels of prediction: which household devices will be used, at what time of the day and for how long. This information represents just the same input required by demand management mechanisms.

The paper is organized as follows: in Section II we review previous works on home energy management and home automation; Section III presents the basic characteristics of the system under development within the BEE Project; in Section IV we describe the proposed forecasting system, focusing on the prediction algorithm; Section V presents the results from both simulations and experimental tests; finally, in Section VI, we discuss conclusions and future works.

II. Related Work

In recent years, several research efforts have been carried out to define load demand management mechanisms for improving the overall performance of the electric grid. Indeed, in the new Smart Grid, a huge amount of data is made available to users (e.g. devices power consumption, the "real-time" economic value of the energy). This information can be used to adopt energy saving policies, firstly by means of improving users behaviour in using household devices. In order to support people in changing their habits, several energy demand management mechanisms have recently been proposed. In [2], [3] two models are presented that based on energy tariffs and data forecasts for the next day (i.e. PV panels production and devices future usage) are able to automatically and optimally schedule home devices activities for the next day and to define the whole energy plan (i.e. when to buy and sell energy to the grid) with the final goal of minimizing the user bill. The main problem of demand management mechanisms is that, in spite of the great evolution in communication and control capability, an effort is still requested to users to provide a lot of setting information (e.g. at what time of the day they prefer to use every home device), thus reducing the system usability. For this reason, in the Smart Grid architectural solution, a key role can be played by power meter networks [4] that allow monitoring the electricity consumption of home devices [5], [6]. By processing data provided by power meters it is then possible to extract meaningful information that can be used to automatically provide inputs to the energy management system, exactly in the same way a user could do. For this purpose, forecasting methods are required in order to predict people preferences in using electricity for the next day. In [7], [8] two algorithms are presented to forecast building energy consumption, but no attention is paid to predicting single device usage, hence preventing their applicability to energy management systems such as [2], [3].

Several attempts to design forecasting systems have also been made in the field of ambient assisted living and home automation [9], [10], where daily life routines are automatically learned and predicted in order to control home devices, assist elderly people, etc. Algorithms based on fuzzy logic are used in [11] to define a system able to learn users preferences, to predict users needs (e.g. light intensity, temperature). In [12], [13] a different approach based on neural networks is proposed to create a system able to control temperature, light, ventilation and water heating. Neural networks, in particular, represent a promising method to forecast future devices usage, but there are problems determining the optimal topology and parameters for efficient learning. Moreover, the optimal neural network strictly depends on the home environment in which it is used.

III. The BEE Project

The BEE (Bright Energy Equipment) Project is a research activity born within an interdepartmental laboratory of the Politecnico di Milano involving researchers from both the Departments of Electrical Engineering and Electronics and Telecommunications. The goal of the project is to develop hardware and software prototype infrastructures capable of providing advanced tools to residential users in order to make them an active part of future Smart Grids. In the considered scenario, synthetically represented in Figure 1, householders can both buy and sell the electricity to the market. Residential houses are equipped with PhotoVoltaic (PV) panels that produce energy, batteries that allow the system to store energy, and a set of home appliances that have to be used during the day and for each of which a reference start time is provided according to users preferences.

In order to support users in managing their energy plan, a novel architecture allowing real-time energy consumption monitoring and control has been proposed. The main elements of the architecture are:

- Meters: Smart Meters are used for monitoring the consumption of home devices; in a future development of the architecture, also the gas and water meters will be introduced in the architecture;
- The local generation (i.e. Photovoltaic panels): the forecasting of the production of non-programmable generation (i.e. photovoltaic) is integrated in the system in order to improve the predictability of the user exchanges with the grid;
- Electric battery: the usage of energy storage devices allows the system to be flexible in managing the energy exchange with the network;
- Sensors: the collection of data plays a key role in the BEE Project system; data of interest are, for example, the user's position within the home or environmental information such as temperature and light;
- User Interface: a Graphical User Interface is developed for both fixed and mobile terminals, enabling a better user experience of the whole system. These application will ease the setup and maintenance of sensor networks and enable the display of the data and results provided by the system in a simple, effective and intuitive way;
- BEE Box: is the core of the proposed architecture; it is a processing unit that based on demand management mechanism, has the goal to manage and optimize the home energy planning for future periods and to exchange information with the other actors of the electrical system, such as other users, the energy provider and the energy market.

The BEE system has been designed as a support tool for managing the electricity consumption and production of a single house or of a group of cooperative houses, with the final goals of both minimizing the energy daily bills and improving the efficiency of the electricity grid. To this purpose, a demand management mechanism based on optimization methods is introduced with the task of scheduling, every day, house appliances activities and power exchanges with the network for the next 24 hours, by means of optimization models. In order to define the energy plan for the next day, optimization models require predictions on both PV panels power production and devices future usage. As for the PV panels, we have defined ad-hoc learning methods that based on weather forecasting downloaded from the web, are able to predict panels production for the next 24 hours. Forecasting algorithms have also been defined to predict houses load demand (i.e which home appliances will be used and at what time of the day) using data provided by power meter sensor networks. Based on data forecasts (PV panels production and load demand) and energy tariffs, optimization models define the energy plan for the next day, that minimizes the daily bill. Models, in particular, are used for scheduling:

- When to buy, sell and store energy;
- When to start home appliances.

In the following we will focus only on the forecasting system that we have defined to predict home devices future usage.

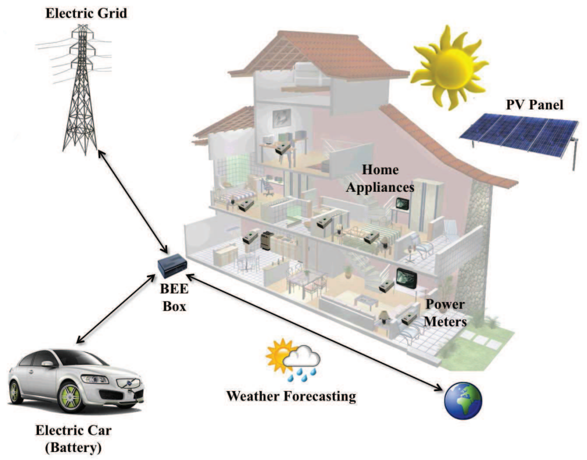

Fig. 1. BEE system architecture for a single house scenario.

IV. Devices Usage Forecasting System

Our approach to reduce human interaction with demand mechanism systems, consists of deploying a wireless power meter sensor network with sensor nodes attached to each household appliance, and using data provided by the WPSN to forecast devices activities for the next day. For collecting information on the state of appliances, we use ACme nodes designed at UC Berkeley [5]. ACmes are sensors based on CC2420 communication chipset with IEEE 802.15.4 technology that are able to measure AC electricity usage of devices they are connected to. Since in the considered scenario the area to be monitored is relatively small and sensors don't need to interact with each other, we propose a star network architecture (Figure 2) that, furthermore, fits very well for the multipoint-to-point traffic of our WPSN. In the proposed network, in particular, each ACme is directly interconnected to a Telosb having the role of a base station. Telosb is the coordinator of the WPSN: it receives data collected by the ACmes and forwards this information to a gateway that finally stores it in a database.

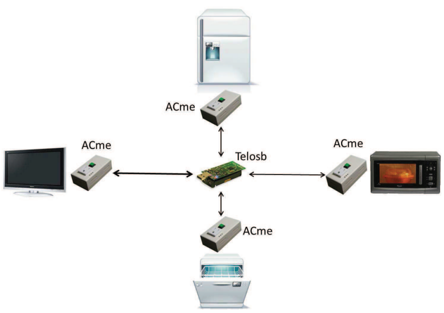

Fig. 2. Power meter sensor network topology.

The final result of the WPSN activity is the collection, for every day and household appliance, of a profile representing the daily power consumption of the appliance itself. The power profile is then processed in order to obtain the daily device status:

- The 24 hours are divided into time slots of 1 minute each;
- For every time slot, the device is said "On" if the average power consumption is higher than a threshold (experimentally defined for each appliance in a previous calibration phase), "Off" otherwise.

An example of power consumption and device status profile is represented in Figure 3.

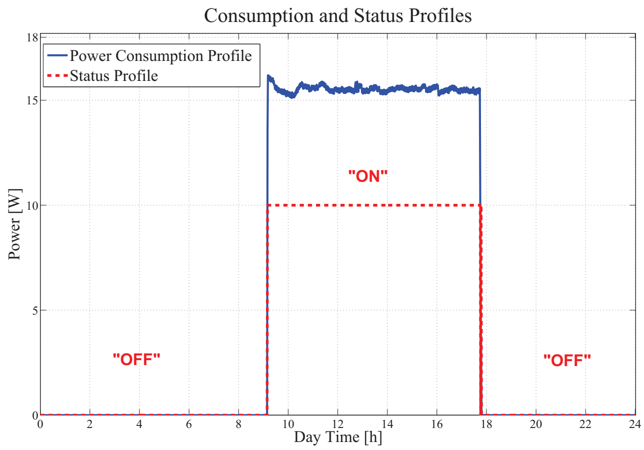

Fig. 3. Daily power consumption and status profiles for a PC monitor.

The proposed forecasting algorithm finally processes, every 24 hours, the daily status profiles collected in the last N days (i.e. the training period of the algorithm), in order to predict the following information for the next day:

- Which devices will be used: Status Prediction;
- At what time of the day: Time Prediction;
- For how long: Duration Prediction.

Using this information, some settings of the demand management system can automatically be made. Notice that the system is not able to forecast devices usage during the very first N days of activity for not having enough information for the status, time and duration predictions.

In the following, the three prediction steps are described, with reference to a generic household appliance. The basic idea that we use here is that people habits in using a device are nearly periodic. Thereby, processing data collected in the past, the behaviour period can be extracted and used to predict how the device will be used in the future.

A. Status Prediction

Daily status profiles are used to create a string, here called "I", of N characters, each corresponding to a day of the monitoring period. Element j of the string has value 1 if the appliance has been used on day j, 0 otherwise. The goal of the status forecasting algorithm is to predict if the device will be used or not on the day following the monitoring period "I".

For this purpose, the probability that 1 or 0 occur at the end of the string is computed, using the following method:

1) A status string "S" of length i (starting from i=1) is selected, representing the status of the device in the last i days of the monitoring period;
2) The Number of Occurrences (NO) in "I" of "S", "S+1" and "$S+0$" are counted and the probability that 1 or 0 occur at the end of the sequence "S" is computed as follows:

$$Prob[1|S] = \frac{NO[S+1]}{NO[S]}, Prob[0|S] = \frac{NO[S+0]}{NO[S]} \quad (1)$$

3) If $Prob[1|S]$ ($Prob[0|S]$) is equal to 100%, the algorithm stops, the device is predicted to be used (not used) in the next day and "S" is said "Prediction Sequence"; otherwise i is increased by 1 and the algorithm goes back to step 1 (if $i = N - 1$ the procedure stops anyway and returns the most probable status computed till that iteration).

Notice that from a qualitative point of view, when the algorithm stops it means that in the training period, on the days following the "Prediction Sequence" and here called "critical days", the device has always been used (not used) so that the same behaviour is likely to be experienced in the future. An example of the proposed algorithm is presented in Table I, stopping for i=2 and predicting the device to be used on the next day.

TABLE I
STATUS PREDICTION ALGORITHM WITH N=9 AND A TRAINING PERIOD STRING I="100100100".

	"S"	NO(S)	NO(S+1)	NO(S+0)	$Prob[1\|S]$	$Prob[0\|S]$
i=1	S="0"	5	2	3	40%	60%
i=2	S="00"	2	2	0	100%	0%

If the device is predicted not to be used the forecasting system stops, otherwise the Time and Duration prediction steps are performed.

B. Time Prediction

The second step of the proposed system, has the goal to predict how many times and at what time of the day the device will be turned on. For this purpose, not all the days of the training period are used, but just a subset composed by the "critical days" found in the status prediction (i.e. day 4 and 7 in the example of Table I) that are indeed supposed to be a good representation of what will happen in the next 24 hours. For each of these days, in particular, the corresponding status profile is selected and a critical profile is designed adding a normal function, with variance σ minutes (experimentally set to 30), for every start time of the device, thereby representing the probability that the appliance is started at a given time of the day (Figure 4).

In order to forecast when the appliance will be used, the sum, sample by sample, of all critical profiles is computed.

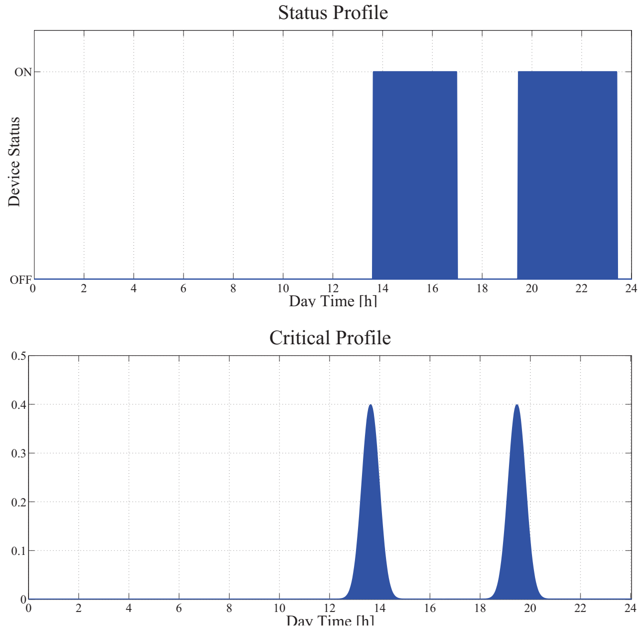

Fig. 4. Daily status and critical profiles.

Day times associated with the peaks of the resulting profile represent the predicted start times of the device for the next day. In Figure 5 an example of time prediction is presented, with reference to the instance described in Table I.

C. Duration Prediction

In order to predict for how long the device will be used since it will be turned on, critical profiles are used. In particular, for each normal function composing this profile, we store the duration, D, of the device activity it is associated with. When a peak is detected in the time prediction step, normal functions numerically contributing to the peak value are selected and the mean value of the associated parameters D is computed, hence forecasting for how long the device will be used. In Figure 5 an example of duration prediction is presented, with reference to the instance described in Table I.

V. NUMERICAL RESULTS

To evaluate the performance of the proposed algorithm we have performed both simulations and experimental tests. Simulations have been used for defining the system parameters and testing the algorithm based on a large data set that would have hardly been collected in an experimental scenario, mainly because of the long period of time required for gathering data in a real environment.

In our simulations three devices have been considered with a simulating period of one year: oven, air conditioner and dishwasher. For each of them a sequence of realistic power consumption and status profiles has been created, introducing some random variations and exceptions in the way users run appliances in order to simulate a real use case scenario. Users, in particular, change their habits in running home devices during the 365 days (e.g. the air conditioner is not used in

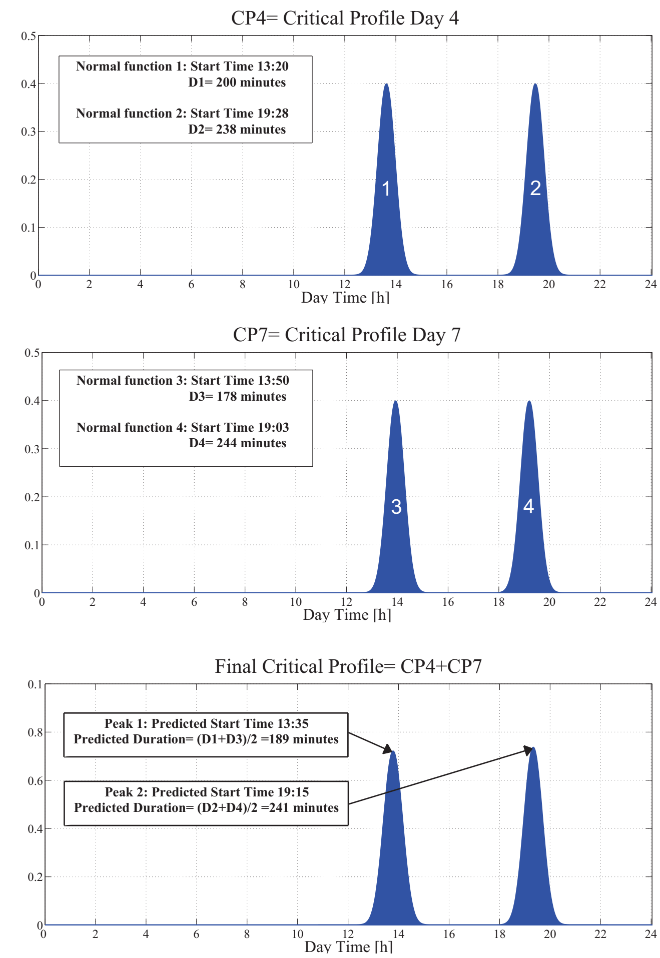

Fig. 5. Device time and duration prediction.

winter and autumn). Moreover, in 20 isolated days of the year, users run devices contrary to their habits. Test results are shown in Table II and Table III.

TABLE II
PERCENTAGE OF CORRECT STATUS PREDICTIONS FOR DIFFERENT LENGTHS OF THE TRAINING PERIOD.

Status Prediction

N	Air Conditioner	Dishwasher	Oven
11	36%	42%	38%
21	82%	84%	78%
28	94%	95%	94%
45	95%	94%	96%
60	94%	95%	96%

As it can be seen from results in Table II, a low value of N brings to bad performance of the algorithm in predicting home appliances usage for the next day. Increasing the length of the training period, the system becomes more and more accurate, even if no major improvement is observed for N higher than 28. For this reason, we decided to use N=28 for experimental tests. As for time and duration prediction performance, results presented in Table III show a very good accuracy of the system, except that for the time prediction of the oven. In our simulated data, we have indeed supposed users to run this device about two hours later on the weekend than on the working week, hence explaining the bad performance of the system in predicting the oven starting time.

TABLE III
DIFFERENCE IN MINUTES BETWEEN THE PREDICTED DEVICE START TIME (DURATION) AND THE OBSERVED ONE.

N=28	Air Conditioner	Dishwasher	Oven
Time Prediction Error	13 m	22 m	91 m
Duration Prediction Error	22 m	8 m	14 m

In addition to simulations, we have also run some experimental tests in order to evaluate the performance of the system in a real use case scenario. For this reason we implemented a prototype version of the proposed power meter sensor network. The WPSN was used for monitoring the power consumption of 4 devices (i.e. oven, TV, boiler and computer) of a residential house of about 45 m^2, inhabited by one person. Data were collected for 45 days, experiencing the results presented in Table IV.

TABLE IV
STATUS, TIME AND DURATION PREDICTION PERFORMANCE EVALUATED THROUGH EXPERIMENTAL TESTS.

	Oven	TV	Boiler	Computer
Status Prediction	76%	82%	94%	88%
Time Prediction	71 m	32 m	42 m	18m
Duration Prediction	7 m	22 m	32 m	4 m

As it can be seen, experimental tests confirm the system performance experienced with simulations. Our algorithm, in particular, has a good accuracy in predicting devices status and usage duration, while a performance degradation is detected in the time prediction, reflecting the fact that users habits are just partially predictable. However, prediction errors experimented in our tests should not have negative impacts on demand management mechanisms since they don't require a full accuracy in forecasting household appliances usage.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper we presented a system to forecast household devices usage. A wireless power meter sensor network is proposed in order to automatically gather information on appliances power consumption. Data provided by sensors are processed every 24 hours in order to predict which devices will be used on the next day, at what time, and for how long. Based on these predictions some settings of the electricity demand management mechanisms can automatically be made, thereby improving the usability of these kinds of mechanism and easing their proliferation in the Smart Grid.

In order to evaluate the performance of our system we have implemented a prototype version of the proposed architecture and showed its effectiveness in predicting devices usage through experimental tests. Moreover, some simulations have been performed for defining the system parameters and testing the algorithm based on a large data set.

Although having discussed the efficacy of the solution, this study represents just one first cut analysis and further investigation is therefore required. First of all, additional experimental tests will be used to verify the practical applicability of the system in real use case scenarios. Moreover, extending the proposed method by detecting devices usage correlation patterns and by introducing users presence forecasting algorithms, will allow improving the accuracy of prediction.

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