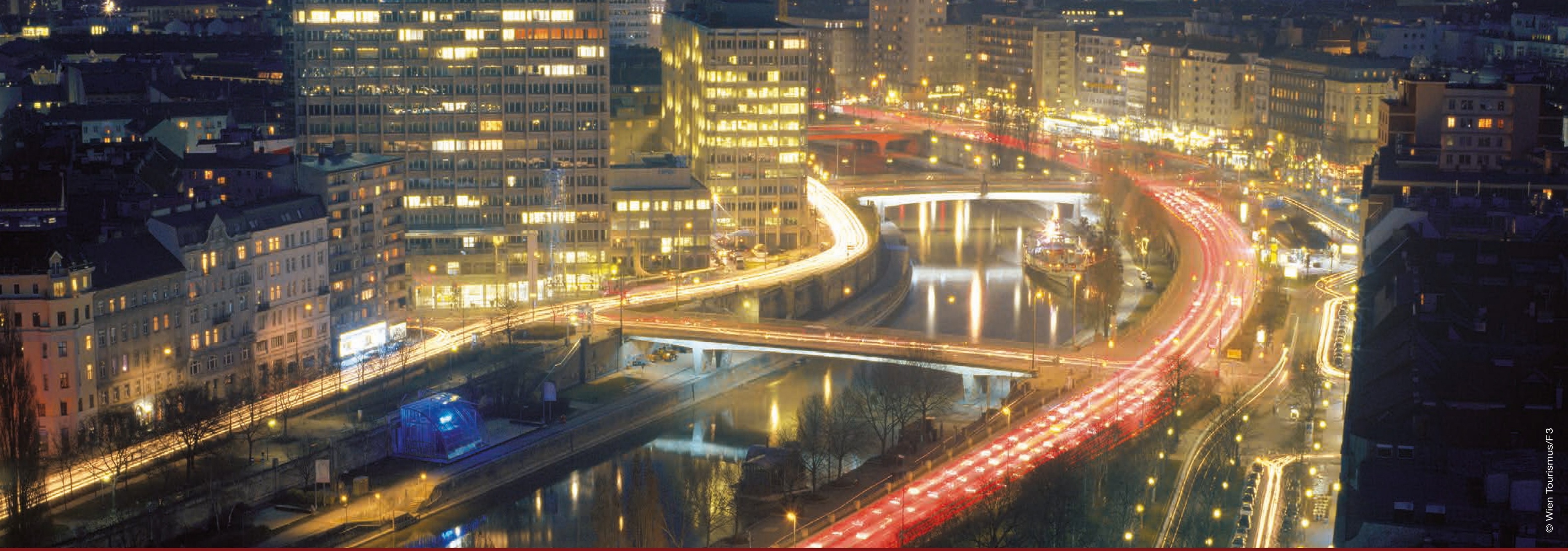

IECON 2013 November 10–13 2013, Vienna, Austria

Conference Booklet

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IWIES 2013: 1st International Workshop on Intelligent Energy Systems (14.11.2013)

Austria Center, Vienna, Austria
10-13 November 2013

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MONDAY 11th of November

	D-349	D-351	D-355	D-358	D-441	D-445	D-446	D-447	G-5432	G-560	G-631	H-633	Hall-D	Hall-G	Hall-H	Hall-I	Hall-K	Hall-P	I-140	I-141	K-142	K-246	K-253	K-255	K-261	S-357	U-556	U-637
08:00-09:30													Opening						PC Brief									
09:30-10:00																												
10:00-12:00	TT02 12	SS68-1	SS73	TT08 1	TT06 1	SS52 1	SS27 1	SS18 1	SS17 1	TT07 1	TT07 12	TT12 1	TT01 2	TT01 13	TT01 21	TT01 40	TT01 18	TT02 1	TT00	SS16 1	TT06 12	Press Conf	SS23 1	SS01 1	TT03 1	TT02 15	TT10 1	SS06 1
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16:30-17:30						TC ESOC	TC SG	TC MEMS																				
17:30-18:00	TC AT	TC BACM	TC IA	TC HM	TC CRM	TC EEIT	TC EEIT		TC II	TC FA		TC ES							TC NCSA	IFC	TC RES		TC MC	TC RSIA	TC EM	TC SA	TC STD	TC PETC
18:00-18:30																												

TUESDAY 12th of November

	D-349	D-351	D-355	D-358	D-441	D-445	D-446	D-447	G-5432	G-560	G-631	H-633	Hall-D	Hall-G	Hall-H	Hall-I	Hall-K	Hall-P	I-140	I-141	K-142	K-246	K-253	K-255	K-261	S-357	U-556	U-637
08:00-10:30	SS60 1	SS71 1	SS72 1	TT08 4	TT06 4	TU-EVCIDG	TU-PHM	TU-IETCPC	SS46 1	TT07 4	TT07 15	TT12 4		IF	TT01 8	EI13	TT01 27	TT01 29	TT00	SS41 1	TT09 3	TT06 15	SS23 4	TT05 1	TT03 4	TT02 4	SS62 1	SS09 1
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16:30-18:30	SS58 2	SS20 2	SS53	SS63 2	TT06 7				SS45 2	TT07 7	ICELIE 1	SS42		IF	TT01 11	EI13	TT01 24	TT01 32	SS50 1	SS34 1	TT09 6	TT06 18	SS28 2	TT05 4	TT03 7	TT02 7	TT11 3	SS03 2

WEDNESDAY 13th of November

	D-349	D-351	D-355	D-358	D-441	D-445	D-446	D-447	G-5432	G-560	G-631	H-633	Hall-D	Hall-G	Hall-H	Hall-I	Hall-K	Hall-P	I-140	I-141	K-142	K-246	K-253	K-255	K-261	S-357	U-556	U-637
08:30-10:30	SS32 1	SS15 1	SS59	TT04 1	TT06 8	TU-EH	TU-SSTC	TU-NET	SS26 1	TT07 8	ICELIE 2	SS43 1		IF	TT01 12	EI13	TT01 25	TT01 33	SS02 1	SS04	TT09 7	TT06 19	SS28 3	SS19 1	TT03 8	TT02 8	SS49 1	SS44 1
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THURSDAY 14th of November

	D-349	D-351	D-355	D-358	D-441	D-445	D-446	D-447	G-5432	G-560	G-631	H-633	Hall-D	Hall-G	Hall-H	Hall-I	Hall-K	Hall-P	I-140	I-141	K-142	K-246	K-253	K-255	K-261	S-357	U-556	U-637
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Load Identification and Management Framework for Private Households

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***Abstract*—This paper describes a framework for the identification of household appliances based on a measured aggregated load profile. Device activation and deactivation events are detected by a set of non-intrusive algorithms collected in the software structure. These detections are then matched to a database of load values. The result which is basically a detection probability in combination with consumption data of the device, is displayed to the customer as energy feedback. This motivates users to apply energy-saving measures, or in combination with an home automation system appliances can be turned off automatically. Another concept is to implement more intelligence directly into the devices. Such smart appliances communicate with an energy management gateway and plan their activation autonomous. For the proof of concept a simulator for smart home appliances was developed and integrated into a demonstration setup. Finally the discussed results suggest that disaggregated energy feedback in combination with smart home appliances is a feasible approach in order to using the available energy in a more efficient way.**

I. Introduction

Electrical energy supply at competitive prices in sufficient quality, quantity and under the constraints of uninterrupted service is a serious challenge for electricity suppliers. Rising consumption and increasing peak load periods requires effective methods to counteract against these trends. The main goal is to reach a well balanced distribution of loads, grid stability and high supply quality anywhere and anytime in a extremely decentralized network of suppliers, consumers and storage. A continuous information flow of status parameters and customized data between grid nodes must be supported. The parallel architecture of information and power distribution is called a Smart Grid architecture.

At the customer's side, in private households update information from the supplier is received at a centralized home energy gateway. Home automation systems connected to this gateway can motivate an inhabitant to use the available energy in a more efficient way or automatically apply control algorithms. Additionally new fully electronic metering devices (smart meters) offers on-time information about the current aggregated consumption. At least users should power off devices if they are not used, reduce the standby power level and have an overview of their appliance's consumption. The feedback can be seen as a customer's learning tool which allows teaching themselves through experimentation [1]. These positive demand side effects will help supplies reaching load balancing requirements and decrease the total energy consumption. Several research articles as [1], [2], [3] and [4] report about positive effects of energy feedback related to increase efficiency and finally reduce costs. Feedback requires measurement of electrical data at the main distribution line of a household or monitoring each of the installed appliances. As finally stated in [5] data and device management can be used for demand response driven systems which combine monitoring and control tasks.
The rest of the paper is organized as follows. Section II and III inform about state of the art energy feedback systems and how presented data are evaluated. Section IV introduces into the main concept of the GREEN HOME research project, and finally Section V and VI report about the results of the implemented load identification and energy feedback prototyping system.

II. Energy Feedback Information

Numerous examples in our daily non technical life show that systems naturally contain feedback. Feedback need to be planed and must serve a particular purpose or objective. Data are pre-computed, displayed and it must be clear how to impact the system in a way to reach the desired objective. The user translates feedback information into input actions on the system. For feedback systems including a human actor an abstracted and modeled view represents a complex system architecture. An adequate view hides detailed internal signals. This keeps modern home automation systems usable at increasing internal system complexity.

A. Feedback Methods

For technical energy feedback systems in households according to [1] it can be distinguished between direct and indirect feedback methods.

Indirect Feedback describes methods that have been processed in some way before reaching the customer, normally via billing or other informal notifications. This form of energy feedback is more suitable than direct feedback for demonstrating effects in changing some structural aspects of a household (*e.g. investments in thermal insulation, replacement of high consuming appliances, etc.*) [1].

Direct Feedback are methods where information is displayed in real-time. For visualization different types of displays categorized to their feedback complexity are used. For example so called direct displays show the same information as the smart meters but are located at a convenient location in

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the home. The major feature of direct displays is that they are a pure presentation of data without any mathematical computation [1]. Disaggregated feedback methods offer in addition to direct displaying an analysis of the measured values. Ambient displays are a smart and minimalistic solution for energy feedback information which do not show any text or numbers. This type of display alerts the customer if there are some relevant changes in the electricity supply or consumption of the household [1]. Due to our modern and high communicative way of life all display data mentioned previously can also be redirected on mobile devices. In the context of this this work we implemented all three introduced feedback types. Aggregated and disaggregated power consumption including historical values and a traffic light view as an ambient display.

B. *Impact of Energy Feedback on Energy Efficiency*

Internal motivation opposed to external incentives, the need of feedback over time allowing customers to monitor the positive effects in energy efficiency, changes their lifestyles, housing and appliances [1]. The saving from energy feedback are not only depending on the technology under consideration. There are several more factors like institutional and cultural backgrounds, quality of feedback, regional aspects, etc. However all reviewed studies do show the usefulness of energy feedback information which is specific to customers [1]. In comparison to standard smart metering applications direct energy feedback can reach higher saving rates. This is caused by more flexible reactions and learning effects of the user. A recent project in Korea uses so called "In Home Displays" for the direct energy feedback. The display presents current smart meter data and historical consumption values. 48 of 53 households in Cheongju showed reductions in daily power consumption. The average decrease was 15.9 % from 7.92 kWh to 6.66 kWh [4]. In a second study 22 of 24 households in Seoul showed an energy reduction of 7.5 % from 9.77 kWh to 9.04 kWh [4]. The reasons why the study in Cheongju reached a higher rate of energy savings are social factors and different variations of the day/night temperature profile in the cities [4]. An American research study using ambient displays results in 16 % saving over a three week period [6]. The functionality of the system is that a red light flashed in case of the outside temperature dropped below 20 degree Celsius in summer. This reminds the customer to open the windows for cooling and the air conditioning will be turned off automatically. Best results could be evaluated by using TVs or PCs displays for direct energy feedback. The rate of electricity savings reached up to 18 % for ten householders who took part in a ten-month trial [2]. As a summarization Table I will show typical average energy saving rates reached by a specific feedback structure.

III. LOAD MONITORING

Continuous monitoring of loads in a household requires the implementation of a feedback system described previously. The monitoring task can be split into individual measurement of loads with the help of external sockets, or aggregated measurement by a smart meter. In combination or at integration within a state of the art home automation system loads can be switched on and off automatically and subsystems (*e.g. air conditioning*) are controlled by updating their input parameters. A further important task after the measurement of an aggregated load profile is the identification of appliances in the totally random overlapping of individual device's power profiles.

TABLE I. TYPICAL AVERAGE ENERGY SAVING RATES REACHED BY THE DISCUSSED ENERGY FEEDBACK METHODS

Method	Savings	Study / Source
Indirect feedback with smart meters and customized tariff schemes	2 % to 3 %	UK, [7]
Direct feedback with In-Home Displays	7.5 % to 15.9 %	Korea and UK, [7]
Ambient displays with simple non textual feedback	16 %	America, [6]
Direct feedback with presentation on TVs or PCs displays	18 %	Japan, [2]
Direct feedback with presentation on interactive web page	8.5 %	Netherlands, [2]

A. *Monitoring and Identification of Household Appliances*

In homes load monitoring methods can be classified as centralized or decentralized. Decentralized measurement can be realized by a star or bus topology where each device of the household is connected to an individual measurement unit. Load data can be shared via a data network for displaying and control applications. This method can also be used for a centralized realization where all appliances are monitored by a master controller unit (single point of failure). Centralized non-intrusive load monitoring and identification as we use it in context of this project are software algorithms non influencing the functionalities of the electrical installation. The used algorithm types are:

1) Edge-based Parameter Matching: Parameters are extracted from edges in the measured quantities [8]. For example if a device has a real power consumption of 200 W, a corresponding positive/negative step increase indicates a turn-on/off event of the appliance. The identification probability can be increased by considering a set of different electrical parameters. Parameters variations at an edge event can be used as unique signature of a device. This algorithm type returns accurate results for devices having a stepwise profile [8]. Extensions are the detection of multi-state load signatures indicating internal components of a device and three phase loads. The problems and disadvantages within this algorithm are the quantisation of an event, detection of ramps, fast fluctuations in the power level and other fading events [8]. For example a fan generate different power states depending on the rotation speed.

2) Detection of Real and Reactive Power Signatures: Another drawback of the edge based parameter matching algorithm are mobile loads which can be plugged into different sockets supplied by different lines of the grid. A combined identification including activation times can only be accomplished if the turn-on event of the appliance is successfully detected. These two disadvantages can be eliminated by using a ΔP - ΔQ approach. The algorithm is based on the first derivation of real and reactive power consumption. If a positive or negative edge in the profile occurs the in/decreases in real power ΔP and reactive power ΔQ can be calculated. As illustrated in Figure 1 the evaluated sample highlights a coordinate in the two dimensional ΔP - ΔQ space. Sampling points which can be assigned to a specific load, form a cloud around the template sample which is marked by the bold cross. Each sample has a quadratic distance in ΔP and ΔQ direction to any template record. This distance is inverse proportional to a matching probability. The distribution function rating the probability is a two dimensional Gauss function. The peak value of the function is normalized to a probability of 1 and located at the templates ΔP and ΔQ values.

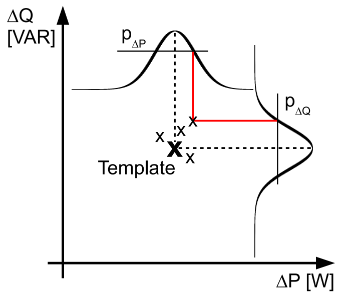

Fig. 1. ΔP-ΔQ plane. Identification probabilities are evaluated by Gauss functions.

Other related techniques not used in this work came from pattern matching, handwriting or environmental sound recognition applications. They use sample matching and especially dynamic time warping (DTW) algorithms.

B. Analysis of Typical Aggregated and Individual Load Profiles

Figure 2 shows a zoomed section for the real power and line three current of an aggregated load profile. The activation of the freezer device can be matched at 20:08, 20:56, 21:44 and 23:20. For an automatic edge based algorithm the corresponding detection rule can be realized as: Rising edges of 120 W and 0.647 A and after 17 minutes falling edges of 100 W and 0.615 A indicates a cooling process of the freezer. At considering the activation times there is a gap between 21:44 and 23:20. The cooling period of the freezer is constantly 48 minutes (*e.g. 20:08 to 20:56*), and the distance between 21:44 and 23:20 is 96 minutes (exactly 48 times 2). So theoretically there must be an activation of the freezer at 22:32. An indication for the activation of the freezer at this time is the negative exponential progress of line current three for 17 minutes. The real power consumption for this period of time is overlapped with other appliances and totally unstructured. As a result of the analysis and manual matching of the freezer template three facts can be focused for the automatic identification of automatically and cyclic activated appliances:

- For an edge based algorithm the height of the rising and falling edges independent of the offset level is important. For single phase loads there must be equivalent timed edges at the power profile and at one of the line currents.
- The time difference between rising and falling edge (on and off event) is a characteristic parameter of an appliance.
- The period of activations is characteristic value of automatically activated devices.
- The progress and shape of the signal (real power or current) is characteristic for an appliance type.

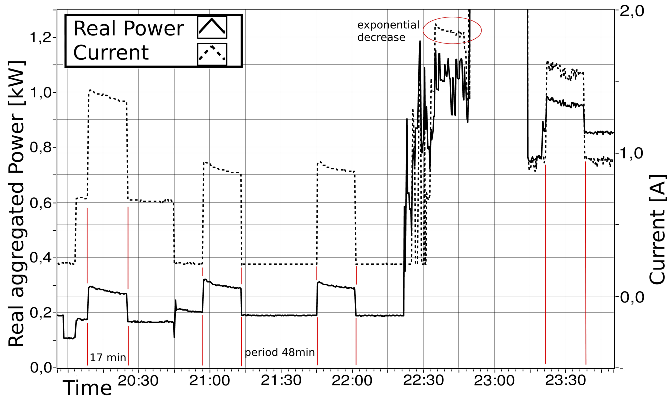

Fig. 2. Freezer load profile characteristic in a smart metering trace.

The second load identification algorithm introduced in Subsection III-A2, is the $\Delta P - \Delta Q$ method. This method also detects the freezer in profile 2. The configured template for the device is a spot of $\Delta P = 120$ W and $\Delta Q = 100$ VAR values. The turn-off event are equivalent negative values. For the implementation the following facts can be identified for the automatic algorithm design:

- The $\Delta P - \Delta Q$ space method can be used for the identification of non-cyclic activated appliances.
- With a $\Delta P - \Delta Q$ based algorithm devices with the same amount of real power consumption can be distinguished (see discussion in Section VI).

For the previously described detection of loads based on the aggregated measured load profile, we need a database of load templates. These measured template profiles are used for the extraction of typical device parameters needed for the detection algorithms. The database created for this project is filled with individually measured profiles of typical devices like freezers, washing machines, dryers, multimedia equipment, lighting, etc. Device's traces and parameters are stored in an XML based file. An example of a washing machine is shown in Figure 3. The illustration shows the real and reactive power consumption of one dedicated washing program. Parameters for each phase of the process can be extracted. 1800 W for nine minutes for the water heat up, and continuous rotation sequences of the washing drum with peak power consumptions of 200 W. These measured templates are the basis of the load identification framework and the home appliances simulator described in the next Sections.

IV. THE GREEN HOME CONCEPT

The GREEN HOME project (Grid Responsive Energy Efficient Networked Home) [5] has its focus in impact analysis of information and communication technology (ICT) onto the energy consumption in private homes. Main element of the system architecture is a smart energy gateway which supports a constant communication channel between energy

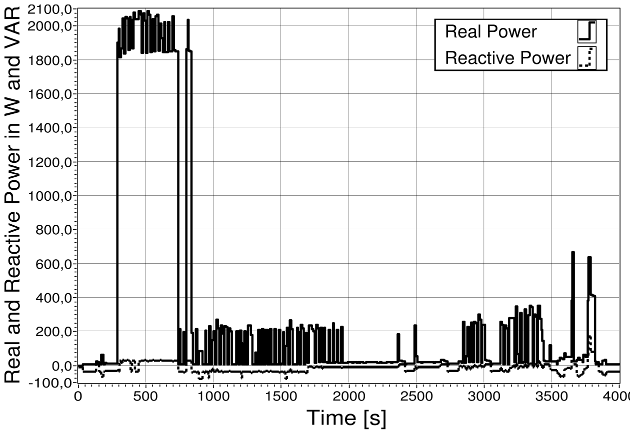

Fig. 3. Power consumption profile of a washing machine for a 60 degree Celsius laundry program.

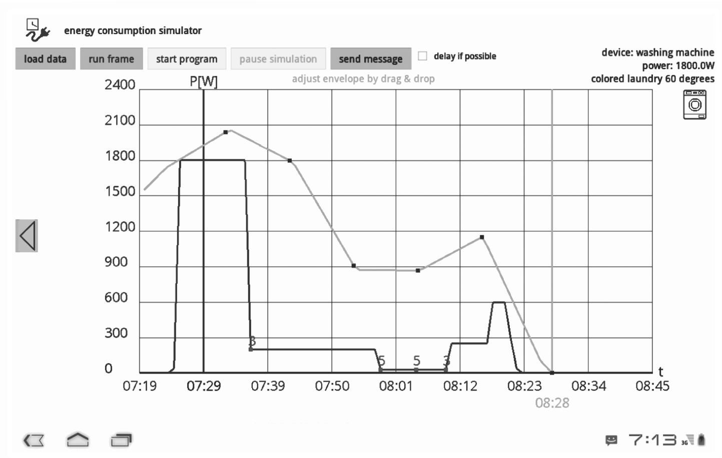

Fig. 4. Screenshot of the simulator showing a washing machine load profile [9] which is evaluated from the measured data set of Figure 3

supplier and customer.

One key technology for this concept is the hybrid measurement structure of electrical loads. Smart metering in combination with a non-intrusive load identification system and individual power measurement (smart plugs) guarantee a continuous energy feedback information (direct feedback). A further driving factor is that future appliances will implement more and more intelligence in the view of autonomous energy management. They receive a full energy time table containing the limitations of electrical power consumption from the central energy home gateway. Based on this time table an appliance itself can schedule its activation under best fulfillment of the requirements.

Such smart household appliances are not available for competitive prices at the time of writing and in-home communication is not standardized. So for the proof of the GREEN HOME concept we developed a simulator for future home appliances [9]. The simulator software is executed on an Android based tablet PC and can emulate twelve types of household devices having different levels of intelligence. The large touch screen of the tablet PC can be the user interface of a future device supporting direct energy feedback information. The digital communication interface of the tablet (USB-OTG) is used for the connection to the energy gateway (realized as serial wired, wireless or power line communication). For future research the simulation platform can be used for requirement analysis of communication technology, energy management algorithms and user interaction.

As previously mentioned the simulation software can emulate twelve appliances which are classified according to their intelligence and controlling ability.

- ON/OFF devices are simple device which have two steady states in power consumption. Their operation must be supported immediately and can not be shifted in time.
- Devices having a dynamic load profile. In this case the energy gateway can influence the activation of a device by defining an energy price level (low, middle and high). For example at refrigeration devices at a low energy price the internal temperature can be held low. If the price changes to high the low internal temperature can be used as a buffer to delay the reactivation of the cooling process as long as possible [9].
- Devices having a dynamic load profile under the consideration of a maximum end time. These devices receive an estimated energy plan from the gateway. According to the dedicated load profile for one process (*e.g. one program of a washing machine - Figure 3*), the device can calculate the optimal activation timing window. In the case the gateway updates the energy plan due to wrong estimations a washing machine can pause its operation for a finite timing interval without a decrease of the washing quality [9]. The global requirement that the process must be finished at least at the configured end-time will be always satisfied.

V. Load Identification Framework

The load identification algorithm implemented in this work has an object oriented structure. The architecture and main functioning of the implementation is to offer an integration of several sub-algorithms. Sub-algorithms implemented in this work are described in Sections III-A and III-B. The main object oriented idea for this application is that the load identification functionality is distributed into parallel executed software objects. Each object is assigned to solve a sub-task. So load identification techniques work independent and creates their individual detection results. Finally each implemented sub-algorithm of the framework delivers its probabilities and solutions for the identification of the activated load. This architecture satisfies the dynamic changing requirements over time and a customer dependent setup on the detection of appliances can be fulfilled.

Figure 5 illustrates the architecture of the identification framework. Each block is a software object which interacts with other objects, external sensor devices or the user. Energy consumption data are received independently from

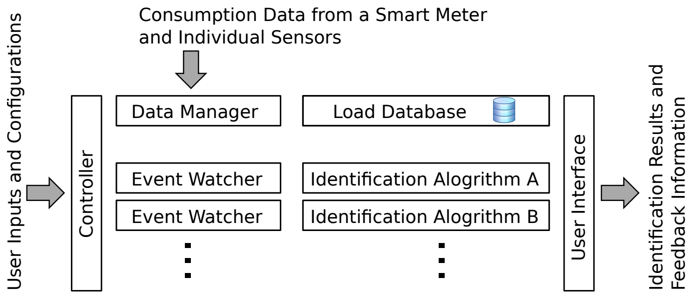

Fig. 5. Architecture of the object oriented load identification framework.

individual power sensors distributed in the home (smart plugs) or from a smart meter. Proprietary software objects not shown in the Figure implements interface functionalities for the used communication networks. The *Data Manager* converts all received sensor information to a common format and distributes them to *Event Watcher* objects. The *Event Watchers* can be instantiated and destroyed dynamically. If an event is detected (*e.g. stepwise change of a value*) the according quantity is observed. After the observation, which is closed by an dedicated closing event the set of detected events is passed to all implemented identification algorithms. With the help of templates stored in the load database each algorithm returns a detection result and an appropriate identification probability for the detected appliance. Results and disaggregated consumption data are displayed on a Graphical User Interface (GUI).

In the view of extensibility of the framework our object oriented structure has several advantages. Additional power measurement sensors and systems can be added by implementing appropriate interface classes at the *Data Manager* module. Additional configurations in the Controller declare the new module in the full identification framework. For the detection of events new types of watchers can be added (*e.g. an object which observes trace shapes*). The new objects can be created and destroyed dynamically according to their start and end occurrences. Additional identification techniques are added parallel to algorithms A and B shown in Figure 5. Each object operates as an autonomous module interacting via standard queues. The classification of detection results and the decision which results are displayed to the user are implemented mechanisms of the user interface. So for extending and hiding information views the user interface object can be configured (see different types of energy feedback in Section II-A). To keep the software independent of target platforms it is written in standard C++ language and uses only free available libraries (GNU gettext, libxml2, etc). The framework can be cross compiled and deployed at any state of the art embedded Linux system (*e.g. arm-linux-gnueabi*).

VI. RESULTS

For the evaluation of the implemented load identification framework, a benchmark pre-recorded load profile is applied. It is in total an one hour random overlapping of nine typical household appliances listed in Table II. In the full test time appliances are activated and deactivated for 32 times. This test load profile is used for rating load identification results at changing algorithm configurations.

The first 16 minutes of the test profile (real power data) are illustrated in the upper chart of Figure 6. In the lower two charts the identification results of the water boiler and freezer devices are shown. Styles of lines represent different implemented identification algorithms. Solid line sketches an edge based pre-identification where the probability just depends on the turn-on event of a device, and dashed lines indicates an edge based combined identification. The identification at this algorithm is on one side based on the turn-off event of an appliance. On the other side the parameters of the turn-on event are considered in combination with appropriate timing information (turn-on time, activation period). The dotted line represents the $\Delta P - \Delta Q$ identification algorithm which is based on the unique signature of real and reactive power consumption of a device. The gray areas in the lower result charts indicate the timing intervals where the appliance is really physically activated. For the discussion of the evaluated identification probabilities some interesting points in simulation time are as follows:

- t=170 The activation of the freezer is detected at a probability of 1 by the pre-identification algorithm. For the water boiler the result is just 0.4 and not displayed at the GUI. The successful identification is registered at an event watcher which observes the input load profile inspecting the turn-off event of the freezer.
- t=280 The load profile shows a large drop of 2000 W at the real power trace. The identification probabilities of the pre-identifier (solid lines) returns to 0 because this is definitely a turn-off event. But the post-identification probability (dashed line) also stays at 0. This means that the turn-off event can not be matched to both of the illustrated appliances.
- t=450 At this point in time the water boiler is activated. The turn-on event is successfully detected by two algorithms. The $\Delta P - \Delta Q$ results in a probability of 0.7 and the pre-identification in 0.5.
- t=580 The water boiler is turned off. Due to the unique signature in real and reactive power consumption the turn-off event is again detected by the $\Delta P - \Delta Q$ method at the same probability. The combined-identification of this turn-off event results due to insufficient timing in a minimal probability.
- t=980 The deactivation of the freezer's cooling process is detected by the post-identification algorithm. The negative edge event in real power consumption is combined with parameters from the turn-on event and an activation time of 13.5 minutes. This extended parameter set results in a detection probability of 0.75. If there are any unpredictable occurrences influencing the cooling time of the device (*e.g. opening the door*) the combined-identification probability will be significant lower.

Table II holds an overview of successful identification results for all devices included in the test profile. An 'X' in the table indicates that the device is detected under optimal

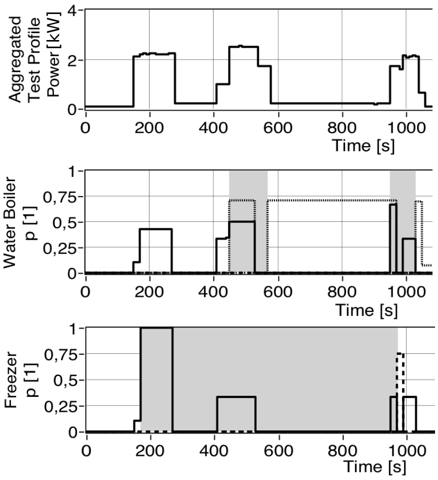

Fig. 6. Identification results for the detection of the water boiler and freezer device.

configurations of the detection framework. As discussed in the last Section for example the vacuum cleaner can not be detected by the combined algorithm due to undefined time of vacuuming. The vacuum cleaner is also a mobile device, which can be plugged in at different sockets fed by different lines of the power supply grid. So the most promising detection method for this appliance is the $\Delta P - \Delta Q$ algorithm. As a second example the electric heater and the motor device are compared. Both appliances have a similar real power consumption of 1050 W and 1000 W, respectively. The pre- and post-identification algorithms are very precisely configured to detect the motor device. The electric heater can strongly vary in its real power consumptions (self-heating effects). So there is no successful detection by the pre- and post-identifier due to the low contrast to the motor appliance. The solution for the determination is the $\Delta P - \Delta Q$ algorithm. Due to the high inductive internal parts of the motor it highlights a completely different spot in the $\Delta P - \Delta Q$ plane.

TABLE II. SUCCESSFUL IDENTIFICATIONS OF APPLIANCES

Appliance	Pre-Identification	Post-Identification	Combined-Identification	ΔP-ΔQ Identification
Freezer	X	X	X	
Water pump	X	X	X	
Vacuum cleaner	X	X		X
Halogen light	X	X		X
PC monitor				X
Water boiler	X	X	X	X
Motor	X	X	X	X
Toaster	X	X	X	X
Electric heater				X

Under the optimized system configurations used for the evaluation of Table II 30 of 32 events and appliances included in the test load profile can be detected successfully. The most problematic device of the test set is the halogen light. With a power consumption of 25 W it is a relatively small load compared to all other devices. By decreasing the threshold values triggering events, the activation of the halogen light will be fully covered. The negative side-effect of decreasing the configuration values is a high amount of over-detection due to real power fluctuations.

VII. Conclusion

This paper presents the implementation of an energy feedback and load identification system within the context of the GREEN HOME project. GREEN HOME deals with topics concerning the communication between the customer and an energy supplier as well as with load management in private households. The main purpose of energy feedback is a constant and disaggregated view of loads which motivates the user to activate appliances in a more energy saving way. The disaggregation can be achieved by individual measurement of each device (smart measurement plugs) or by non-intrusive identification algorithms based on smart meter data. Within this work we implemented an object oriented load identification framework which is able to combine different identification algorithms to increase identification probabilities. In the view of automatic load management functionalities the GREEN HOME concept provides to decentralize more intelligence into appliances itself. To prove this concept we realized a simulator for future smart home appliances which offers a digital interface for the communication with a private home energy gateway. Power profiles used in this simulation software are evaluated from individually measured load database.

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