On the Utilization of Smart Gadgets for Energy Aware Sensitive Behavior

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***Abstract*—The conscious, efficient, and economical consumption of energy is being identified recently as crucial topic for industry, politics, and research. Limited earth resources that are still used for the majority of energy production head towards increasing energy prices and stress world climate and the budget of people. We present the PowerIT System that utilizes smart gadgets to achieve a more efficient and economical use of the available energy. By providing instant feedback of the current energy consumption in households by leveraging power metering technology and therefore raising awareness about the economics of the own energy usage, this work aims at reducing the energy consumption of people in their homes. The real-time energy consumption is captured, whereas the power signatures of electrical devices measured by power metering systems are the input modality for the system. This data is provided in real time as visual feedback to the residents using today's available smart gadgets (e.g., smart phones, tablets, and smart watches) in order to raise awareness about the current power demands. Beside the pure monitoring and control of power consumers, the system additionally collects data about the activities of people by using smart watches. This data can be used to generate activity models resulting in activity aware power saving schemes. We argue that the awareness of people about their energy consumption can induce a behavioral change resulting in a more efficient use of energy without affecting their level of living.**

Keywords*—*Power Management; Efficient Power Usage and Power Awareness; Behavioral Change; Sensor Networks; Activity and Context Recognition; Smart Gadgets.

I. Introduction and Motivation

It should be common knowledge that energy is a scarce resource. In opposite to that knowledge, we see a dramatic increase in the use of energy in the last years [1]. Due to the fact that our society is not aware of how many energy they consume, a technique of unobtrusively making them aware of their daily energy consumption should be identified. We focus on electrical energy as a part of the global energy composition because its consumption can be controlled and changed easily by people. Hoelzl showed in [2] that with the utilization of context [3] data in households, in this case the modes of locomotion in combination with different locations, it was possible to save on average 17% of electrical power. As the results were mostly gained by analyzing a collected dataset of 15 households, we focus in this work on deploying a realtime system to bring the gathered results out in the field.

The last years, especially the last months showed that the developments in the consumer market proved the augur that everyone would be able to get a wearable digital and smart artifact. Concerning nowadays developments, these gadgets are becoming smaller and smaller and people tend to use them as artifacts of daily living. Starting with the development of *smart phones* [4] that is de facto standard equipment of people in the researched living habits, the development goes towards 24 hours usage of smart watches [5]. We argue to make use of these already deployed gadgets to make users aware of the current electrical power consumption of their household devices and to control them in an unobtrusive way. As the definition of unobtrusive is recognized differently by different people, a value sensitive design [6] has to be taken into consideration when designing such a system. We made our system working completely autonomous without the need of any user interaction. It's incumbent upon the user if interaction with the system is wanted on different levels (be referred to Section III for further detail).

Using our system, the user is aware, at each point in time, of his energy consumption in realtime for each connected single device. This is a tremendous benefit compared to the nowadays deployed SmartMeter Technology were the data has a resolution of up to 15 minutes, is only available with one full day lag due to legal aspects (depending on the used technology and countries, here exemplarily picked for Austria), and can only be viewed for the aggregated power consumption of all the devices in the household. Concerning the facts that, (i) the measurements are not available for single devices, (ii) have a big lag in time, and (iii) that the measurements can be transmitted or stored at third party entities (e.g., energy provider) one is not in control of, raising security and privacy issues [7], [8] of people that they are spied on, we designed the system to capture energy readings at an interval of 10 seconds for each single energy consumer. This data is kept completely local as the system can operate without any Internet connection. Only if the user agrees on it, the data can be transmitted to a remotely connected storage.

To alter or at least to influence the behavior [9] of people is an ambitious goal that can not be fulfilled immediately. It is more or less a long term process, or to be more precise, an evolution. Fogg describes in [10] that three elements must converge at the same time to affect behavioral change: (i) Motivation, (ii) Ability, and (iii) Trigger. From our point of view the motivation of people is high, because saving energy directly affects their budget in a positive way. The missing thing is a tool, to give them an easy way to observe and control their power usage. We developed a system that can be split into two distinguishable components: (i) a completely autonomous system that records and analyzes the power consumption of connected power consumers (as described in Section II) and (ii) an easy to use App based on the Android Framework that can be installed on already deployed smart phones or tablets to monitor and control the electrical power consumptions in an unobtrusive way (see Section III). Using this App, people become aware of how many power their electrical devices consume when they are turned on, or when they are in standby mode and can react accordingly in, e.g., turning them completely off using the App to avoid standby losses.

Beside the pure monitoring and control capabilities, the use of sensory input that can be used to infer user activities, thus can be used for implicit control of energy consumers, is the last major aspect of the system. Recent advancements in Activity Recognition [11] deal with long-term evaluations to achieve higher performances and better recognition rates. Todays available results are mostly gathered in closed and controlled laboratory settings [12], [13]. Bringing this research out in the field, to collect real world data for empirically underpinning the research results with a highly flexible system, as sensors can dynamically appear and disappear [14], [15], [16], on a large scale can improve the recognition models dramatically [17].

The remaining paper is structured as follows. Section II describes the System Architecture that is used for autonomous collecting energy consumption and user activity data. In Section III we present the interaction gadgets that can be used to monitor the system and keep the user up to date about the energy consumption in realtime. The deployed hardware components of the system and the first preliminary results gathered during the first rollout phase are described in Section IV. Section V closes the paper and summarises the achievements.

II. System Architecture

To measure and collect the energy consumption of power consumers, to control them, and to record the user activity data via a wrist worn smart-watch sensor platform, we defined the architecture of the PowerIT Framework as shown in Figure 1. For each power consumer that is connected to the system, an *Energy Consumer Control* device has to be plugged between the device itself and the power outlet. Using the Energy Consumer Control Unit, the system is capable of monitoring the power consumption and to switch the connected device on or off. Using a power distribution block, it is possible to form ensembles of devices (e.g., home entertainment system consisting of the smart TV, surround sound, and the video recorder) that are treated as one 'single' device. The Energy Consumer Control unit is connected, dependent on the household infrastructure, via WiFi or Power-Lan-Communication (PLC) [18] to the Background Intelligence. PLC utilizes the already exiting electrical wiring infrastructure in households for networking and communication thus eliminating the expense and inconvenience installation of new wires or antennas.

The Background Intelligence is responsible for managing the Power Readings from the Energy Consumer Control Units. This includes the storing of the data, its synchronization, its realtime analyzation (device in on-, off-, or standby-mode) and its preprocessing for visualization in the PowerIT-App. Beside the management of the collected power readings from the different devices, the Background Intelligence also handles the collection of the Smart-Watch activity readings. This consists of storing the raw accelerometer readings and the corresponding User Activity (i.e. the semantic label that marks the activity of the user). Capturing this sensor data via an easy to use smart-watch allows to build a comprehensive dataset in a real world setting. Having the activity labels of the users allows to relate the used power consumers to the activities of the user. If this relation is known, one can implicit control power consumers in turning them on or off according to the current activities of users.

Beside the pure collection of generated power consumption and user activity data, the Background Intelligence also manages the User Generated Control Messages. These Control Messages allow users to explicitly switch power consumers on and off. Based on an Energy Management Constraint Set, that contains conditions that always have to be met (e.g., never turn the fridge off), the User Generated Control Messages are forwarded to the Power Consumer Control Logic that is responsible for transmitting the message over the network (WiFi, PLC) to the corresponding Energy Control Unit.

Location Information [2] is seen as an important part of context data. Accurate Indoor Positioning is still an open issue always connected with high costs and maintenance effort (e.g., body worn sensor equipment, learning of RSSI or WiFi Maps, etc.). Nevertheless it can contain useful information for an energy management system that can react according the location of persons in the household (e.g., all people are in the living room can imply to turn off the lights in all other rooms). In the proposed architecture, this information is (i) transmitted directly from a user worn location / positioning sensor, (ii) inferred from the Power and Smart Watch activity readings or (iii) used to cross-validate (i) with (ii) and vice versa. Deploying the proposed architecture out in the field will show which resolution of location data is necessary and useful for an energy management system. This can range from cartesian coordinates to a spatial abstraction at room level.

To enable the proposed system to work completely autonomous, in turning power consumers on and off implicitly without any needed interaction from the users, an Energy Management Rule set can be defined. Based on the Event-Condition-Action principle, each rule consists of the tuple $\langle$Person, Activity, Location, Time/Date$\rangle$ and triggers a defined set of *Actions* in terms of turning power consumers on or off. Based on the Power Readings, the Smart-Watch Activity Readings, the Location Information, and the Time&Date, the system can autonomously switch to predefined energy management states. This system behavior needs, on the one hand nearly 100% accurate sensor data and on the other hand a well defined rule set that has to be defined for each household. Neither of them is easy to achieve. In many complex houses the level of granularity can require some aggregation. Evaluation of the system over time will show the level of granularity at which implicit, rule based power management is possible and brings benefit to the users.

In this section, we described the system architecture of the PowerIT-System. It consists of two parallel working principles, specifically (i) an autonomous data collecting unit for Power and Activity Readings, and (ii) and explicit control and monitoring unit were the user can switch electrical power

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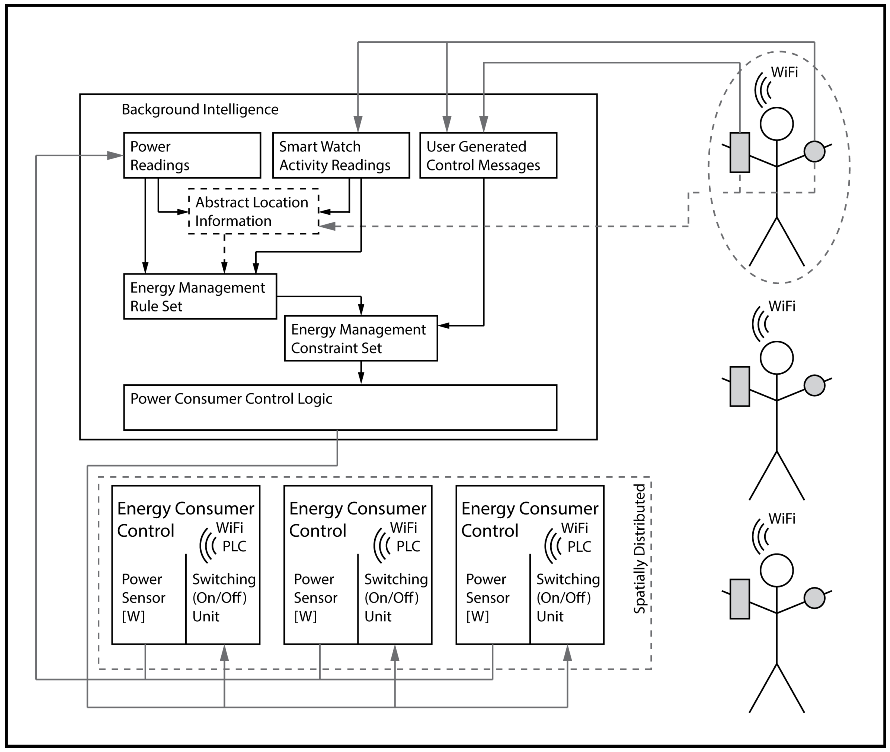

Fig. 1. System Architecture of the deployed Smart Energy Management System showing its components and their interplay as described in Section II.

consumers on and off. Switching a device off means completely disconnecting it from the power supply and therefore zero power consumption. Having the ability to autonomously collect power and activity data allows, on the one hand to generate power statistics and profiles over time (e.g., aggregated power usage of the monitored devices (be referred to Section III)) that can be shown to the users to make them aware and sensitive to their power consumption, and on the other hand to collect data sets and time use surveys to train accurate activity models. If the activity models are accurate enough, the proposed system could work completely autonomous and adjust the power consumption using the Energy Management RuleSet (i.e., the used electrical devices) accurately to the needs of the users.

III. User Experience and Awareness

The PowerIT system (as presented in Section II) is designed to collect and analyze data in an completely autonomous manner once deployed. As the user should be made aware of his energy consumption, we developed a PowerIT App that can be used by the user on variant different gadgets (tablet, smartphone, and smart-watch) to monitor and control the system at various levels. The user involvement is different at each of the 4 levels. It raises from level 1 to level 4 and is explained in detail below:

1) *Energy Consumption Recognition and generating of Load Profiles for each connected device.*
   This is done completely autonomously by the system for each connected power consumers. Results can be shown in real-time for the current energy consumption and for informative purposes for all collected data on a daily, weekly, monthly, and yearly base.
2) *Collection of raw sensor data from the Wrist Worn Sensor (3-axis accelerometer) of the Smart Watch sensor platform.*
   In principle, this process is also handled by the system in a completely autonomous manner. The involvement of the user is limited to wearing the smart-watch.
3) *Assignment of User Activity Metadata to the recorded sensor data via the Smart Watch (exemplarily shown in Figure 2; The Activities from left to right are: Travel, Eat, Education, Entertainment, and Family-Care).* Users can select a subset out of a set of 28 predefined activities that best fit their needs and makes selection more easily. Additionally the set can be extended by user defined activities for flexibility reasons.
   The user has to set the current performed activity by selecting the correct activity label on the smart watch. Dependent on the granularity of activities, the user involvement can be quite high.
4) *Implicit power consumer control based on a user defined Energy Management Rule Set and the collected sensory data that is used as input for the system.*
   This implies (i) a fully trained activity recognition model and (ii) a defined rule set which power consumers are activated based on the sensory input. This level needs high user involvement in training the activity model where steps 1-3 build the base, and in defining the energy management rule set. Especially when more than one person lives in a household, resolving conflicting rules can make the rule base unmanageable. This is especially true when the rule base management is done by non experts.

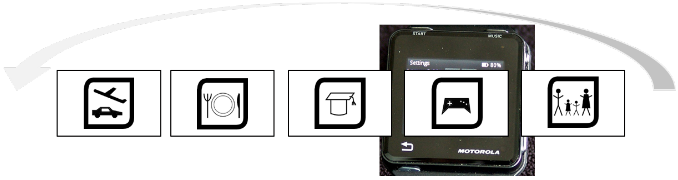

Fig. 2. Realtime assignment of the User Activity to the collected Sensor-Data on the wrist worn Smart Watch Sensor Platform.

Beside the above presented four levels of user involvement, the user is, at each point in time able to monitor and control the system using the PowerIT-App (as shown in Figure 3) that can be deployed on android based tablets, smartphones, and smart-watches. The center of the app is a floorplan containing all attached electrical power consumers (as shown in Figures 3.ii and 3.iii). This novel navigation schema allows the user to swipe through his home in a natural way. For each room, the corresponding devices are displayed (presented in Figure 3.iii). The user can select one of the shown devices to see the current, real-time energy consumption and an zoomable energy consumption history log for the one device (see Figure 3.iv). This makes the user aware about how many energy the electrical equipment in the household is consuming. This is especially interesting for the so called standby modes, where power consumers are expected to consume power near the 0 watt level that is usually not the case. This, without the PowerIT-App, often unperceived waste of energy can be prevented. Therefore, the PowerIT-App offers the possibility to fully disconnect the power consumer from the power supply in simply switching it off (as long as it is not prohibited by the Energy Management Constraint set as described in Section II). The on/off switch is placed in the device view so the user gets a realtime feedback that the device is now consuming 0 watts as it is completely disconnected from the power supply by the Energy Consumer Control Unit (see Section II).

In this section, we briefly discussed the smart gadgets that can be used by people to interact with the system. The focus was to build on the one hand an easy to use phone- or tablet based App that makes the user aware of his power consumption and on the other hand a smart-watch based App that allows to record and annotate user activities in an easy and unobtrusive way. The interface design of the App allows easy navigation through the household based on a floorplan. Electrical devices can be selected, their realtime power consumption can be viewed, a zoomable power-history is available, and they can be switched on or off. Furthermore, the power consumption can be aggregated for free definable time spans (preset: current day, week, month, and year) at device, room, floor, and building level. Using these options people get aware of how many power their devices are using and when. Having this information at different levels of granularity, they may tend to alter their behavior to a more efficient use of energy if they want.

In addition to the phone- or tablet based PowerIT App we ported its functionality also to a smart-watch. Extending the above described functionality, the smart watch allows to record activity data, in this case the raw values of a 3-axis accelerometer, that can be annotated with the corresponding activity by the user (as exemplarily shown in Figure 2). Depending on the quality of the annotated data, that consists of the energy consumption of the monitored devices and in addition the raw values of a 3-axis accelerometer of the used smart watches, activity models can be trained to implicitly control the system in the future. If it is sufficient to just take the smart watch to infer the user activities, as human behaviour and activity has a high variance, will be analyzed offline using the collected dataset.

IV. Deployment and Preliminary Results

To deploy the systems in households and test its suitability for everyday use, we defined a Deployment Kit Case consisting of four MotoACTV Smart Watches (Figure 4.i), one Low Power Embedded Computing Platform (PandaBoard) that hosts the Background Intelligence (described in Section II), and twenty Energy Consumer Control Units. The technical description of the deployed hardware components is presented in Table I. The PowerIT-App (as described in Section III) was deployed on the tablets and smart phones of the test household residents if available, otherwise we gave them a Nexus 7 with the preinstalled App. We are currently testing the system in two households with 3 (man, woman, son) and 4 (man, woman, son, daughter) people in parallel. After the test period that will last up to 4 month, and depending on the gathered results, we plan to deploy the system in up to 20 households to get representative data on a larger scale.

The needed deployment and setup steps for the system once arrived at a household are described in the following:

1) Unpack Deployment Kit Case and Check for completeness of Components.
2) Setup Background Intelligence System (PandaBoard)
3) Create the Floorplan (Rooms and assigned devices) of the Household using the Web-Service of the Background Intelligence.
4) Deploy Energy Consumer Controls according to the created Floorplan and Devices and check their communication (PLC, WiFi) network.
5) Deployment of the Smart Watches to the household residents.
6) Register Metadata (Person,- and Device Information) using the Web-Service of the Background Intelligence.
7) Initial test of all system components (Energy Consumer Controls, Background Intelligence Platform, Wrist Worn Smart Watch, PowerIT-App).
8) Introduction of the system usage to household residents.

TABLE I. Technical details of the deployed hardware components of the System.

MotoACTV: Processor: ARM Cortex-A8; Frequency: 600Mhz; Memory: 256MB RAM, 8GB Flash; Radio: 802.11b/g/n, BT 4.0, Display: 1.6” 220x176 capacitive multitouch LCD; Sensors: GPS, Accelerometer, Ambient Light, Compass; Weight: 35g; presented in Figure 4.i.
PandaBoard: Processor: ARM Cortex-A9 MPCore; Frequency: 1.2Ghz; Memory: 1GB RAM; Weight: 74g; presented in Figure 4.ii.
Energy Consumer Control Unit: Processor: ARM Cortex-M3; Memory: 256KB Flash Memory, 96 KB SRAM; Interfaces: UART, SSI, I2C, I2S, CAN, Ethernet MAC and PHY, USB; presented in Figure 4.iii.

To clarify the usage of the different system components, Figure 5 shows the schematic of the components used in the demonstration setup as shown in Figure 4.iv. to test the system for longtime stability. Four devices, a Coffee-Machine, a Radio, a Lamp, and a TV are connected to the system

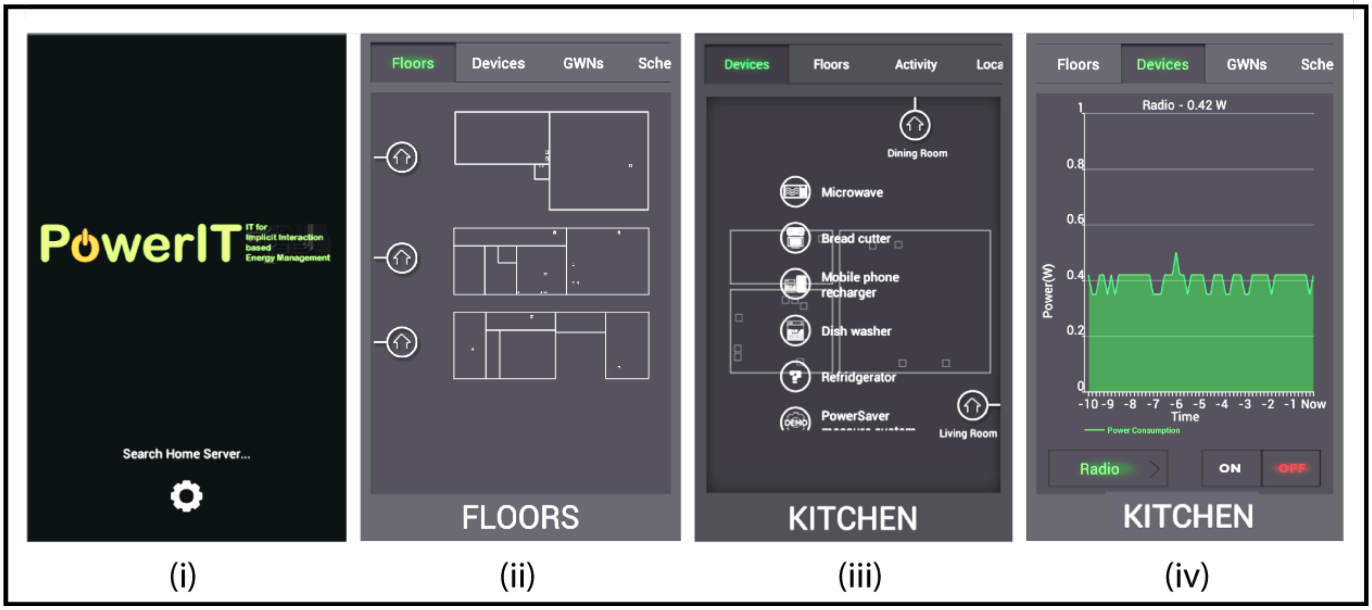

Fig. 3. Developed PowerIT App based on the Android Platform to monitor and control the system. The four views present (i) the starting screen, (ii) the floorplan-view for easy navigation, (iii) the room-view with the assigned energy consumers, and (iv) one selected power consumer (radio) and its realtime power-consumption and power-consumption history ($\sim$ 0.42 Watt).

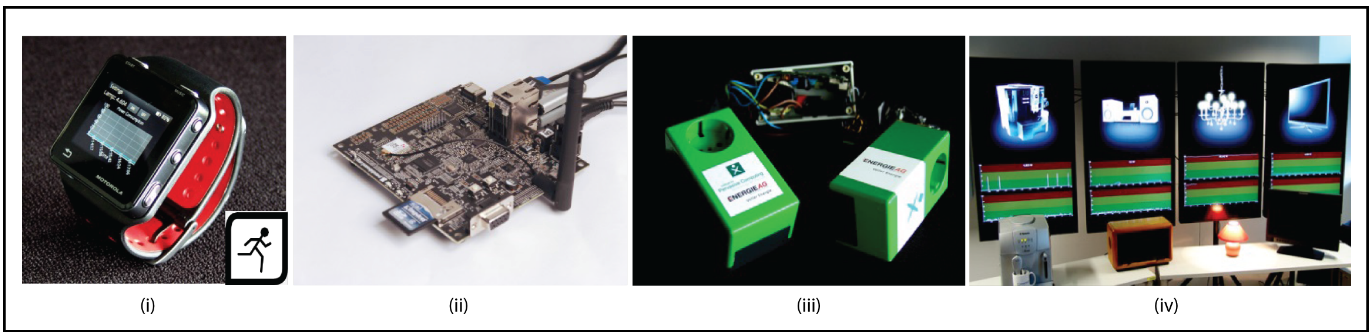

Fig. 4. Demonstration Setup of the PowerIT-System showing (i) MotoACTV Smart-Watch with PowerIT-App and Energy Usage Visualization, (ii) Embedded PandaBoard Platform that hosts the Background Intelligence, (iii) the self-designed Energy Consumer Control Unit and (iv) a demonstration setup with 4 devices (Coffee-Machine, Radio, Lamp, and TV).

using the Energy Consumer control units. The PowerIT-App is deployed on various smart phones and tablets, and a wrist worn smart watch is used as Activity Sensor. These tests were performed for a period of three months before the system was put into action in the field. Four electrical power consumers, a Coffee-Machine, a Radio, a Lamp, and a TV are each connected to an Energy Consumer Control Unit. The Energy Control Unit allows to monitor the power consumption of the connected devices, and offers the ability to turn them on and off. The Energy Consumer control units communicated exclusively using PLC (Power-Line-Communication) with the Background Intelligence System that was hosted on an embedded platform (PandaBoard). As the PandaBoard is not capable of using PLC, we connected it to a Fritz!Powerline 546E to establish the connection. We installed the PowerIT-App on various different Android devices (Nexus 4, Nexus 7, Sony Xperia, Samsung Galaxy SII / III) to test its functionality and stability on different hardware platforms. Tests showed that the functionality and stability was given over all devices. Major differences were only observable in the battery drain rate that can be mostly related back to the different screen sizes that highly influence the power consumption of the mobile devices. Regarding the smart watch that is highly limited in battery capacity, we managed to extend the runtime from around 3 hours with the original firmware, up to 24 hours with a modded firmware and additional optimizations regarding the data transmission intervals and therefore the WiFi-On times. A 24 hour runtime is a good achievement and makes the smart-watch usable for one full day. So, the user can wear it throughout the day, when most of his activities will take place, and can recharge it during the night (while sleeping) where less (and therefore, more predictive) activities are expected to happen.

After performing the previously described tests over a period of three months, that proved the stability and functionality of the system and its components, we installed the system in two households with 3 (man, woman, son) and 4 (man, woman, son, daughter) people in parallel. Both households have 16 devices connected to the system to monitor and control them. A common subset of devices of both are: the microwave oven,

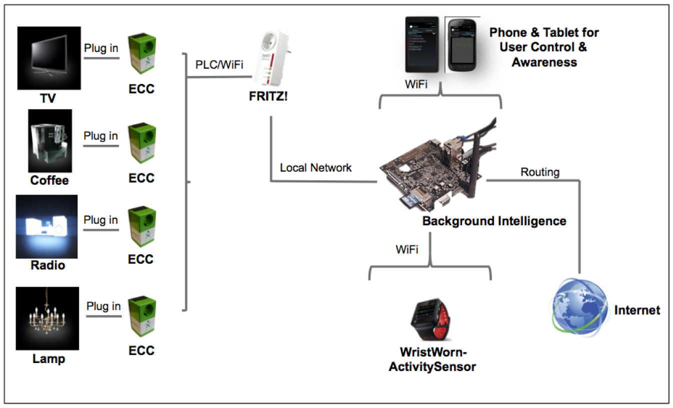

Fig. 5. Schematic of the System Components and their interconnection as used in Figure 4.iv for the demonstration setup.

bread cutter, coffee machine, various lamps, TV, HiFi, radio, the washing machine, deep freezer, fridge, vacuum cleaner, and a multi battery recharger (for, e.g., phones, tablets, etc.). Complementing the fix installed Energy Consumer Control Units, each household got two 'mobile' ones, that they can use to measure different devices (e.g., eBike, electrical lawn-mower, angle grinder, drill machine, ice cream machine, etc.) on purpose.

Beside the pure technical results of the recorded and annotated datasets containing energy logs and activity data, as exemplarily shown for one week in Figure 6, we also collected preliminary results concerning the question if people have changed, or at least began to change their behavior of using electrical energy in a more effective way. These results are based on interviews we conducted with the people after our system was deployed for four weeks, thus people were aware of their energy consumption during this time. Summarizing these interviews, the main statement was that people realized how many energy their devices consume when they are turned on, or switched to standby mode. The data for standby modes showed that this can range up to 40 Watts for Hifi- or television equipment. People stated that they knew that standby modes consume electrical power but they were not aware of how much. Also devices that do not have an explicit standby mode, such as microwave ovens, were thought by people to consume now power when they are not active. Results showed that also these devices consume a lot of electrical power, e.g., one microwave oven consumed 25 Watts nobody was aware of. This was figured out by people either in realtime, or more systematically in using the electrical energy history logs in the PowerIT-App for single devices, rooms, or floors.

As a result, people immediately used the PowerIT App to disconnect these devices from the power supply resulting in zero use of energy of the disconnected devices. As the users started to be aware of the energy consumption of their devices, regardless if they are used, in standby mode or turned off, they switched through all their devices, and turned the not needed ones off according to their current situation. In doing this, one household who owned the one microwave oven and had three TVs saved up to 60 Watts by just turning these devices off. During the interviewing process, we definitely noticed that people now know the energy consumption of their devices and use them more efficient in terms of energy as they can easily switch not needed power consumers off using the PowerIT-App (as described in more detail in Section III).

The first two households that use the PowerIT system are now online for two months. A brief description of the collected data of the two households that is used for (i) analyzing the behavior of people and their electrical power consumers (e.g., cooling cycles of the fridge) and (ii) for training of activity models, is presented in Table II. This dataset can be used to make the behavior of people more efficient (making them energy-aware) in terms of using electrical energy, as power profiles of devices can be analyzed in detail and presented to people beside the information they get from the PowerIT-App (as shown in Section III).

TABLE II. RECORDED DATA OF THE POWERIT DATASET UNTIL 30. OCTOBER 2013 RESPECTIVELY A PERIOD OF 2 MONTHS THAT IS USED FOR OFFLINE ANALYSIS.

Recordings: Two households, 7 people (2 men, 2 women, 2 boys, 1 girl)
Sensor Recordings: 40 Energy Consumer Control Units at an interval of 10 sec; 7 wrist worn activity sensors with a recording speed of 100Hz.
Sensor Online Time: 40 x 1440h ($\sim$57600h) of energy recordings for single electric power consumers. Activity labels for $\sim$ 6 x 5 hours/day (300h) ($\sim$1800h)
Recording Size: Energy Recordings 753MB, Activity Recordings 1997MB

Collecting the energy consumption of power consumers and giving technology to people that allows to monitor and control these devices, showed already in the first month to be an effective method to make people aware of their power consumption. Knowing their power consumption, people tended to change their behavior in that way, that not always all devices have to be turned on or in standby mode. Especially the easiness of switching power consumers on and off remotely using a smart gadget and an App made people change their behavior and thinking of how they use electrical energy.

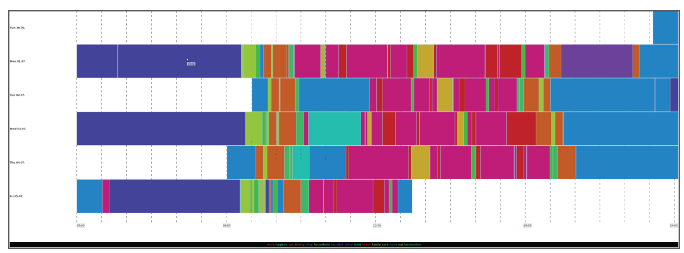

Fig. 6. Activity Traces gathered during a test installation of the system for calendar week 27/2013 for 24/7 yielding to a time use survey with implications to energy management.

To make energy aware behavior even more comfortable, we work on switching from the pure user awareness and explicit control to an implicit control based on the current user activities. Knowing the user activities, electrical power consumers can be switched on- or off automatically without explicitly needed user interaction. To collect the needed activity labels, stating what one user was doing at a specific point in time, according to the recorded energy- and wrist worn sensor data, the smart-watch allows to select the current activity of the user and logs it. This collected metadata is exemplarily shown in Figure 6 for one person for the period of one week. The data was collected for calendar week 27/2013 for 24/7. Each line represents a full 24h day starting with Sunday 30.06-00:00. This recorded activity metadata, in combination with the collected sensor data (energy consumption, accelerometer data from the wrist-worn watch) can be used to train activity recognition models. The color coding for exemplarily selected main activities (not complete) is: *pink*:work, *green*:hygiene, *orange*:car, *violett*:socialize, *dark_blue*:sleep, *light_blue*:don't care, *light_orange*:eat.

Using the activity metadata and the recorded sensor readings, activity recognition models can be trained and evaluated to be further used to implicitly control electrical power consumers based on an Energy Management Rule Set. This frees people to explicitly turn power consumers on and off and can make energy saving even more comfortable.

V. Conclusion

Within this paper we have presented and evaluated the use of smart gadgets (i.e., smart-phones, tablets, and watches) to make people aware of their energy consumption. We designed the PowerIT System that permanently collects the energy consumption from connected devices. We developed the PowerIT-App based on the Android Platform that can be used by people on different gadgets to monitor and control the energy consumption of the connected devices. We deployed the PowerIT system in two households with 3 (man, woman, son) and 4 (man, woman, son, daughter) people in parallel, and in sum 40 connected electrical power consumers for a period of two months. Using the PowerIT system to monitor their electrical devices in realtime, turning them on- and off remotely, and additionally showing energy history logs made people aware of how many electrical energy is consumed by their devices. Interviewing the participants showed that already in the first four weeks of the test installation, gaining awareness about the power consumption of their electrical devices, people changed their behavior to a more attentive use of electrical energy. People used their phones, tablets and smart-watches to check if their currently not used devices were turned on and switched them off. This resulted in a more efficient use of energy as only devices were turned on that were needed at the specific point in time. The fact that the PowerIT system works completely autonomous and uses already deployed smart gadgets for monitoring and control of the system, like smart phones and tablets, the system can be used without affecting the level of living of people. Although the behavioral change of people towards a more energy aware and efficient behavior was already noticeable after four weeks, the future will see an implicit control of power consumers based on inferred user activities. To address this issue, we additionally collect activity labels using a smart watch that will provide the necessary information to train activity recognition models for the future implicit energy management approach.

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