Alaa Alhamoud, Felix Ruettiger, Andreas Reinhardt, Frank Englert, Daniel Burgstahler, Doreen Böhnstedt, Christian Gottron, Ralf Steinmetz:
SMARTENERGY.KOM: An Intelligent System for Energy Saving in Smart Home. In: Nils Aschenbruck, Salil Kanhere, Kemal Akkaya: Proceedings of the 3rd IEEE LCN International Workshop on GlObal Trends in SMART Cities (IEEE goSMART 2014), p. 685-692, EDAS Conference Services, September 2014. ISBN 978-1-4799-3784-4.

SMARTENERGY.KOM: An Intelligent System for Energy Saving in Smart Home

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***Abstract*—Over the last twenty years, energy conservation has always been of great importance to individuals, societies and decision makers around the globe. As a result, IT researchers have shown a great interest in providing efficient, reliable and easy-to-use IT services which help users saving energy at home by making use of the current advances in Information and Communications Technology (ICT). Driven by the aforementioned motivation, we developed SMARTENERGY.KOM, our framework for realizing energy efficient smart homes based on wireless sensor networks and human activity detection. Our work is based on the idea that most of the user activities at home are related to a set of electrical appliances which are necessary to perform these activities. Therefore, we show how it is possible to detect the user's current activity by monitoring his fine-grained appliance-level energy consumption. This relation between activities and electrical appliances makes it possible to detect appliances which could be wasting energy at home. Our framework is organized in two components. On one hand, the activity detection framework which is responsible for detecting the user's current activity based on his energy consumption. On the other hand, the EnergyAdvisor framework which utilizes the activity detection for the purpose of recognizing the appliances which are wasting energy at home and informing the user about optimization potential.**

I. Introduction

Over the last thirty years, energy demand has shown a huge increase in residential as well as industrial sectors. Electricity demand in EU-27 increased by 70% between 1980 and 2008 [1]. This resulted in a huge increase in greenhouse gas emissions. As a result, the EU decided to reduce the annual energy consumption by 20% by the year 2020 [2] aiming at reducing the greenhouse gas emissions by 30%. In the EU, buildings are responsible for 40% of the total energy consumption and 36% of the total CO2 emissions.

Therefore, creating intelligent home energy management systems which are able to save energy while meeting user preferences has become an interesting research topic. Due to their relatively low-cost, wireless nature, flexibility and easy deployment, wireless sensor networks represent a promising technology for providing such systems. Furthermore, modern buildings are already equipped with building automation infrastructure which can be used as an essential part of such energy management systems.

Driven by the aforementioned goals, we present our framework which enables the user to save energy at home while being non-intrusive which is a very important criterion for the user acceptance of the system [3]. Our solution is based on the idea that most of human activities at home are strongly related to a number of electrical appliances which are used in order to perform these activities. Therefore, by detecting the user's current activity, it is possible to determine which appliances unrelated to the current activity are turned on. Based on this data, we generate energy recommendations which are sent to the user's smartphone informing him about the potential for energy savings.

The research field of human activity detection mainly focuses on the development of software solutions which are able to detect the user's current activity based on her/his context. In order to achieve this goal, different ICT solutions have to be combined together, namely machine learning and sensing technologies.

Sensors such as infrastructural sensors, wearable sensors, cameras, and microphones have to be deployed in the environment in order to collect information about the user current context. Machine learning techniques such as artificial neural networks are used to train the model which is responsible for detecting the user's current activity based on the current sensor readings. Activity detection has a variety of applications such as Ambient Assisted Living (AAL) and energy savings in Smart Home.

The wide spread of wireless sensor networks has given a great advantage to the research field of human activity detection. The ability of sensor nodes to measure different kinds of environmental parameters as well as other parameters related to the user makes the task of activity detection simpler and more accurate. Moreover, having computing as well as wireless communication capabilities makes wireless sensor networks suitable to be easily deployed in user environments such as homes and offices. Different kinds of environmental parameters such as temperature, humidity, and brightness can be measured with sensor nodes. Infrared sensors provide us with information about the user presence. Another kind of sensors which focus on the user as a main point of interest is wearable sensors. Wearable sensors provide us with an approximate knowledge about the user physical state which can be used as a hint to determine the user's current activity. Another emerging sensing technology is power sensors such as Plugwise sensors which make it possible to monitor the energy consumption of each house appliance separately and therefore as shown in our paper make the task of activity detection much easier and quite more accurate.

In this paper we present three main contributions, namely:

- The introduction of power sensors as an enabler for context recognition and energy savings systems
- The activity detection framework
- The EnergyAdvisor framework which is responsible for reporting all the unattended appliances to the user

The remainder of this paper is structured as follows. In Section II, we introduce several related projects that dealt with the topic of energy conservation in smart homes. We introduce the hardware components as well as the network topology of SMARTENERGY.KOM in Section III. In Section IV and Section V, we introduce the activity detection framework as well as the EnergyAdvisor. We evaluate our design with respect to the accuracy of the activity detection framework and the amount of energy saved by the EnergyAdvisor in Section VI. Finally in Section VII, we conclude the paper and introduce potential ideas for future work.

II. Related Work

The idea of energy efficient smart homes has attracted many researchers in academic as well as in industrial domains. Most of the researchers e.g. [14], [9], [15] have started by following the classical approach of building automation where automatic control of home appliances is directly applied in order to save energy and achieve user comfort. Machine learning combined with sensing and actuation technologies has been the most used technique to achieve these goals. One of the first attempts to realize energy savings in smart homes was the neural network house [14]. Mozer et al. [14] have developed the ACHE system which is able to control the environment in a way which realizes the user comfort while minimizing the energy consumption. A wired network of sensors has been deployed to monitor different environmental parameters such as temperature and brightness in addition to the motion of the user. ThinkHome ([15], [12]) and MavHome [9] are two other examples where intelligent automatic control based on sensor data processing has been applied to achieve energy savings in residential Buildings. Barbato et al. [4] have designed a solution with the main goal of intelligently managing and conserving energy based on user behavior modeling. They utilize wireless sensor networks to provide the necessary context information for creating a user profile which can be used at later stages to predict the future user behavior and to set the home appliances to proper configurations which meet user preferences and save energy. Other projects [17], [6], [16] have also followed the classical approach of automatic control combined with the usage of multi-agent systems to realize the distributed smartness of the system. However, all these approaches face the problem of user acceptance since the automatic control and configuration of home appliances are still difficult to be accepted by users [3].

Different machine learning techniques such as neural networks [14] [15] and Markov chains [9] have been used to achieve the primary tasks of the system, namely energy savings and user comfort. Moreover, the concept of multi-agent systems has also been utilized in [15] [9] where multiple intelligent software agents cooperate together to achieve a complex task.

Other researchers have followed new approaches for achieving the goal of energy efficient buildings. In [13], Kim et al. developed the SPOTLIGHT system whose main goal is to make the users aware of their individual energy consumption and any energy saving potential. SPOTLIGHT utilizes wireless sensor networks in order to monitor appliance-level energy consumption. Moreover, the system tries to detect which user is using which device by the means of physical proximity estimation between the user and the device. By combining these information, the system marks the energy consumption of a certain device as a wasteful energy consumption if no user was in the proximity of this device during the time the device was turned on. In [7], Chen et al. developed CASAS Sustain System which has the goals of detecting anomalies in house energy consumption and relating this consumption to the user different behavioral patterns. The authors apply data mining techniques on the energy consumption historical data in order to detect certain anomalies in energy consumption. Furthermore, they predict the energy consumption of a user based on his/her current activity. A web-based interface is used to provide the user with all the information produced by the system. Therefore, the user will be able to understand his individual energy consumption and the effect his behavior has on it. By making the user aware of this information, the authors try to leverage a more energy efficient behavioral pattern.

In [8], Lee et al. developed a system which is able to detect the operating mode of house appliances and inform the user about possible unattended appliances based on his current activity. A machine learning algorithm is used to detect the current operating mode of an appliance based on its power consumption. Furthermore, the authors built an activity-appliance model which is relating each activity to a set of appliances. They built this model using common sense knowledge where they asked the users to tell which appliances they mainly use with which activity. Based on this activity-appliance model, the authors detect the current activity of the user and inform him about potential unattended appliances which are not related to his current activity but still turned on. The main disadvantage of this work is the lack of adaptivity. This system can not adapt to the user behavior. This means, the activity-appliance model is fixed and the system can not learn it from the interaction with the user. In our work, we use an interactive approach in which the user periodically reports to the system what activity he is currently doing using his smartphone. By the means of machine learning and sensor readings, the system learns which appliances are related to which activity and predicts the user current activity based on the learned model. The interactivity of our system makes it able to adapt to different users with different activity patterns.

Compared to the previously mentioned related work, our work is avoiding the approach of automatic appliance control while providing the user with periodic recommendations which directly and clearly identify the potential energy wastage. Compared to [13] and [7], our work does not put any analysis burden on the user side. In [13] and [7], the user has to look at the data analysis results and find out himself if he was wasting energy. On the contrary, our approach provides a real-time feedback in the form of short messages sent to the user smartphone informing him about any ongoing energy wastage. Compared to [8], our system has the property of being adaptive and interactive as will be clarified later. Our activity detection framework is loosely coupled with the EnergyAdvisor framework and therefore can be used for other application scenarios such as Ambient Assisted Living (ALL).

III. System Architecture and Components

The main functionality of the proposed system is to generate energy saving recommendations which make the user aware of his energy consumption and help him saving energy in a nonintrusive way. The proposed system should be able to recognize the context of the user by monitoring his appliance-level energy consumption as well as other environmental parameters such as motion, brightness, and temperature. As shown in Figure 1, our system is composed of the following components:

- Data collection units (power sensors, motion sensors, temperature and brightness sensors).
- Data processing units (Raspberry Pi[1], control server).
- Data visualization and feedback unit (smartphone).

Figure 1 shows the network topology as well as the hardware components of the system. As we can see in the figure, different communication technologies, namely ZigBee, Wi-Fi, and Ethernet have been utilized in order to establish the communications between the different system components. Furthermore, Figure 1 clarifies a situation in which our system can help the user saving energy. As shown in the figure, the TV as well as the oven are connected to power sensors which monitor their power consumption. Moreover, environmental sensors are deployed in the kitchen as well as in the living room to monitor the temperature, brightness and motion in both of them. Based on the sensor readings, our SMARTENERGY.KOM detects the user's current activity as cooking and therefore informs the user about the energy wastage which is caused by the TV assuming that the user forgot to switch it off. A smartphone has been used as the feedback channel to the user.

[1]http://www.raspberrypi.org/

*a) **Sensor nodes**:* In order to collect the different environmental, appliance-related, and user-related parameters which are necessary to detect the different activities of the user, we deploy two different kinds of sensor nodes. On one hand, we deploy power sensors which measure the individual power consumptions of electrical appliances connected to them. On the other hand, we deploy environmental sensors which measure the temperature, brightness and motion in the environment. We consider our system to be one of the first solutions which deploy power sensors for the purpose of activity detection. We decided to use the Plugwise system for power sensing[2]. Each appliance whose power consumption needs to be monitored is connected to a Plugwise dongle which is in turn connected to a power source. Each Plugwise dongle monitors the power consumption of the appliance connected to it and transmits its readings to a USB adapter which is responsible for collecting the sensor readings and serially communicating them to the Raspberry Pi. Plugwise dongles are also capable of wirelessly switching the appliances connected to them on and off. They utilize ZigBee technology to establish a mesh network between each other.

As environmental sensors, we use Pikkerton sensors[3]. Pikkerton sensors are able to sense temperature, brightness and motion in the environment. They utilize ZigBee as a communication technology and they submit their readings to an XStick USB adapter which acts as a network coordinator and a gateway to other systems such as the Raspberry Pi.

*b) **Raspberry Pi**:* The main task of the Raspberry Pi is to act as a gateway which collects all the sensor readings and transmits them to the control server which can be remote or local. Furthermore, it provides the means to remotely control the different parameters of the sensor nodes which operate using different proprietary protocols.

*c) **Smartphone**:* The user's smartphone represents an important part of our solution. It is used in two different stages. On one hand, we use it to let the user tag his ongoing activities. This data will be stored at the control server and provided at later stages to the machine learner which will learn the user different activities. On the other hand, it will be used to display the energy saving recommendations generated by the EnergyAdvisor in the form of text messages.

*d) **Control Server and Data Collection**:* The control server realizes and implements the system intelligence. It has three main tasks, namely the storage of the sensor data combined with the user feedback, the execution of the machine learning algorithm, and the generation of the energy saving recommendations. For each of these three different tasks, we designed and implemented a software component with the help of the Spring framework. The control server can be local or remote depending on the user needs and the privacy considerations. In our implementation, we decided to make our whole system local so that we assure the privacy of the

[2]http://www.plugwise.com/
[3]http://www.pikkerton.com/

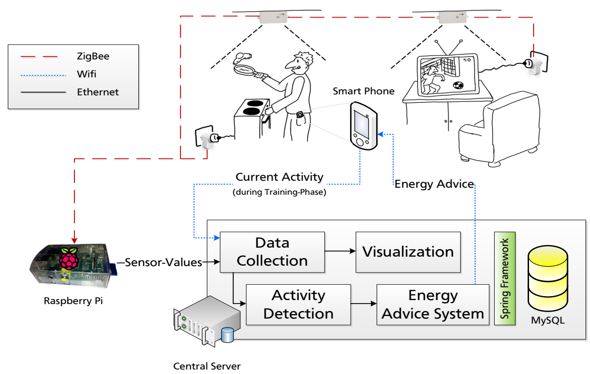

Fig. 1. System architecture and network topology

user data.

IV. Activity Detection Framework

In this section, we present our activity detection framework which represents the core component of SMARTENERGY.KOM. As we have mentioned before, we suppose that most of the user activities at home imply the usage of several electrical appliances which are necessary to do these activities. Therefore, we try to detect the user's current activity by detecting which electrical appliances are running. However, this information alone is not always sufficient to detect the current activity. The user might e.g. forget to switch certain appliances off which leads to errors in the appliance-based activity detection. Therefore, we deploy additional Pikkerton sensors which report the temperature, brightness and most importantly the motion in the environment. We follow the approach of supervised learning where the user, using his smartphone, reports his current activity to the system. In this paper, we restrict ourselves to the one-user/one-activity scenario. We do not detect multiple or overlapping activities. By means of machine learning as will be described later, we build the model which performs the activity detection.

A. Data Processing and Feature Extraction

Our time series data consists of a sequential set of activities accompanied with another sequential set of sensor readings. In order to train the machine learner, we need to build a training set which includes training instances that match the current activity with the features extracted from the sensor data. Therefore, our sequential sensor data needs to be divided into time windows so that each window can be provided as an input to the learning algorithm with the activity during this window as an output. We divide the time series into equally sized time slots as shown in Figure 2. For each time slot we take the features extracted from sensor data as an input and the current activity as an output.

The time slots shown in Figure 2 define the boundaries of the feature extraction algorithm. The algorithm runs for each time slot and extracts the features required for the machine learner. For each sensor we define a feature that represents the arithmetic mean of the readings related to this sensor during the time slot as shown in Equation (IV-A.1) where F_x is the feature that represents sensor x, n is the number of sensor readings during the time slot, and r_i is the sensor reading i.

$$F_x = \frac{\sum_{i=1}^{n} r_i}{n} \qquad \text{(IV-A.1)}$$

V. EnergyAdvisor: Energy Saving Framework

EnergyAdvisor represents one of many application scenarios for our activity detection framework. It realizes its main functionality of energy saving by the generation of energy saving recommendations which are directly sent to the user's smartphone. As mentioned before, there are two variants of energy saving systems, namely the active variant which directly controls the electrical appliances at home and the passive variant whose main goal is to make the user aware of his energy consumption and urge him to save energy. EnergyAdvisor follows the passive approach which proved to be less intrusive and more acceptable by the user [3].

As a first prototype, we designed the EnergyAdvisor to be a static rule-based recommendation system. As we mentioned before, each user activity is strictly related to a set of electrical appliances. Based on the user's current activity, EnergyAdvisor detects the devices which are turned on and not related the user's current activity. We realized this functionality via a rule based approach in which we designed a set of rules that define the relations between the activities and the appliances. As an example, we present the following rule which determines the set of appliances which are not related to the activity of watching TV at house B. The rule says: *When the activity "Watching TV" is detected and an appliance which is not "the TV", "the satellite receiver", or "the living room lamp" consumes energy, then inform the user.*

VI. Results and Evaluation

In this section we introduce the evaluation results of SMARTENERGY.KOM. We evaluate the accuracy of the activity detection framework as well as the energy saving achieved by the EnergyAdvisor. In order to test and evaluate

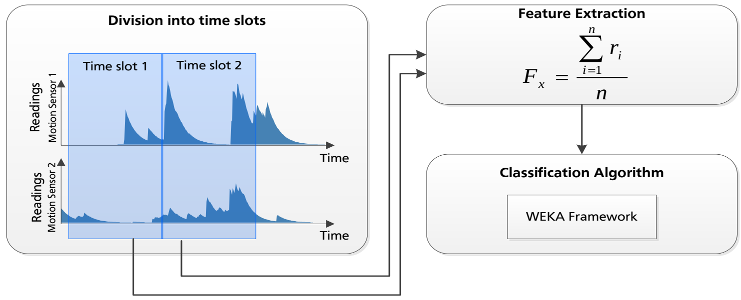

Fig. 2. Feature extraction

TABLE II
DETECTABLE ACTIVITIES FOR EACH OF THE HOUSES

House A	House B
Cooking	Cutting Bread
Watching TV	Watching TV
Working at the PC	Listening to Radio
Eating	Eating
Making Coffee	Making Tea
Washing Dishes	Ironing
Reading	Reading
Sleeping	Sleeping
Not at Home	Not at Home

TABLE III
CLASSIFICATION ACCURACY OF THE ACTIVITY DETECTION FRAMEWORK

Deployment	Accuracy	F-Measure
House A	98.8%	98.8%
House B	98.3%	98.3%

our system in real world settings, we deployed it in two different houses, namely "House A" where one of the researchers was the user of the system and "House B" in which the user was a person who does not have any experience or knowledge with regard to the development of the system. In each of the houses, we monitored a set of electrical appliances as shown in Table I.

Based on the available electrical appliances, we designed a set of activities which can be monitored and learned in each house as shown in Table II. Beside monitoring the electrical appliances with Plugwise sensors, we deployed a Pikkerton sensor in each of the rooms shown in Table I except the bedroom and the office room in "House B" and the bedroom and technical room in "House A" upon user request. The set of chosen activities are strongly related to the available electrical appliances and therefore does not apply to each house in which the system might be deployed. For example, having a Plugwise sensor connected to the TV and a Pikkerton sensor in the living room in "House B" makes it possible to learn and detect the activity of watching TV. A Plugwise sensor connected to the lamp in the bedroom in "House B" makes it possible to detect the reading activity supposing that the user reads for some time before going to sleep. The duration of the deployment for "House A" was 82 days with around 22.5 million collected data points. For "House B", we deployed the system for 62 days with about 20 million collected data points.

A. Activity Detection

We use the machine learning tools provided by WEKA framework [11] in order to evaluate the accuracy of the activity detection framework. Using 10-fold cross validation [10], we divide the dataset collected over the whole deployment period into a training set and a test set. For each sensor we calculate a feature that represents the arithmetic mean of the readings of this sensor during a time slot as shown in Section IV-A. We chose the duration of the time slot to be 2 minutes. Table III shows the classification accuracy as well as the F-Measure for the two deployments as calculated by WEKA using a Random Forest classifier [5]. As we see in the table, our activity detection framework achieves a very high classification accuracy up to 98.8% by only using the arithmetic means as features.

Evaluating the overall accuracy of the system does not always imply that the system is able to classify all instances that belong to different classes with the same accuracy. Therefore, we evaluated the accuracy of the framework with regard to each activity. Table IV shows the recall and the precision for each activity at "House B" as calculated by WEKA using a Random Forest classifier. As we can see in the table, there are certain activities such as "Making Tea", "Cutting Bread", "Reading", and to some extent "Ironing" which have a low recall value. Having a low recall value for some activity means that several instances which belong to this activity have been classified as another activity. In order to clarify this issue, we computed the confusion matrix shown in Table V where each letter represents the first letter of each activity and the numbers represent the percentage value of confusion.

As we can see in the confusion matrix, 30% of the instances that belong to the activity of "Cutting Bread" have been classified as "Eating". Both activities take place in the kitchen with the difference that for "Cutting Bread" the user needs to turn the bread cutter on. However, by looking at the dataset we found out that "Eating" has quite more instances than "Cutting Bread" and therefore can be seen as a dominant class. "Cutting Bread" is a short activity when compared to

TABLE I
AVAILABLE ELECTRICAL APPLIANCES AT EACH HOUSE

Room	**In House A**	**In House B**
Kitchen	Coffee machine, Radio, Electric kettle, Lamp above the hob,Lamp above the kitchen sink, Oven, Fridge	Radio, Electric kettle, Electric iron, Cooking mixer, Electric bread cutter
Living room	Projector, Audio system, Lamp	Television, Satellite receiver, Lamp
Office room	PC, PC accessories (screen, loudspeaker, etc.)	-
Bedroom	-	Lamp, Radio alarm clock
Technical room	Warm water	-

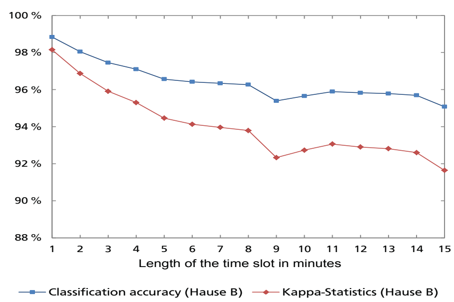

Fig. 3. The relation between the length of the time slot and the accuracy of the activity detection framework

TABLE IV
CLASSIFICATION ACCURACY OF INDIVIDUAL ACTIVITIES FOR "HOUSE B"

Activity	**Recall**	**Precision**
(S)leeping	99.7%	98.8%
(W)atching TV	99.2%	99.3%
(E)ating	94.6%	91.7%
(L)istening to Radio	90.1%	97.6%
(P)reparing Tea	60.6%	83.8%
(I)roning	80.4%	97.6%
(C)utting Bread	66.7%	95.7%
(N)ot at Home	98.7%	98.1%
(R)eading	55.9%	86.7%

"Eating" which leads to the fact that "Eating" will span more time slots and therefore has much more instances. The same explanation applies to the activities of "Ironing" and "Making Tea" which both take place in the kitchen. Furthermore, the confusion between "Sleeping" and "Reading" comes from the fact that both of them take place in the sleeping room with one of them, namely "Sleeping" as a dominant class.

Furthermore, changing the length of the time slot affects the accuracy of the activity detection framework as well. As we see in Figure 3, increasing the length of the time slot decreases the accuracy of the activity detection framework. Two reasons are behind this decrease. On one hand, having a longer time slot will increase the number of time slots in which two activities might happen after each other. The shorter the time slot is, the less probable it is that two activities happen after each other in the same time slot. Having two consequent activities in the same time slot will lead to wrong training and classification. Therefore, by shortening the length of the time slot, we reduce the number of instances affected by this problem. On the other hand, by increasing the length of the time slot, we decrease the number of time slots available for training which also decreases the accuracy of the classification algorithm.

In order to improve the classification accuracy for these activities, we designed an additional set of features which are based on externally defined domain knowledge. As we have seen before, each activity is strongly related to a set of electrical appliances. Feeding this information into the machine learner helps increasing its accuracy. Therefore, the purpose behind these features is to model the relation between each of the activities and the sensors deployed at home. Examples of such a relation can be seen in Table VI. For example, the activity of "Eating" is mainly based on the kitchen motion sensor, the kitchen brightness sensor as well as the radio in the kitchen. The machine learner itself should be able to model this relationship. However, it might be useful to provide it as a set of features. For each activity i we define a feature f_i which is computed as follows:

$$F_i = \sum_k w_{k,i} * max(x_k(t)) \qquad \text{(VI-A.1)}$$

Where:

$$\begin{aligned} k:&\ \text{sensor } k \\ w_{k,i}:&\ \text{weight of sensor } k \text{ in activty } i \\ max(x_k(t)):&\ \text{maximum reading of sensor } k \\ &\ \text{during time slot } t \end{aligned}$$

$$w_{k,i} = \begin{cases} 1 & \text{if sensor } k \text{ is related to activity } i \\ 0 & \text{otherwise} \end{cases}$$

Table VII shows the recall and the precision for activities in "House B" before and after utilizing the domain knowledge features. As we can see in the table, the recall values for the activities "Cutting Bread", "Ironing", and "Making Tea" increased by 3% to 10%. For dominant activities, namely "Sleeping", "Watching TV", "Not at Home", and "Eating", the introduction of the domain knowledge has decreased the recall and the precision but only by a very small amount. This leads us to the conclusion that the introduction of the domain

TABLE V
RECALL CONFUSION MATRIX FOR "HOUSE B"

	(S)	**(W)**	**(E)**	**(L)**	**(P)**	**(I)**	**(C)**	**(N)**	**(R)**
(S)	99.68	0.10	0.05	0.00	0.01	0.00	0.00	0.01	0.15
(W)	0.31	99.18	0.33	0.00	0.04	0.01	0.00	0.14	0.00
(E)	0.56	1.91	94.57	0.92	0.35	0.00	0.07	1.62	0.00
(L)	2.66	0.00	6.07	90.09	0.00	0.00	0.00	1.18	0.00
(P)	6.38	11.70	15.96	0.00	60.64	0.00	0.00	5.32	0.00
(I)	0.00	0.00	15.69	1.96	0.00	80.39	0.00	1.96	0.00
(C)	0.00	3.03	30.30	0.00	0.00	0.00	66.67	0.00	0.00
(N)	0.57	0.15	0.46	0.04	0.08	0.00	0.00	98.70	0.00
(R)	44.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	55.86

TABLE VI
RELATIONSHIP BETWEEN ACTIVITIES AND SENSORS IN HOUSE B (DOMAIN KNOWLEDGE)

Activity	**Sensors strongly related to this activity**
Eating	Motion (Kitchen), Brightness (Kitchen), Radio (Kitchen)
Ironing	Motion (Kitchen), Brightness (Kitchen), Iron (Kitchen)
Watching TV	Motion (Living Room), TV (Living Room), Satellite Receiver (Living Room), Lamp (Living Room)

TABLE VII
CLASSIFICATION ACCURACY OF INDIVIDUAL ACTIVITIES FOR "HOUSE B" AFTER USING THE DOMAIN KNOWLEDGE

Activity	**Recall**	**Precision**
Sleeping	99.7%	98.6%
Watching TV	99.1%	99.0%
Eating	91.7%	91.2%
Listening to Radio	88.6%	95.2%
Making Tea	63.8%	88.2%
Ironing	90.2%	93.9%
Cutting Bread	72.7%	92.3%
Not at Home	97.4%	97.4%
Reading	54.3%	88.0%

knowledge features helps increasing the accuracy of the system in general.

B. EnergyAdvisor

In this section we evaluate the amount of potential energy saving that could be achieved by utilizing EnergyAdvisor in smart homes. We follow an evaluation approach in which we utilize the dataset collected over the whole deployment period in order to collect the amount of energy that could have been saved during the deployment if the EnergyAdvisor was installed. As we have mentioned before, the dataset we have collected consists of a sequential set of activities accompanied with another sequential set of sensor readings. In this evaluation, we are interested in calculating the energy which can be saved during each activity. This means, we try to find out which appliances that are not related to certain activity are turned on during this activity and we consider the energy consumed by them as wasted energy. For example, if the TV is running and the user is doing the activity of cooking in the kitchen, we consider the energy consumed by the TV as a wasted energy. We go through the whole dataset and we calculate at the end the average amount of energy that could have been saved during each activity. We follow the assumption that the user is doing one activity at a time and that there is only one user in the house. The next system prototype which considers multiple users with overlapping activities is already under development. The evaluation of the potential energy saving is realized in the following steps:

- As a first step, we run the activity detection framework as explained in Section IV over the whole collected dataset and we detect each activity.
- After detecting a new activity, we run the EnergyAdvisor rule-based system. The EnergyAdvisor should report all the appliances which are turned on and not related to the current activity
- We calculate the total energy consumption caused by the appliances reported in step 2 and we consider it as a potential energy that could be saved during the activity detected in step 1
- Finally, we sum up all the energy which could be saved during all activity instances and we compute the average as shown in Table VIII

The drawback of this approach is that the potential appliances which have been detected as energy wasters by EnergyAdvisor could be intentionally kept turned on by the user. However, using this evaluation approach we try to show the maximum potential energy saving. Table VIII shows the evaluation results for "House B". The table shows the average amount of energy that could have been saved for each activity during the deployment period by utilizing EnergyAdvisor. As shown in the table, a significant amount of energy could be saved with regard to each activity. As an example, the user can save up to 67% of the energy consumed during the eating activity when he turns off unnecessary appliances after being notified by our system.

TABLE VIII
SAVED ENERGY IN "HOUSE B"

Activity	**Consumed Energy**	**Potential Savings**	**Proportion**
Eating	1818 Wh	1231 Wh	67.70%
Ironing	287 Wh	4 Wh	1.54%
Listening to Radio	218 Wh	71 Wh	32.72%
Making Tea	1118 Wh	84 Wh	7.47%
Not at Home	1258 Wh	647 Wh	51.47%
Reading	244 Wh	114 Wh	46.89%
Sleeping	3644 Wh	1952 Wh	53.56%
Cutting Bread	20 Wh	13 Wh	65.30%
Watching TV	18682 Wh	176 Wh	0.94%

VII. CONCLUSION AND FUTURE WORK

In this work we introduced SMARTENERGY.KOM, our framework for conserving energy in smart homes. Building on the idea that human daily activities at home are strongly related to the home electrical appliances, we have shown that the introduction of power sensors opens new perspective for the field of activity detection. By utilizing power sensors combined with environmental sensors, we were able to detect human activities at home with an accuracy up to 98%. Consequently, our EnergyAdvisor framework has shown a significant potential for energy saving which was greater than 50% for certain activities.

Another significant contribution of this work was the collection of two datasets with up to 42 million data points. To the best of our knowledge, these two datasets represent the first datasets to contain readings of both power and environmental sensors combined with a user feedback.

With regard to future work, a great potential is already foreseen. This work focused on the one user/one activity scenario. As a next step, we will start working on scenarios where multiple users can utilize the system at the same time and where multiple and overlapping activities are taken into consideration. Moreover, the interactivity of the EnergyAdvisor will be another main concern for us. The EnergyAdvisor should be able to adjust its rules over time so that they adapt to the user's behavioral patterns and his interaction with to the generated recommendations.

ACKNOWLEDGMENT

This work has been financially supported by the German Research Foundation (DFG) in the framework of the Excellence Initiative, Darmstadt Graduate School of Excellence Energy Science and Engineering (GSC 1070).

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