# A Smart Energy System: Distributed Resource Management, Control and Optimization

Yong Ding, *Student Member, IEEE,* Christian Decker, *Member, IEEE,* Iana Vassileva, *Student Member, IEEE,* Fredrik Wallin, *Member, IEEE,* and Michael Beigl, *Member, IEEE*

***Abstract*—This paper presents a novel concept of distributed energy resource and consumption management, which proposes to design a networked and embedded platform for realizing a dynamic energy mix and optimizing the energy consumption dynamically. Based on heterogeneous wireless sensor networks and a local Web of Things platform, the environmental parameters and energy data can be acquired and processed in a distributed manner in real time. In order to improve understanding on how different environmental factors and user behaviors influence the end use of energy, we propose a User Profiling module to investigate the characterization of user's goals and behaviors in terms of energy consumption. Besides the wireless sensor networks, the User Profiling module acquires data also from a questionnaire which mainly concerns four categories, *i.e.* characteristics of the residents, electrical appliances, attitudes towards energy and building structural information.**

**Furthermore, based on the real-time information from the sensor network platform and the user profiling module, an embedded Resource and Consumption Controller will then adapt automatically for instance the regulation processes of energy consumption in a household locally for the users, so that the costs of all energy resources will not exceed the predetermined budget and be regulated in a user-preferred way.**

***Index Terms*—User profiling, Web of Things, energy management, multi-agent systems, PID controller, dynamic energy mix.**

## I. Introduction

In recent years, the growth rate of energy demand is always faster than the speed of energy supply, which means, no matter how significantly the global sustainability developed, efficiency improvement from power generation, transmission and distribution to consumption is still very necessary. In other words, energy-using waste and inefficient energy use are the status of global energy use in general.

Due to great demand on heating, cooling and lighting, building is a large energy consumer, which consumes more than $40\%$ of the total energy use worldwide [1]. Among the new building blocks, the energy-using waste is a very common phenomenon. By 2050, it is estimated that many energy inefficient buildings from today will still be in use. Regarding the $40\%$ of global energy consumption from buildings and increasingly high demand of real-time information for every aspect of a building energy management network, a more efficient energy management system, such as a distributed agent-based solution [2], should be considered to control the energy units (producer, consumer, storage, etc.) of the building locally and autonomously towards interactions with the environment, in order to optimize the building energy consumption dynamically.

People have only a vague idea of how much energy they are using for different purposes and what sort of difference they could make by changing day-to-day behavior or investing in efficiency measures. Key issues are for instance the lack of real time information management around consumption [3] and the influence of energy use information on energy-saving behavior [4]. Hence, in this work we propose a distributed energy resource management as the infrastructure of the Smart Energy system, which uses Web services based on a WoT (Web of Things) platform [5], [6] to integrate sensor networks with existing IT systems as part of distributed applications. With this distributed architecture, we introduce a questionnaire-based User Profiling (UP) as the central module of the system to correlate the consumption behaviors with the user's preferences by means of user profiles. The Smart Energy system forwards then the preference information to Resource and Consumption Controller (RCC) for determining the controller parameters dynamically. The controller is configured to control autonomously services of the regulation/control processes of building energy consumption in local domain (*i.e.* energy mix), which are characterized by:

- ***Data acquisition***: the local WoT platform as a stand-alone server manages the environmental and energy data in a distributed manner and could then connect with interfaces to the other local WoT platforms. Based on this platform, the information of current state of local energy consumption and activities will be classified and transmitted to the UP; while the energy resource and pricing information will be forwarded to the RCC.
- ***Anticipation***: the RCC identifies disturbances which affects the achievement of the predefined goal (*e.g.* budget) under considering the preference information of users.
- ***Control and enforcement***: network embedded control realizes a "truly distributed" system [7]; a service-oriented future control center is not only stipulated for the Smart Grid [8], but also efficient for the small-scale energy control for instance in Smart Home, Smart Building or Microgrids [9], [10]; instead of centralized control by a single planning and control entity, the distributed

Yong Ding and Michael Beigl are with the Research Group of Pervasive Computing Systems (TecO), Karlsruhe Institute of Technology (KIT), Germany, (e-mail: firstname.lastname@kit.edu).

Iana Vassileva and Fredrik Wallin are with the Research group for Energy Savings, Load Control and Energy Efficient Buildings, School of Sustainable Development of Society and Technology (HST), Mälardalen University, Sweden, (e-mail: firstname.lastname@mdh.se).

Christian Decker is with the INIT GmbH, Germany, (cdecker@init-ka.de).

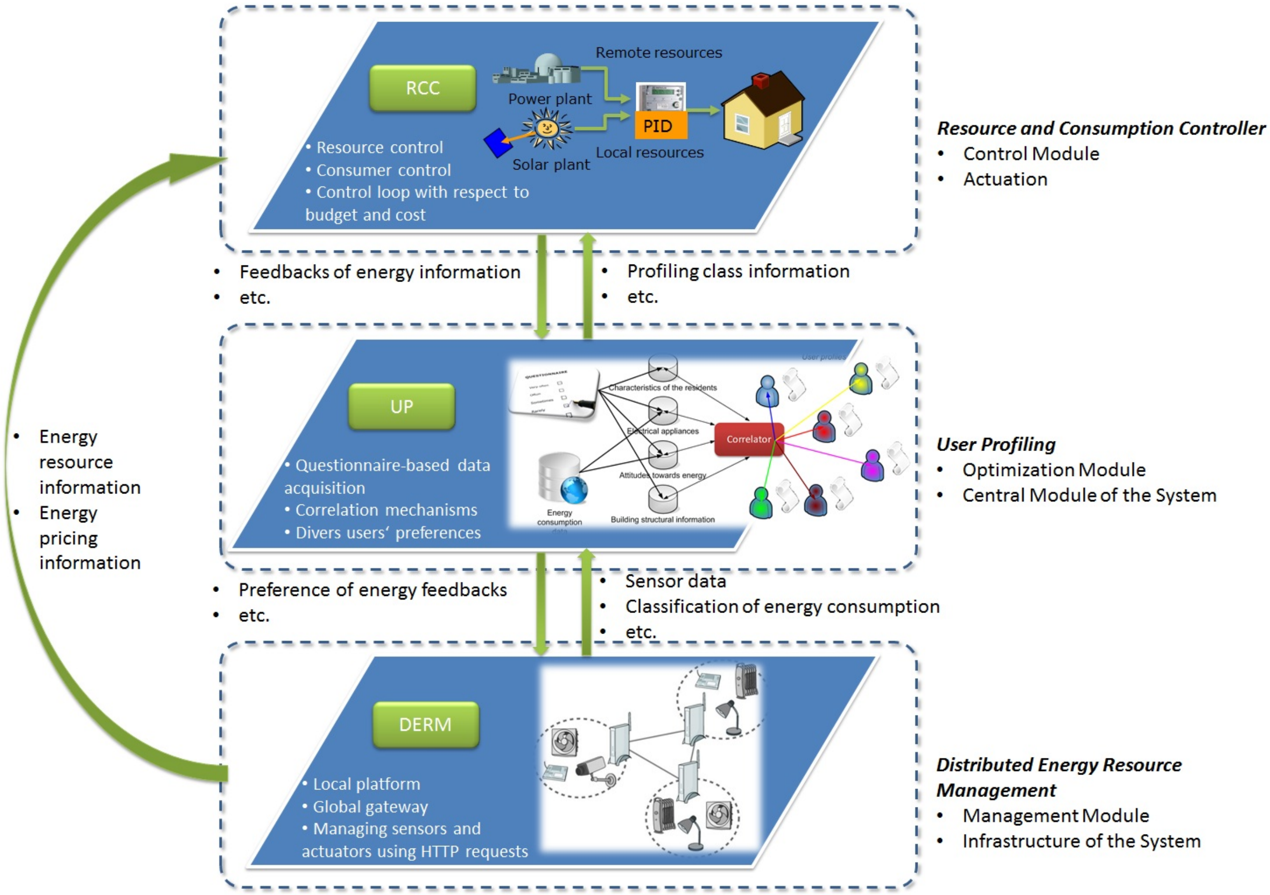


Fig. 1. Three main modules of Smart Energy system architecture: DERM, UP and RCC

decision-making imposes corrective actions locally, such as a multi-agent system [11].

The rest of the paper is organized as follows: In the next section, we will review the state of the art in multi-agent systems in Microgrids. In Sec. III, we focus on the proposed Smart Energy system. The system components will be detailed individually in terms of their functionalities and interactions with each other. Finally, Sec. IV concludes the paper.

## II. Related Work

In recent years, multi-agent systems (MAS) [12] have been proposed to provide various power engineering applications [13], such as intelligent energy control and management systems in microgrids [14]. Many previous works have proposed multi-agent system architectures that deal with buying and selling of energy within a microgrid and algorithms for auction systems. Most of them [15]–[18] use a two- or three-layered architecture.

MGCC (Microgrid Central Controller) [15] and PowerMatcher (a market-based control concept) [19] both employ a kind of central controller agent to optimize the control of microgrids by coordinating the local controllers accordingly for the energy exchange of the local loads and the production units. A central coordination or a hierarchical coordination could not exclude any single point of failure and may have scalability problems. Therefore, Qiu *et al.* [20] propose a distributed multi-agent system for the matching of energy resource units and consuming units in a microgrid. The proposed BDI (believe-desire-intent) architecture adopts all agents and delegate agents individually for local tasks according to the characteristics of the energy resources and load, and realizes under considering the dynamic pricing mechanism an energy exchange between the supplying units and the local user. But the multiplicity of the existing energy dispatch approaches which try to match generated power with consumed power, implies that no ideal solution guarantees the market clearing [2]. Trading and meta-heuristic algorithms are the most popular for now, such as auction algorithms based on agents' negotiation [15], [18], PoolCo algorithm based on an energy market and schedules [16], and artificial intelligence (AI) algorithms [21] like genetic algorithms, particle swarm optimization and ant colonies using a single central agent for the optimization.

From the point of view of MAS applications, Funabashi *et al.* [17] present a trading method based on a hierarchical multi-agent architecture for the power market of a microgrid. Another hierarchical multi-agent system architecture [22] is proposed for a power distribution network, with lower layer agents for sensing the absence of energy and higher layer agents for restoring energy by negotiating with their peers. The use of a multi-agent system to control a small microgrid that comprises PV generators, batteries and controllable loads is discussed by Dimeas and Hatziargyriou [15], [23], [24]. A control strategy for buying energy from the distributed energy resources (DER) to meet the demand at lowest possible price is presented by Qiu *et al.* [20]. Another scalable multi-agent system for microgrids is proposed by Logenthiran *et al.* [16], which realizes bidding for buying and selling power within a microgrid by the Load controllers and the same bidding but at a high level of several microgrids by microgrid controllers. Some other applications using multi-agent systems [15], [25] emphasize control and communication strategies, which cope with energy trading within a microgrid through load agents (operating the loads) and DER agents (controlling the DER resources). The last application which is to be mentioned is the multi-agent based energy management system from Feroze [14], which monitors voltage level from the main grid, controls the status of the main circuit breaker, monitors and controls the power consumption by each load in the example microgrid community of five houses, monitors and controls the power supplied by the DER units and the on/off status of each load by controlling the electronic circuit breaker associated with it.

We note that in most of the previous multi-agent systems in microgrids, an automated agent technology is used to establish a distributed control architecture instead of SCADA (Supervisory Control and Data Acquisition) systems for the power operation system at a grid level. However, The focus of this paper is to discuss a distributed architecture of local energy consumption management in the context of a distributed smart building located at a distribution level.

## III. System Design

In our Smart Energy System, we propose to design a multi-layered architecture consisting of three functional modules:

- **Distributed Energy Resource Management (DERM):** for energy consumer and pricing information, and energy-related environmental information based on the local WoT platform
- **User Profiling (UP):** for matching divers users' preferences, like means of getting energy feedbacks (in a more visible way or a typically numerical way), attitudes of budget use
- **Resource and Consumption Controller (RCC):** for realizing a dynamic energy mix and optimizing consumption control

The basic illustration of the system architecture is depicted in Figure 1. The entire Smart Energy network is inspired from the Internet of Things (IoT) [26], which establishes a connection for real-time communication between system components (*e.g.* heterogeneous sensor networks, control loops, etc.) and systems (*e.g.* DERM, UP and RCC). In order to meet the customers' requirements of energy consumption and control, based on feedbacks of the User Profiling module, the RCC can provide them with certain adequate energy control with respect to energy resources and consumers. Thus the information of passive consumption behaviors can be transformed into an active optimization of energy consumption. Ultimately this Smart Energy solution with the visible and amenable energy feedbacks can change their energy use behaviors and attitudes, which describes the character of:

1) Application of an open architecture
2) Significant changes in consumer behavior of energy use

The overall procedure with information flow within the whole system is illustrated in Figure 2 and Table I

TABLE I
An overview of the interactions between DERM, UP and RCC

| No. | Interaction |
|---|---|
| 01 | The first block defines the infrastructure of this web-based system: DERM, which collects the sensor data (energy, environment, etc.) of heterogeneous wireless sensor networks and classifies situational activities of energy consumption. |
| 02 | The energy-related sensor value and classification information are forwarded to the UP module and integrated with the questionnaire data into the data acquisition subprocess. |
| 03 | Through classification, aggregation and correlation algorithms, divers user profiles can be generated in terms of requirements of energy consumption. |
| 04 | The preference information decides the controller parameters ($k_p(t)$, $k_i(t)$ and $k_d(t)$) in RCC. |
| 05 | Accordingly, the adapted PID controller regulates the energy mix subprocess with respect to the optimization of budget use, in order to satisfy the load demand with less power source which is bought from the grid. |

### A. Distributed Energy Resource Management

Distributed Energy Resources (DER) are used in many publications as a synonym of Distributed Generation (DG) [27], which are electric generation units located within the electric distribution system at or near the end user. However, in this paper we use the term "Distributed Energy Resource Management (DERM)" to propose a distributed resource management architecture to create a WoT platform of energy information in both local and global views, whose topology is Mesh like as shown in Figure 1, DERM part. In this architecture, there are stand-alone local WoT platforms for each WoT domain, which gives an aspect of local resource management. Then an add-on middleware can interconnect those local WoT platforms as a global network. This method decentralizes the resource management and solves the problem of total dependency.

Each our local WoT domain is a smart resource management environment [28], which employs $\mu$Part sensor nodes [29] to detect movement around the chairs, the tables or of the devices, and to monitor temperature and lighting status in the rooms. Each socket is equipped with a Plugwise[1] Circle and each heater is controlled with FHT[2] sensor and actuator. As the penetration of renewable energy continues to increase, not only a smart grid must have real-time information of renewable energy, but also our small-scale energy system have to manage the renewable energy information of *e.g.* wind and solar. The different energy resources with their availability and price information from all WoT domains are categorized into two types: *Local Resources* and *Remote Resources*, which will be

[1] http://www.plugwise.com/idplugtype-e/how-does-it-work

[2] FHT is a German wireless thermostat, which enables a convenient and direct control of the supplied actuator for heater-controlling

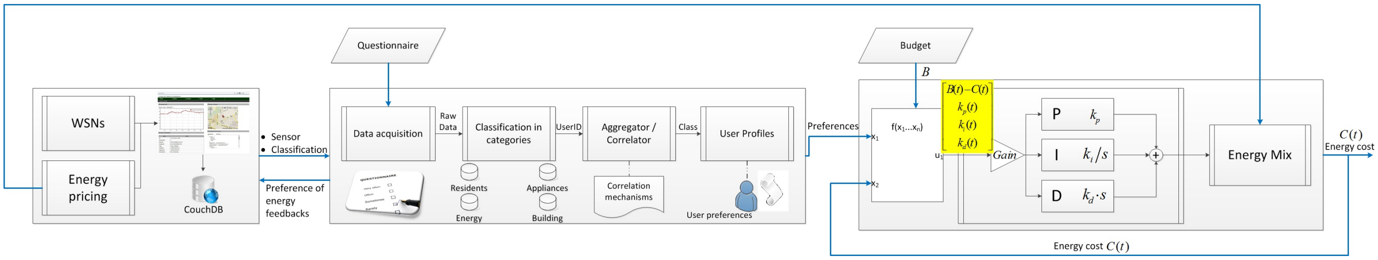


Fig. 2. A flow chart of proposed Smart Energy system between all three modules

transmitted forward as inputs to the Energy Mix process of RCC, see more in Section III-C.

The entire sensing network consists of three heterogeneous sensor network components, each has three parts: *Monitoring/Control Terminal (uBox)*, *Base Station* and *Sensor Nodes*.

- **$\mu$Parts:** are $1cm^2$ low power wireless sensor nodes with temperature, light and movement sensors. The D-Bridge [30] serves as a programmable base station for $\mu$Part, which receives $\mu$Part packets and forwards them to uBox network manager via PUT Requests, see Figure 3 a).
- **Plugwise-Network:** measures the energy consumption of connected appliances and switch them on/off with the plug. The Plugwise Stick receives data from and transmits tasks to the installed Plugwise Circles, see Figure 3 b).
- **FHZ-Network:** a FHT thermostat measures the room temperature. Based on the embedded receiver module, the thermostat can communicate wirelessly with the FHZ base station, see Figure 3 c).

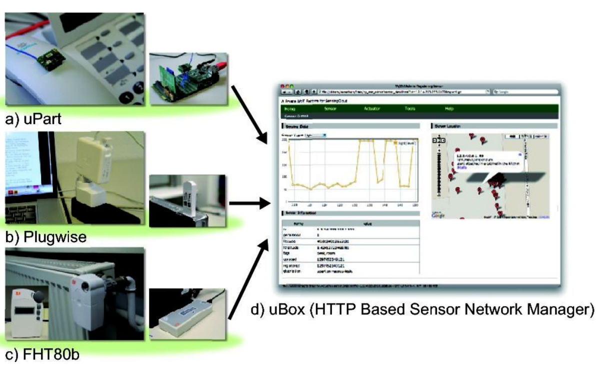


Fig. 3. Sensors and actuators with network manager: a) sensor node $\mu$Part and base station "D-Bridge"; b) sensor node Plugwise and base station "Stick"; c) sensor node FHT and base station FHZ; d) network manager uBox

The uBox middleware is based on a layered abstraction. Each layer can be manipulated via RESTful interface. If sensors or actuators register to this platform by POSTing themselves and the users or applications within the network can discover them and utilize them with a simple unified HTTP based interface.

On the top layer, users can *e.g.* generate HTTP requests which dynamically aggregate power sensors tagged as "light" and located within 1000m circle from coordinates (49.00, 8.38) and process the average value for each unit. Feature generation or classification of your own can be added to the uBox with posting server-side JavaScript.

This prototype idea not only provides an information management system of energy resource and pricing for the RCC-based energy consumption control, but also enables web-based energy-saving applications, such as a smart heating system, which can set all thermostats in the room via the FHT80b actuator according to the average temperature value of personal preferences.

*1) Environmental Impact:* As we know, the prediction or day-ahead plan of the energy demand for customers is currently still a lump-sum estimation, which is not adapted to the dynamically changing real-time power consumption. However, it was shown that a distributed architecture with wireless sensor technology [31] for various environmental factors, like location, weather, device operating mode, device's nominal power, etc. have a significant impact on the power demand. Determining or at least estimating these factors in real time enables spatially fine-grained evaluation and control of power consumption, so that energy management systems can optimize dynamically the intraday prognosis based on the day-ahead power demand plan, which refers directly to reducing the monetary loss [31].

*2) Energy-related Classification:* In order to gain a more in-depth knowledge of the environmental impact on the local energy consumption, we design a energy-related classification process consisting of four functional steps:

1) environmental and energy data acquisition through lightweight WSNs based on $\mu$Part sensor nodes and "Plugwise" power plug;
2) interpretation of the in real time acquired temperature, lighting, movement and energy data through different abstraction levels of energy-related contextual information:
   - Low level contexts, e.g. window open/closed, day or night, which can be derived directly from the raw sensor data of the $\mu$Parts fixed on the windows.
   - High level contexts, e.g. user is working on PC, user has left the office or meeting is being held, such situational information could only be classified through combination of various low level contexts.
3) correlation of different local interpretations for a global view of the monitored situation. The collected sensor data and contextual information are assumed to be temporally dynamical and have uncertain effects on an environment, so we model the correlation module as a MDP (Markov Decision Process) using HMM (Hidden Markov Models) method:

- ***observable states:*** such as time of day, internal temperature and the status of devices
- ***hidden states:*** such as the performing task of the users like working on computer, holding a meeting, etc., and the health status of the individual

4) the output of the correlation algorithm will then give a decision-making algorithm a proper energy-saving context as input through a certain information management system to motivate the actuators, such as turn off the heating system after the meeting or the lights and monitors according to the presence of users, etc. As actuators we utilize "Plugwise" for controlling on/off state of the power plug via ZigBee and "FHT" for controlling heater via wireless network. A web-based environment has been implemented, which could visualize the real-time sensor data and realize device control via RESTful interfaces.

Besides the questionnaire, the above described classification is aggregated providing inputs for user profiling, which includes the interaction of users with the home/office environment, the status of the available appliances, etc. Thus, the user's goals, user behaviors and the user's interaction preferences in terms of energy consumption in the home/office area represent in this case the main contents of user profiles.

*B. User Profiling for Understanding Energy Consumption Behaviors*

Energy feedback is the alternative way to inform people about their energy using/saving techniques. In this section, we illustrate the functioning of the UP module, including the internal procedure and details about the information exchange with other two modules.

The basic function of the User Profiling module is the characterization of user's goals and behaviors in terms of energy consumption. As the optimization module of our Smart Energy system, UP tries to match the users' preferences to make energy feedback information more visible for the users through the DERM platform and enable a dynamical configuration of the PID controller in the RCC module. The overall process of User Profiling includes basically four subprocesses as shown in Figure 2:

- ***Data Acquisition:*** To build a user profile, the information needed can be obtained explicitly, that is provided directly by the user (in our case through questionnaire), or implicitly, through the observation of the user's actions (in our case through DERM).
- ***Classification in Categories:*** The questions from the questionnaire are divided in four categories concerning 1) characteristics of the residents, 2) frequency of usage of appliances, 3) residents' attitudes towards energy and 4) building structural information. The energy consumption behaviors in terms of the status of appliances and the user's interaction with appliances and environment, fit in the meantime into the category 2) and 3). Therefore, we normalize the category outputs as follows:
    1) Residents
    2) Appliances
    3) Energy
    4) Building
- ***Aggregator/Correlator:*** A mechanism (Correlator, see Figure 1 and 2) for characterizing users' consumption behaviors and goals, such as *Bayesian Networks* representing uncertain relationships among variables of behavior in the consumption domain, *Association Rules* discovering certain association relationship among the set of consumption objects (residents, appliances and buildings) or *Case-based Reasoning* representing the similarity among the set of consumption objects in the same domain.
- ***User Profiles:*** To define the configuration of RCC and the way of energy feedbacks in DERM, the contents of each user profile are listed in Figure 4. Where $\{0, 1\}$ of building structure and energy feedback stands for $\{apartment, house\}$ and $\{email, display\}$ respectively, and [0 3] of the other three preference contents corresponds to "no knowledge" (0), "low" (1), "intermediate" (2) and "high" (3). The value of consumption behavior implies the consequent energy awareness.

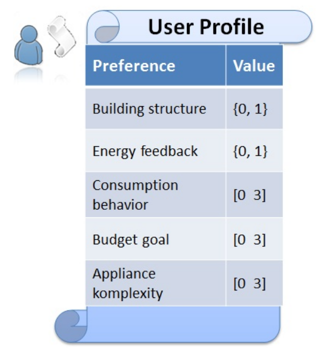


Fig. 4. The main contents of user profiles with respect to the interaction with the other two modules

*1) First Dataset:* To achieve the modeling of different user profiles, an in-depth survey was sent out to 2000 Swedish households (1000 houses and 1000 apartments) in order to better understand users' feedback preferences and energy related behaviors.

The analysis of the responses received shows substantial differences in the energy-related behavior and the preferred feedback methods between users living in apartments and houses. Most of the users living in apartments prefer displays as a main tool for receiving information feedback while most of the house residents prefer the e-mail method. Respondents living in houses also are the most aware of their energy consumption and the ones with better knowledge on their actual consumption. However, apartment residents are trying more to lower their consumption and at the same time would like to receive more energy-saving tips.

Besides the personal information, like *income*, *number of occupants*, *occupants' age*, *type of household* and *education level*, two additional indicators for developing consumption feedback providing technologies have been taken into account in the questionnaire, *i.e.* ***the level of knowledge and interest in energy related topics***, and ***user behavior with respect to energy awareness***. The results of the questionnaire survey indicates that the respondents generally have a good knowledge about their own consumption, know how to maintain the electricity use low. Furthermore, e-mail is the most preferred by the group with knowledge and display is always chosen by households without any knowledge. However, the results are less positive with respect to increasing respondents' knowledge about approaches of reducing power consumption, since we notice that they already state they have a high knowledge level.

Due to the double increase of the household electricity use in Sweden for lighting and different electric appliances between 1979 and 2006 (from 9.2 TWh to 22.1 TWh) [32], it is important to make sure that consumers know about the percentage of their electricity used for lighting and focus on some of the strategies towards reducing this type of electricity use. For this reason, presenting real-time consumption of electric power (in Watt) would allow the consumers to observe the instant effect on the total power when switching different appliances on and off through DERM platform.

### *C. Resource and Consumption Controller*

As we know, more and more photovoltaic and MicroCHP (micro cogeneration: combined heat and power) devices are installed in the modern home, office or building area, which enables a kind of decentralized microgrid scenario. Instead of an energy management system with a central controller, we develop a scalable and embedded controller for both energy resource and consumption, which integrates computer hardware with software in it as one.

Although the Smart Metering enables new forms of the energy management and the Demand Response process [33] as a function of dynamic pricing can switch on or off one single or multiple electrical devices, that entails but a lot of costs and operating expense. The customers must spend much time to observe the pricing and react to changes accordingly. The Resource and Consumption Controller (RCC) can undertake the task of these time intensive applications locally for the customers and then enable the control of a local energy management. Compared to the Demand Response, the RCC is much more flexible, which operates only locally and is considerate more of the concrete and personal needs of the customers.

The RCC operates only individual parts and works as a controller agent for the global energy management system (EMS). It receives goals, constraints and rules, such as to keep the energy consumption at a certain level. The RCC contains only services that have a local view and belong to the local environment. Such services are dependent on information and data which come from the User Profiling and Smart Items. In the proposed Smart Energy system, Smart Items mean the heterogeneous sensor networks, which are conducted by the DERM module. Furthermore, each RCC has at least the following functionalities:

1) Collecting data using Smart Items
2) Identifying disturbances
3) Scalable and dynamic control configuration dependent on user profiles
4) Control with respect to the predefined goals for both resource and consumption

In this paper we utilize RCC to model energy services, which can respond consumer specifically to any price fluctuation in energy markets. Through the control loop depicted in Figure 2, a decision making such as an adjustment of the energy consumption could be done, which means for instance that you have less energy on your hands at higher energy price and much more at lower energy price.

The right part of Figure 2 shows schematically the overall process of the RCC module, which consists of two main subprocesses, *i.e. Mapping Function* and *Control Loop*. The mapping function $f$ is responsible for a dynamic configuration of the parameters ($k_p$, $k_i$ and $k_d$) of a PID controller based on preference information of user profiles.

In order to introduce the control loop of RCC, we firstly assume that in the execution of energy services, two types of energy resources are available:

1) ***Local Resources:*** are resources on the customers' hands (already bought), which are practically free of charge, *e.g.* the installed photovoltaic device.
2) ***Remote Resources:*** are all resources for what you actually have to pay later. Their prices may change dynamically over time.

As aforementioned in Section III, the RCC has a main task of dynamic energy mix. This subsystem should therefore regulate the resource consumption. By means of the current energy prices, the resource consumption is then related to the predefined budget (goal).

$$B(k+1) = B(k) + C(k+1) \tag{1}$$

Where $B(k)$ describes the consumed budget in time point $k$ and $C(k)$ is the current costs. Due to the hourly energy price information, we consider the budget and consumption costs also in discrete time step $k$ instead of $t$.

$$T(z) = \frac{B(z)}{C(z)} = \frac{z}{z-1} \tag{2}$$

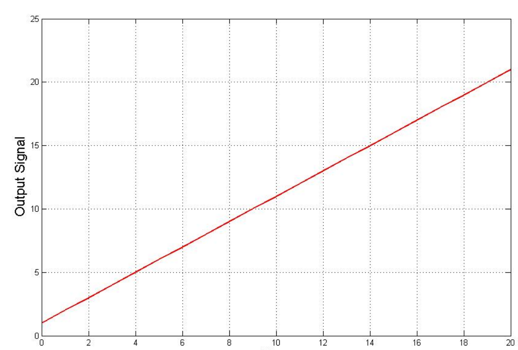


Fig. 5. Step response of the controlled system

Analysis of the system step response with z-transform in Equation 2 can confirm that the controlled system (plant) described in Equation 1 is instable (see Figure 5) and has an *Integral* behavior inferred from the data in the figure. As there is one simple rule in the control theory [34] for the synthesis of a common closed-loop controller architecture using PID controller, which states that the closed loop will have no steady-state error, only if the open system has an integration behavior. Using this rule we are able to facilitate the controller synthesis that our PID controller muss not have the Integration Element (I) or the Differential Element (D). In order to achieve a best control result, the controller must only feature the *Proportional* (P) behavior, so that we fix the proposed PID controller as $k_i(k) = 0$ and $k_d(k) = 0$.

$$I(k) = (\frac{1}{k_p + 1})^k \cdot \frac{k_p}{k_p + 1} \tag{3}$$

Then we utilize inverse z-transformation on the transfer function of the closed control system. The impulse function in the time domain (see Equation 3) indicates that the closed system remains always stable as long as the parameter $k_p$ is greater than 0.

As fine tuning for the energy mix, we separate the total costs of both types of energy resources $C(k)$ into costs of local resources $L(k)$ and costs of remote resources $R(k)$. Then a MISO (Multiple Inputs, Single Output) system with described controller synthesis can be embedded into a feedback control loop like in Figure 6.

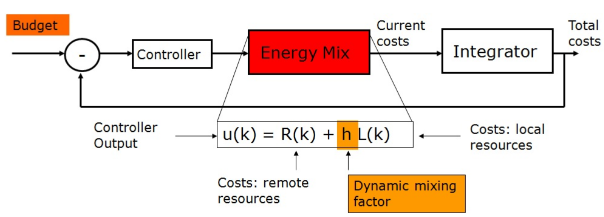


Fig. 6. Block diagram of the control loop of RCC for energy management

We introduce at this point a so-called dynamic mixing factor $h$, which enables the desired consumption behavior of energy mix. $h$ fulfills the role of a valve that limits the consumption of local resources. Its value is determined dynamically by RCC over time and always within $[0, 1]$. Besides the $k_p$ value which with a higher gain leads to a faster convergence of the actual budget progression, the initial value of $h$ can also be determined by the mapping function $f$, see a simple example of the overall algorithm as follows:

```
1 StartTime = Time(k)
2 x_1 = Preference_Vector()
3 x_2 = C(k)
4 IF SUM(x_1)>=6 THEN GOTO 5 ELSE GOTO 6
5 h_init = 1 AND k_p = 0.1
6 h_init = Random(1) AND k_p = 10
7 E(k) = B(k)-C(k)
8 PController(E(k), h, k_p) -> E(k)==0
9 IF Device_Power<=E(k) THEN GOTO 10
                        ELSE GOTO 11
10 Device_Scaling()
11 %Turn off all active Devices until h=1
```

Where the mapping function in this example refers to the sum value of all elements of the user preference vector (consumption behavior, budget goal and appliance complexity). Compared to a threshold (*e.g.* 6), the $h$ and $k_p$ value will be then specified.

## IV. Conclusion and Future Work

This work began by identifying the need for efficient energy use and feedbacks. A multi-functional Smart Energy system was proposed which consists of a Distributed Energy Resource Management (DERM) module, a User Profiling (UP) module as well as a Resource and Consumption Controller (RCC) module. The already realized WoT platform as the system infrastructure enables an ubiquitous resource management environment, which interacts with its environment and provides the information of local energy consumption and classified activities to the UP module, the information of local and remote resources to the RCC module. A questionnaire- and WSN-based User Profiling allows the consumers to get the energy feedbacks in a more perceptive way through the interaction with DERM. With respect to the reference value, *i.e.* budget, and the preference information from user profiles, the RCC realizes a dynamic energy mix and compensates external variations, *e.g.* dynamic prices and dynamic energy consumption.

We described an explicit concept of the User Profiling module and finished the collection of the first dataset from 2000 households. Our future work is considering methods to figure out a more accurate concept for the mapping function in the RCC module to interconnect the UP module. In the meantime, other user profiling methods and non-linear controller concepts will be investigated.

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**Yong Ding** received his M. Sc. Degree of Electrical Engineering in 2008 at Karlsruhe University. His employment experience included 15 months Trainee Program in the energy company RWE and project management of electrical engineering in the division of conveyor equipment and process data processing. He is now a PhD candidate at the Karlsruhe Institute of Technology (KIT), working on behavioral change of energy consumption in urban scale and networked platforms for dynamic energy mix and consumption optimization.

**Christian Decker** received his Ph.D. degree in 2009 at the Karlsruhe Institute of Technology (KIT). He was scientific manager of the TecO research group since 2006 and is now at Init AG. His research interests include feedback controlled computing systems as well as cooperative and collaborative process organisation.



**Iana Vassileva** received her M. Sc. Degree in Environmental Science from Mälardalen University, Västeras, Sweden in 2007. She is now a doctoral candidate at Mälardalen University working on analyzing consumption patterns, behaviors and how different feedback influences them.



**Fredrik Wallin** received his Ph.D. degree in 2010 at Mälardalen University. He has been working for 10 years with energy information, metering systems and demand-response issues. Other research interests are small-scale electricity production, renewable energy technologies and improved integration of energy consumers into the energy markets.



**Michael Beigl** holds a MSc. (Dipl. Inform.) and a Ph.D. (Dr. Ing.) in Computer Science from the University of Karlsruhe. His Ph.D. received the FZI price for the best dissertation of the year in 2000. His employment experience included the chair for Distributed and Ubiquitous Computing at the Technische Universität Braunschweig (2006-2010) and scientific director of the TecO research lab at University of Karlsruhe (2000-2005). Since 2010 Michael Beigl is full professor (W3) at the Department of Informatics and holds the position as chair of the shared new field group Pervasive Computing System at the Karlsruhe Institute of Technology.