Simulating The Potential Savings Of Implicit Energy Management On A City Scale

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Abstract

According to statistics and future prospects in the next few years world-wide energy consumption will increase significantly. Therefore not only more energy efficient technologies but also more extensive energy saving concepts have to be realized. We have developed an "implicit interaction" based power saving concept, which automatically schedules and controls energy consumers depending on the recognized activities of users. Moreover, dynamically schedulable power consumption loads are shifted in time, so as to make use of the cheapest energy prices without compromising user comfort. In order to calculate the potential savings of this concept we have implemented a simulation framework executing energy consumption models on a city scale, which allows for more complex scenarios than being restricted to some devices or buildings only. Both the framework architecture as well as large scale energy consumption simulations are presented. Simulation experiments give strong evidence for our implicit energy management concept as a promising source of energy savings.

1 Introduction

According to the International Energy Outlook of 2007[1] the world marketed energy consumption increases by 57% from 2004 to 2030. The world net electricity generation is expected to grow by 85%. These and similar prognoses and their accompanying negative impacts on the environment drive the politics to legislate for an increased number of energy efficient technologies. For instance the European Commission passed the directive *COM(2006)545* on energy end-use efficiency and energy services in April 2006 [4]. It obligates its member states to reduce total energy consumption by at least 20% until 2020 and proposes ten priority actions including appliance and equipment labeling and minimum energy performance standards, making power generation and distribution more efficient and raising energy efficiency awareness.

In order to reach the defined goal, avoid penalty payments and ensure sustainable energy supply in the future new innovative products and concepts are developed constantly, trying to improve efficiency of devices and buildings. Besides lowering the demand by improved technologies, we believe it is necessary to reduce energy consumption in two ways. The first one is to switch off unnecessary and unused devices (*quantitative*) and the second one is to control energy consumers in a *qualitative* manner. The latter involves the sophisticated combination of a whole set of energy consumers to predefined *ensembles*, which are dependent on the situation (i.e. a situation in a households context could be having dinner or working on the computer). This includes not only the power state of energy consumers but also their operation mode, e.g. the luminance factor of lighting which has different requirements for activities as watching a movie and reading the newspaper. An optimized lighting situation can not only save energy costs but even increase productivity in offices and industrial environments [9]. Considering the fact that lighting is only one aspect besides temperature, air condition, etc. we believe in a high savings potential for both, energy consumption and costs as well as a maximum level of comfort for humans.

Within this scope we have developed a power saving

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[1] Energy Information Administration - http://www.eia.doe.gov

concept, which is based on *implicit energy management*. The proposed energy management system (EMS) automatically adapts to changing situations (context) at runtime in a meaningful way. It operates mostly *autonomously* (i.e. with little human intervention) and interacts with the energy consumers *automatically*. Persons do not have to focus on monitoring or altering device power states (*implicit interaction*) according to their need, although they still have the possibility to decide in first instance if favored. Our approach to distinguish between different situations is based on *activities*, which can be recognized with various sensors and technologies. In addition, the implicit EMS involves common approaches as shifting energy loads to less cost-intensive time of days in order to reduce energy costs supplementary. Our power saving concept finally results in decreased energy demands and costs and offers advantages for both end users and energy providers.

Considering the savings potential of an EMS which is spatially restricted to units as devices, device groups or single buildings has only little significance because of the quite low total energy consumption. Wide spread energy consumers such as public lighting and traffic may not be considered when only regarding small self-contained entities. Benefits for energy stakeholders as operators of power plants are not considered as well. For this reasons we propose a simulation framework which calculates potential savings and allows to take into account more complex scenarios like demographic changes on a city scale. Simulating a realistic savings potential is a main requirement for amortization calculations and decisions about the investment in EMS. The introduced framework is basis for evaluating our implicit energy management concept.

2 Related Work

Due to the fact that energy saving is a hot topic, in the last few years a lot of research effort has been made to improve energy efficiency of devices and materials. Beside this development a lot of concepts for more efficient power grids, energy distribution and intelligent consumption control have been developed. Frequently the simplification of integrating renewable and decentralized power plants as well as new models for energy marketplaces including dynamic energy pricing are presented [3]. For instance, in [2] two main concepts are introduced. Firstly, energy management of distributed generators and loads with decentralized decision by bidirectional energy management interfaces is proposed. Secondly, a market platform supporting spontaneous trading by means of automated contract conclusion and optimization and controlling procedures for the demand as well as the supply side. Functional principles of different energy tariffs and actual experiences with demand response pilot projects (cp. Load Shifting) in the United States and Scandinavia are presented in [11]. In some cases peak loads could be reduced by more than 30%.

The vision of an *interactive energy grid*, where energy consumers as well as providers can benefit in various ways from exchanging information as future loads and energy prices, is enabled by smart metering, electronic control technologies, modern communications means and the increased awareness of customers [5]. *Smart meters* do not only measure energy consumption, but are considered to be the gateways to the future energy grids. They afford a bidirectional connection to the energy stakeholders in order that both sides can savor the savings potentials [8]. Advanced smart meters can also play an important role in costs visualization and controlling devices either locally or remotely by the energy provider.

The increasing penetration of smart meters encourages us to extend their functionality with our concept of implicit energy management. We believe that integrating user behavior to the device control and scheduling system can increase the potential savings significantly by (i) avoiding energy consumption of unused devices by switching them off, (ii) operating necessary devices in the most energy efficient mode and (iii) activating consumers not directly dependent to user interaction when energy prices are low, e.g. at night.

3 Implicit Energy Management

Depending on their location (e.g. homes versus power plants) in general EMS have the purpose of *monitoring, controlling and optimizing* energy consumption and/or production. In this paper we refer to the energy consumption aspect of EMS primarily. Implicit energy management leans on the term ”implicit interaction” from the Human Computer Interaction area [15]. The way humans interact with the EMS is *implicit*, which means people do not have to pay focus on the system by defining numerous rules and operation schedules for energy consumers, etc. Instead the system works at the periphery of human attention, adjusts to changing habits of users *autonomously* and controls devices *automatically* in a most energy and cost efficient way depending on the current situation, always keeping in mind a minimum, imperceptible loss or even increase of comfort.

Our proposed implicit EMS comprises two concepts basically. The first one is *Load Shifting* including an additional feature for trading energy at the stock exchange. We go beyond energy management based on current and future price information and combine this (in the meanwhile) wide-spread approach with novel *Activity Based Energy Management* in order to increase the savings potential significantly. Activities and other context information as the weather forecast, user calendars, etc. will be included to gain a comprehensive EMS that considers energy costs as well as user habits and preferences.

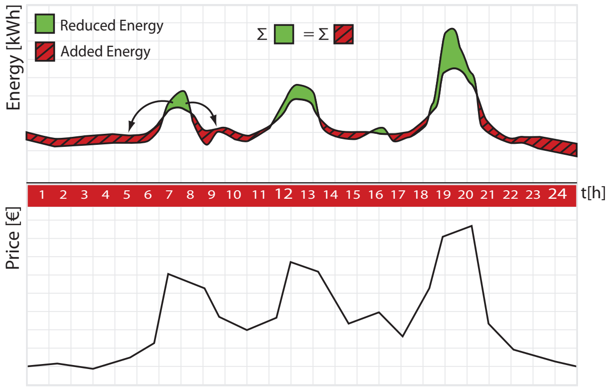

Figure 1: Flattened load profiles due to Load Shifting.

3.1 Load Shifting

The functional principle of Load Shifting (LS) is the shifting of energy consuming tasks to day and week times with a lower energy price in order to save costs. Therefore the concept requires a *variable energy pricing* model in the background where prices change dynamically over time. Some example tariffs are Time of Use, Real Time Pricing and Critical Peak Pricing [11]. The savings potential increases with the difference between the lowest and highest prices. In general the height of the price depends on current and future energy supply and demand. When demand is high the price increases, whereas it will be low when more energy is produced than needed, e.g. if there are good weather conditions for alternative power plants (i.e. windmills, photo voltaic power plants, etc.). Therefore the energy price can be an indirect but powerful way of influencing energy demand according to the current production capacity usually resulting in lower peak demands and flattened load profiles (Figure 1).

Unfortunately the practical execution of the LS concept often lacks because either the kind of device is not appropriate or the amount of the shift is considered to be too little and therefore of no benefit. In fact the amount of shiftable load depends on the energy consumer, especially it's *average time of operation* and need for *human handling*. Best suited are devices, which are not directly dependent on a specific time and person's presence as tumble dryers and dish washers. Long lasting tasks as air conditioners and freezers can be shifted, but only within a limited time slot. Otherwise their functionality would be influenced in a negative way. Energy consumers which are accompanied directly with human activities cannot be shifted automatically, e.g. lighting, radio, TV, electric iron and computer. In the latter case a shift can only be initiated by a person itself having in mind the lower price at another time of day [8].

For end users as households the potential savings resulting from LS is expected to be little, but can be increased significantly when participating in the market for balancing energy [8]. Assumed that energy stock markets as the European Energy Exchange[2] (EEX) will be accessible for end users in the future, we propose an included *Power Brokering* feature for our implicit EMS. It allows buying energy (including short-term balancing energy) for the next few hours, days or even months at the lowest possible price available from different energy providers.

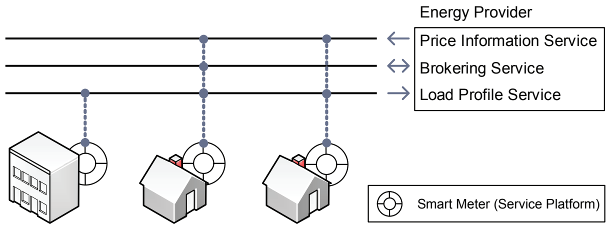

Figure 2: Service based information exchange between energy consumers and providers.

Nowadays most energy meters do not offer the possibility to communicate with energy providers. Advanced meters with implicit energy management have to include a *bidirectional communication channel* in order to exchange information on energy prices and future load profiles. We propose using a service orientated architecture where energy providers offer a price information, a brokering and a load profile service for exchanging future load profiles (Figure 2). Customers are connected to the providers by smart meters consuming the services preferred.

3.2 Activity Based Device Control

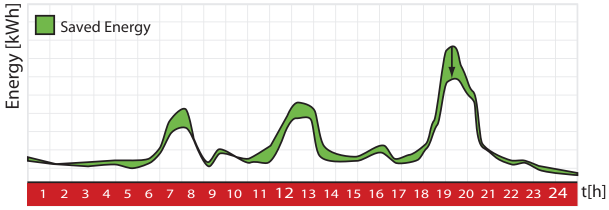

Figure 3: Activity Based Device Control.

In addition to LS we propose our concept of Activity Based Device Control (ABDC). It extends shifting energy loads for cost saving by actually *reducing energy consumption* in harmony with user activities (Figure 3). ABDC goes beyond simple power state control based on occupancy or daylight sensors. It controls whole sets of devices (in the following named as *ensembles*) depending on the situation, which is defined by user activities. A sample ensemble

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[2] European Energy Exchange - http://www.eex.com/

could be related to a meeting situation in an office. The device control involves projectors and all lights in the meeting room depending on the recognized activities (e.g. presentation vs. discussion mode) as well as switching off unnecessary devices as screens, coffee machines and lights in the office areas left behind.

3.2.1 Definition and Recognition of Activities

When talking about activities we refer to everyday activities of people similar to the objects of investigation used in common time use surveys, e.g. cooking, reading, sleeping, watching TV, using a computer, personal care, etc. However, one difference is that we only consider activities which are relevant for changing energy states of devices.

There exist different approaches for activity recognition using both *environment based* and *wearable* approaches [13, 16, 10, 18, 14, 12], using e.g. microphones, RFID, body and gait recognition or tagged everyday objects. The choice of technology strongly relates to the building integration effort and the set and resolution of activities to be detected (Figure 4).

Context sensing is widely available through local and remote sensor units. Weather data, daylight intensity and even traffic information and scheduled tasks in calendar applications can be retrieved easily using network and web based services and sensors integrated into building management systems. They give little to no feedback about a single persons current activity. Tracking a users *location* on a room granularity level may only require low cost movement detectors, while *body worn activity tracking* offers a broader range of recognizable activities at the expense of higher configuration effort and hardware complexity. Some of the most promising results come from accelerometer supported setups including shoe-mounted sensors where certain activities could be extracted ”live” from the data [6, 7, 17, 1]. For example in a living room scenario activities like ironing and watching TV are easily distinguishable by a specific combination of torso, arm and leg movements. *Thing-oriented tracking* [19] including tags on surrounding things and a reader attached to the user or a camera mounted on a wall probably offers the best resolution as every interaction can be recorded. This method however requires a lot of prerequisites and installation effort. Various combinations of these concepts improve overall recognition accuracy.

3.2.2 Mapping Activities to Energy States of Devices

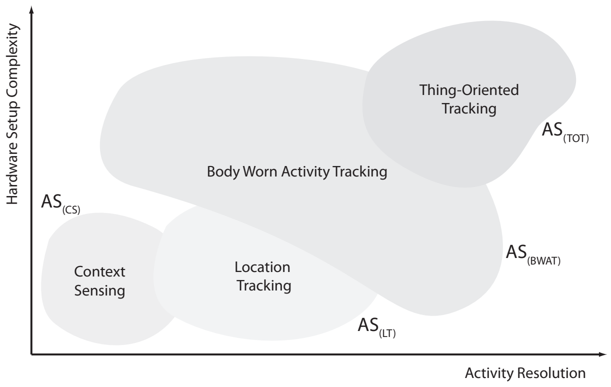

Figure 4: Activity detection accuracy increases with a higher technology installation effort.

ABDC comprises the *quantitative and qualitative* control of devices. The former refers to the basic power states of devices ”on, off and standby”. Unused devices are switched off completely or at least set to standby mode resulting in a smaller total number of energy consuming devices. The latter additionally involves the operation mode of energy consumers (if technically supported by the devices) as well as the adaption of device ensembles to activities. Considering legislative guidelines we believe that necessary technological improvements will be available soon if not common in building management systems yet. In the industrial sector qualitative control could be the automatic change of engine speeds depending on the used materials and tools for different tasks. In offices an employees’ activities having a phone call, reading the mail and working on the computer are typical examples for different lighting situations including the brightness of displays and desk lamps. Table 1 shows an example mapping of a few residential activities to the lighting devices in the affected rooms.

The total lighting energy savings potential is defined by reduced intensity levels and the switch-off of energy consumers in rooms not needed (including standby-loss reduction). Leaning on this use case a more generalized sight on the rules of our implicit EMS includes the following items:

- *Location Based Activity Set* The location of a person defines a constraint on the possible activities (activity set) and subsequently its involved energy consumers. Whereas in the kitchen preparing a meal and eating are valid options, they do not apply to a bedrooms activity set. Excluding activities from certain locations increases the overall recognition rate.

- *Active vs. Inactive Performance Area* An active area defines the awareness and interaction range of a person and thus has influence on the energy states of surrounding devices. Every energy consumer outside of the perception range is forced to switch to its minimal energy performance. This of course requires devices to expose all its energy saving and stand-by capabilities to remote control units.

- *Background Processes* Energy consumers like refrigerators, room or water heatings and manually triggered

Table 1: Activities mapped on the lighting intensity of ambient and task lights (AL and TL).

	Cooking Kitchen	Eating Kitchen	Watching TV Living Room	Reading Living Room	Reading Bedroom	Sleeping Bedroom
AL Kitchen	60%	40%	x	x	x	x
AL Living Room	x	x	10%	50%	x	x
AL Bedroom	x	x	x	x	50%	x
TL Kitchen Work Surface	90%	x	x	x	x	x
TL Kitchen Table	x	90%	x	x	x	x
TL Living Room Reading Lamp	x	x	x	100%	x	x
TL Bedroom Reading Lamp	x	x	x	x	100%	x

washing machine tasks may need to run in the background without constant user interference. On the one hand this is due to the long duration of these tasks, on the other hand due to the slow device response, e.g. when heating all rooms up to temperature the system cannot react on spontaneous user location change in time.

- *Custom Performance* An implicit EMS should allow for adaption to individual user preferences. After applying basic mapping rules the user might want to leave a light on in an inactive area for security purpose or lower the refrigerators temperature level for some time on a special occasion. For this reason in certain cases spontaneous user interaction must have the highest priority.

These basic rules are extended and updated by recording activity chains and evaluating behavior of users. *Repeating activities and usage patterns* can be detected for each defined period of time, e.g. every five minutes, hour and day. Pattern recognition and machine learning algorithms can analyze changing behavior in order to gain more accurate and energy efficient rules over time. The results go beyond typical lifestyles of people and branch profiles which only provide statistical data about activities, behavior and device usage. The exact analysis of daily routines based on the recognized activities allows for extending such data by *precise and individual* information including duration and time of day of activities. Therefore device control schedules can be *predictive* especially regarding long lasting processes. For example, room and water heating can be controlled for each hour and day separately depending on daily working times realizing *optimized energy consumption* and *maximum comfort* for people. By ”having in mind” specific activity patterns of people the system knows for example, that a person is always having a shower after sports or sauna or is washing up after cooking. Therefore it can react on *exceptional activities*, e.g. by triggering the water heating immediately when detecting one of the mentioned activities.

The proposed ABDC can be combined with the LS concept easily. It actually improves it by providing accurate schedules which are the basis for detecting the maximum available shiftable percentage of tasks and timeslots individually. Therefore the system can use the optimal shift of loads depending on the energy price whereas without individual schedules it can only vary in time to meet the average requirements of all humans. We believe that the additional savings potential is significant and user comfort increases, because there is not much programming effort for LS needed any more.

By providing such schedules including expected loads *energy providers can benefit* from the system also. It allows the proper planning of future energy supply thus decreases costs for providing more control energy than necessary which is directly coupled with the number and capacities of power plants. As a result, we propose a bidirectional communication channel between providers and consumers for information exchange (see section 3.1). Among others TCP/IP based networks and power line communication are one of the most apparent technologies which are suited for this purpose.

4 Simulation Data

Our simulation framework is an approach to estimate the savings potential of the introduced implicit EMS. We believe simulating energy management on a large scale is more representative because it can reflect additional developments as demographic changes and energy management technology penetration. It allows not only for detecting energy hogs for single devices and buildings, but also recognizing leaks and shortcomings in the energy production and distribution of a whole city. In the first step of our simulation study we did not involve activities but instead used statistical data on energy consumption. Simulating a cities energy load we consider spatially separated and semantical groupings of single energy consumers such as office buildings and households as our main research issue and leave other city wide subjects as transportation and public lighting apart in the first place. We applied the study to the city of Linz (Austria) using the real distribution of the concerned building units. Besides power based devices in buildings a high percentage of total energy is used for room heating. However, the costs and amount of energy for the latter is strongly dependent on the kind of the building materials and the heating installation itself. Therefore in our simulation only devices consuming electricity are considered.

In order to run simulation studies of our implicit energy management concept on a city scale we had to define our main simulation subjects including its energy related parameters first. Looking at several demographic studies and statistics we identified four building units (i.e. a whole building or semantical parts of it) with characteristical energy consumer groups and their individual load profiles.

4.1 Building Units

When defining the building units our main focus was on *energy consumption in the end user sector*. Therefore we considered households as our main focus including offices, as many concepts and requirements can be adapted to them. The household types are mainly different in the containing number of persons which influences not only the living space and the number of appliances, but consequently also the total energy consumption and the percental distribution of the energy consuming domains. The latter indicate the area with the highest potential savings indirectly and reflect the primary toeholds for implicit energy management. For example, energy costs for cooling (i.e. freezer, fridge) decrease per person while considering tumble drying they increase with the number of people living in one household.

Besides the number of people their family status plays a role as closer ”connections” result in a slower increase of energy consumption, because they are e.g. cooking or washing their clothes together. On the other side the potential savings decrease because more people result in more narrow time slots for using appliances because they are used more often. For example, the dishwasher has to be started more frequently and soon after it’s getting full in order to have always clean dishes available. In addition, the person type (i.e. adult, pupil, child) reflects the average presence in a household. We have defined the following stereotypical types of households including their energy consumption as well as one average-sized office for our simulation:

- *Single Household* A Single Household is considered to be a flat with one person living in it, who is usually at work during the day. For this reason most of the total energy is used in the morning hours or after work till midnight. The average total energy consumption per year is assumed to be 2,000 kWh per year.
- *Couple Household* A Couple Household describes a couple living in a flat. Compared to a Single Household the total energy consumption is not twice as much, but only 3,100 kWh per year. We assume that in most cases both persons are employed, which results in similar times for the main energy consumption as for Singles.
- *Family Household* A typical family consists of two adults and two children. Little children are usually at home all day long and pupils at least in the afternoon. In addition, one parent often does not work (full-time). Therefore more energy is consumed in the household all day long (especially in the afternoon) and is estimated to be 4,503 kWh per year in total.
- *Office* The average office space constitutes eighteen square meters per person in Europe. Assuming that a medium sized office building has 45 employees results in about 800 square meters. The total energy consumption is 40,000 kWh per year based on the average value of 50 kWh per square meter.

4.2 Energy Consumers

In the next step we have identified the major energy consuming device groups for households and offices and their percentage of the total energy consumption depending on the building unit. For households these are: home office equipment, hot water, TV/audio, lighting, cooling, freezing, drying, cooking, dish washing, clothes washing, circulation pump and miscellaneous. In office buildings energy is consumed by: lighting, air conditioning, data processing center, IT/computers, office equipment (printer, fax, etc.), elevators, kitchen, circulation pump and miscellaneous.

For the simulation we have modeled the utilization/average working loads in percent for each energy consumer and building unit per hour. The load profiles of energy consumers one day long depend on their *functionality and the building unit*. For example a fridge will consume energy 24 hours depending only on changes of the room temperature while cooking or lighting at home are dependent on the presence of people. Air conditioning in offices is a mixture of these cases as it is a constant task but one which is only necessary during the working times except for the data processing center.

In order to get the potential savings of our implicit EMS we have defined factors for LS and ABDC for each building unit and all of their above mentioned energy consumers. They are changeable, e.g. when having updated data from real sensors or by using the graphical editor of our framework.

4.2.1 Shiftable Load

The LS capacity of an energy consumer is defined by the following factors (Figure 5):

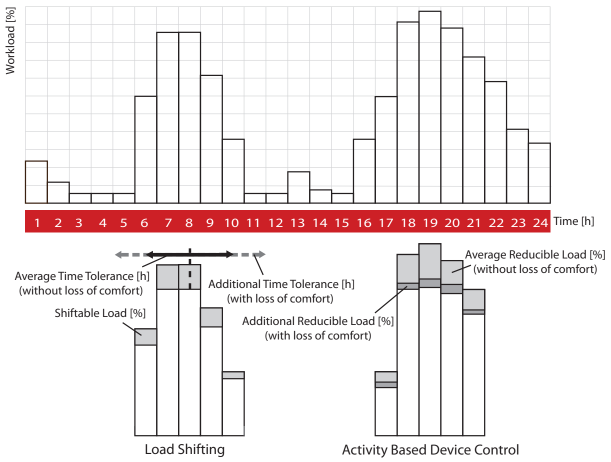

Figure 5: Parameters of Load Shifting and Activity Based Device Control.

- *Shiftable Percentage* This value defines the amount of the total working load which is shiftable to another time. It is defined for each energy consumer and hour and depends on the time of use and the building unit. For instance, the value for washing clothes of a single household is assumed to be 60 - 85% while a family can only shift about 30 - 50% because of a higher amount of clothes.

- *Average Time Tolerance* The average time tolerance is given in hours. A value of two means that the given shiftable percentage of the specified hour can be shifted either forward or backward by two hours *without any significant loss of comfort*. Some examples for a couple household are tumble drying (10 hours), dish washing (7 hours), freezing (2-3 hours) and washing clothes (up to 36 hours).

- *Additional Time Tolerance* In addition one value is given for the maximum shifting potential (additional hours forward/backward) which is associated with a reduced level of comfort. This means that people actually have to adapt their activities to the energy price index slightly, e.g. a person waits longer than usual for washing or drying the clothes and they are in consequence probably not available when needed or more crinkly, having in mind that he/she saves additional costs. For families this value is in general lower than for couples and singles.

4.2.2 Reducible Load

The simulation of our ABDC concept has the following factors in the first instance:

- *Average Reducible Percentage* It defines the reducible percentage of the working load for each hour. There is no loss or even an increase of comfort due to more exactly adapted energy consumers regarding the situation. For offices the highest percentage can be reached for lighting (45 - 80%) depending strongly on the time of day (maximum amount during lunch, minimum during night) while the energy load in a data processing center can be reduced by 2% only.

- *Additional Reducible Percentage* This parameter reflects the additional potential savings when cutbacks in comfort are accepted by persons. Summed up with the average reducible percentage it results in the maximum reducible percentage. Some examples are hot water heating (8%) for a family household and air condition (15%) for an office building.

5 Energy Analysis Framework

Taking into account expected improvements in energy saving technologies and their increased availability in building units we need new methods to cope with the complexity of energy demand outlook involving various energy consumers at a different scale. Especially for decision making in large scale energy environments rapid prototyping and analysis is crucial to identify and evaluate upcoming opportunities in potential energy savings and take actions on time. These requirements are met by our energy analysis framework that allows the modeling and integration of various data to simulate a cities energy load and show the potential of a proposed energy saving technology.

Our framework (Figure 6) is built using Java and service oriented *OSGi*[3] technology to assure flexibility and extensibility for further software iterations. The sum of all data and parameter settings needed for a simulation run is defining a *scenario*. It consists of consumer energy loads, up-to-date energy pricing information and city wide parameters like the coverage of EMS used within all building units. The simulation uses this data to calculate a devices optimized energy profile based on Load Shifting limitations according to best price policy and device control according to user preferences and usage. For convenience only the most intrinsic parameters during several simulation runs are exposed and can be controlled in the simulations user interface. More complex and particularly all time-based parameters like energy loads can only be altered at early scenario design stage.

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[3] Open Service Gateway Initiative - http://www.osgi.org/

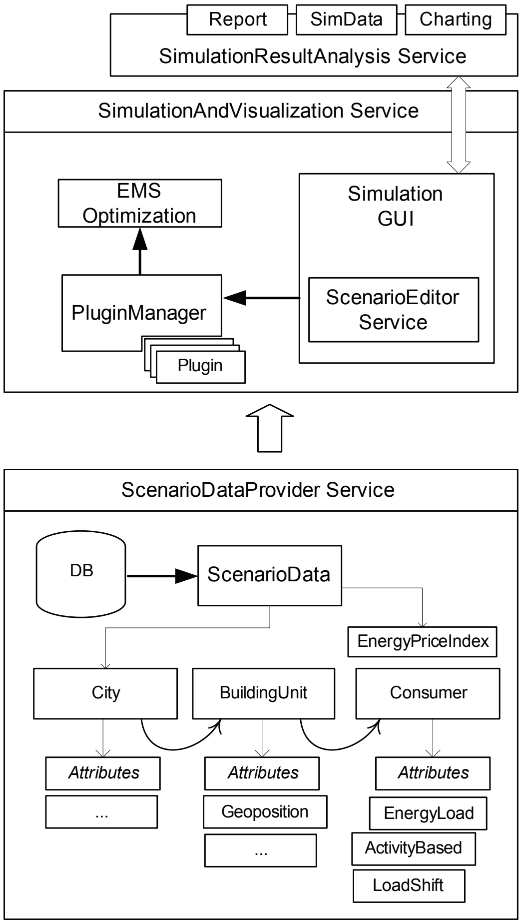

Figure 6: Energy analysis framework architecture.

5.1 Scenario Data Provider Service

For storing and recalling a scenario all its properties are stored in a mySQL database and an additional scenario description file. The *Scenario Data Provider Service* uses a *Database Abstraction Service* to retrieve scenario data. Especially the consumer energy loads, shifting and power saving parameter sets may differ in its available time scale, resolution and duration. These properties are important to determine the simulation constraints and must be specified in the scenario description file along with references to the database tables (see XML fragment for a scenarios consumer configuration below).

```
<entitytype type="consumer">
  <period type="day" unit="01:00:00" start="" />
    <attribute name="type" table="consumertype">
      <id name="consumertypeeid" column="typeid"/>
    </attribute>
    <attribute name="load" table="consumerload">
      <id name="consumerloadid" column="loadid" />
    </attribute>
</entitytype>
```

The data structure of a scenario reflects a hierarchical topology. It consists of a large number of different building units instances that define similar energy characteristics. Each residential and working `BuildingUnit` consists of a predefined set of `ConsumerTypes`. For calculating the optimized energy load through saving technology we have to define a set of parameters at consumer level. Therefore each `ConsumerType` contains two Load Shift parameter arrays namely *shift percentage* and *time tolerance* besides energy load values as well as percental savings for Activity Based Control for each hour in the course of a day. Since these parameters are interdependent and strongly rely on the effectiveness of the energy saving technology and the residents willingness to integrate and use it we perceive each meaningful combination of them as an *energy saving profile* (e.g. the potential shift for consumer devices of persons favoring energy efficiency is higher than for those who are not willing to accept any comfort loss at all). Modifying a profile may not be required for every scenario so they are only available at early scenario design stage. A simulation user might only select between the profiles for convenience.

5.2 Simulation And Visualization Service

The *Simulation And Visualization Service* contains the core functionality for the simulation. It retrieves scenario data and integrates optimization algorithms being used in the simulation run. For customizing the simulation data, GUI input parameters and the output (charts, reports, text data format) a `PluginManager` is available. Each plugin has access to the selected scenario data, the predefined optimization algorithms and export functions for reporting, charting and raw data output. To create a customized simulation model the scenario designer has to implement three classes derived from `SimPanel`, `SimHandler` and the intermediary `SimBean`. `SimPanel` allows easy user interface development by exposing and customizing the desired simulation parameters in a single form based on the *JGoodies Forms* Toolkit. The `SimBean` object is a placeholder to transfer the selected simulation run parameters to the `SimHandler`. By using a `SimHandler` the scenario designer can easily build a customized simulation run based on predefined or self-defined simulation data, GUI settings and optimization models.

6 Simulation Scenarios

To demonstrate the use of our framework as a solution for easy modeling and simulating energy loads on a city scale we used statistics about the building unit distribution of the city Linz[4] for first simulation results. Using the four

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[4] Linz city statistics - http://www.linz.at/zahlen/

building units and linked consumer types introduced in section 4.1 and a hypothetic power price index based on the energy market EEX that is available to end users we simulate the energy load of Linz for a year and estimate the potential savings by assuming a random distribution of energy saving technology among the building units using various coverage percentages.

Linz has about 106,000 households in 18,800 residential buildings. According to official statistics from Statistik Austria[5] the distribution of households is shown in table 2. For working place an additional 1,400 buildings are identified as office buildings.

Table 2: Distribution of households in the city Linz 2007.

Household type	Distribution
Single household (1 person)	37,160 (35.06%)
Pair household (2 persons)	30,196 (28.49%)
Family household (>3 persons)	38,644 (36.46%)

For modeling the saving technology we use an EMS that combines both energy optimization approaches outlined in section 3. For first simulation results we define three EMS usage profiles:

- *Business As Usual* - The residents are not aware of any energy saving potentials and the building does not feature any energy efficient building measures nor is it equipped with low energy devices or energy saving technology.
- *Energy Aware* - House owners and facility managers know about potential energy and cost savings and are willing to invest into promising technology as long as it does not affect their user behavior and comfort in any way.
- *Ambitious Energy Saving* - These residents are ambitious to save energy and costs whenever possible and embrace new energy saving building technology. They even accept a small cut in comfort by shifting loads on a big scale if it helps to reduce costs and save the environment.

Assuming citizens are willing to use EMS technologies for energy consumer control, potential savings get evident when looking at one family households energy load in detail: A moderate energy management optimization model (*energy aware*) estimates potential savings of 558.71 kWh (12.41%) per year based on an initial load of 4,503 kWh and lower expenses dropping by € 136.82 (17.31%) from € 790.26. Exploiting the potential at the expense of user comfort (*ambitious energy saving*) results in increased energy savings up to 16.54%. Figure 7 shows the daily energy load of a *business as usual* family household compared to an *energy aware* one. Besides energy reduction using ABDC during the day loads we can see that loads are shifted to cheaper night hours to reduce costs whenever applicable. The peak at 3 a.m. is the result of a static pricing model. Assuming a dynamic market these peaks will be smoothed because a high demand during night hours lead to an increasing energy price.

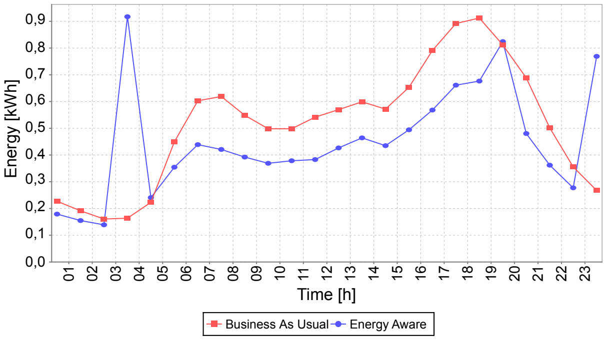

Figure 7: Family household energy load per day with an *energy aware* EMS optimization.

Like in the family household the proposed EMS optimization applies to all building units and subsequently energy consumers within a city. When designing our city wide scenario we wanted to expose the absolute building unit distribution, the simulation period and the coverage percentage to the user. Without any end user energy efficiency measures taken the consumption of the city is about 398.02 GWh per year with energy costs amounting to € 191,368.64 according to the modeled end user energy price index and the average energy consumption per year for each single building unit mentioned in section 4.

Based on the mentioned parameter settings and the building distribution of Linz we can simulate a city wide energy load and impact of saving technology. Therefore we define a low, medium and high city wide implicit EMS coverage distributed over all building units. The simulation results are shown in table 3. Assuming a 50% coverage together with an *energy aware* EMS results in a city wide potential energy savings of about 10.5% decreasing from 398.02 GWh to 356.14 GWh (Figure 8). With a 80% coverage and the *ambitious energy saving* profile city wide energy savings are 19.3% dropping from 398.02 GWh to 321.32 GWh.

7 Conclusions

This paper proposed an implicit management concept consisting of two approaches - *Load Shifting* and *Activity Based Device Control* - to reduce energy demand and cost by considering usage context defined by activities of people. For both a formal model describing the savings poten-

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[5] Statistik Austria - http://www.statistik.at/

Table 3: Simulation results of the cities energy load per year (in GWh) with a varying EMS coverage.

City EMS Coverage	Business as usual	Energy aware	Ambitious saving
0%	398.02	-	-
10%	-	375.61	368.70
50%	-	356.14	341.62
80%	-	341.62	321.32

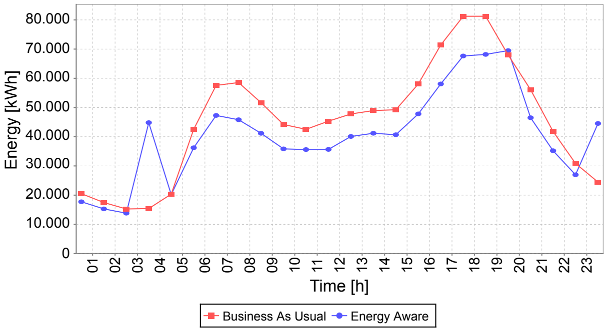

Figure 8: City energy load per day with an *energy aware* EMS optimization.

tial has been developed, and the major energy consuming device groups for different types of households and offices have been parameterized with realistic assumptions.

A simulation study for a whole city shows a reasonable savings potential of 10.5 - 19.3%, depending on the technology coverage across the city and the accepted decrease of comfort. By applying implicit energy management total demand as well as peak loads during the day are reduced significantly. In addition the results indicate new peak loads during the night when using state-of-the-art energy pricing models. Changing prices dynamically depending on actual available production capacities offers a powerful way for energy providers to steer energy demands. This does not only reduce the amount of required balancing energy (and therefore the number of power plants) to cover fluctuations in demand but also simplifies the integration of decentralized renewable energy sources.

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