PeerEnergyCloud – Trading Renewable Energies

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Abstract. An increasing number of private households are becoming producers of renewable energy. From an economic perspective it is beneficial to utilize this energy both locally and promptly. This does require the ability to be able to deal with local excess production at short notice using, for example, an electronic trading platform. In this paper we describe a future energy scenario demonstrating techniques which are necessary for implementing a civil marketplace for trading renewable energies. We will especially focus on the learning of individual activity and load profiles and the prediction of energy consumption and production.

Keywords: Smart Grid, Renewable Energies, Cloud Computing, Activity Recognition, Multiagent Systems

1 Introduction

End-users have traditionally been consumers of electrical energy but nowadays more and more private households are becoming producers of electrical energy, like solar and wind power. Unfortunately solar and wind are not constant and reliable sources of power, since wind power fluctuates from moment to moment and solar power is generated only in the daytime to name just a few reasons for their unreliability. From an economic perspective it is beneficial to utilize this energy both locally and immediately, and hence, to preserve fossil energy resources bearing in mind that their availability is decreasing which increases their prices. That is the much-needed future electrical grid, an interconnected network for delivering solar and wind-based electricity from suppliers to consumers.

One approach would be to let other power plants compensate for this variability and unpredictable power fluctuations, which may only work if more energy is demanded than produced. Peaks in both direction may cause a shutdown of the energy grid. To avoid this either producers have to be shutdown or additional consumers have to be switched on automatically to achieve a so-called load balance. In Germany things are even more complicated due to the shutdown of several old nuclear power plants which decreased already the elasticity of the power grid. This elasticity will be decreased in the future when more and more nuclear power plants will be shut down as planned and no countermeasures

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would be taken. One possibility to safeguard the quality of the power flows and to reduce the current amplitudes and additionally to enable a significant level of penetration and effective use of renewable energy sources amid growing energy demands, would be the ability to deal with local excess production at short notice using, for example, an electronic trading platform.

The objective of PeerEnergyCloud is to research and develop cloud-based technologies for such a trading platform [1]. The partner consortium consists of the German Research Center for Artificial Intelligence[1], the Karlsruhe Institute of Technology[2], AGT Germany[3], Seeburger AG[4] and Stadtwerke Saarlouis[5].

2 Load Balancing & Energy Trading

As a concrete application a micro grid in the city of Saarlouis (Germany) will be considered which consists of about 500 residential units and several photo voltaic systems. The residential units (smart homes) are connected to the local energy provider (Stadtwerke Saarlouis) via a dedicated secured fiber-optic cable which allows for processing of data in real time, e. g. for forecast purposes. The integration of local sensors and actuators in the smart homes will be done via this fiber-optic cable. In this micro grid the provision of power won't be controlled anymore centrally by the current energy consumption instead consumer and local producer are trading locally their renewable energies on a virtual market place. To facilitate this trading the conception and the development of innovative acquisition and forecasting procedures are needed.

Figure 1 depicts in brief the system's components and the data flow from a smart house to the market place for trading renewable energies. First step is the acquisition of data coming from different sources like calendar, weather station and other sensors. To do inference with this data we have to cope with the problem of uncertainty, noisy sensors, and sensor fusion. Dynamic Bayesian networks [2] are a computational framework for the representation and the inference of uncertain knowledge that takes into account previous states as well as new data. To fit the needs to serve as input in the sensor nodes of a dynamic Bayesian network selected data will be preprocessed resulting in sub-symbolic data. All data will serve as input for learning and adapting of fine-grained profiles like user profiles or load profiles. After a first learning phase dynamic Bayesian networks will be constructed from these profiles. In the second phase the dynamic Bayesian networks will be adapted from time to time (given there is enough data). A smart combination of the results of the dynamic Bayesian networks with the profiles then will result in the long-term and short-term forecast of

1 www.dfki.de
2 www.kit.edu
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4 www.seeburger.de
5 www.stadtwerke-saarlouis.de

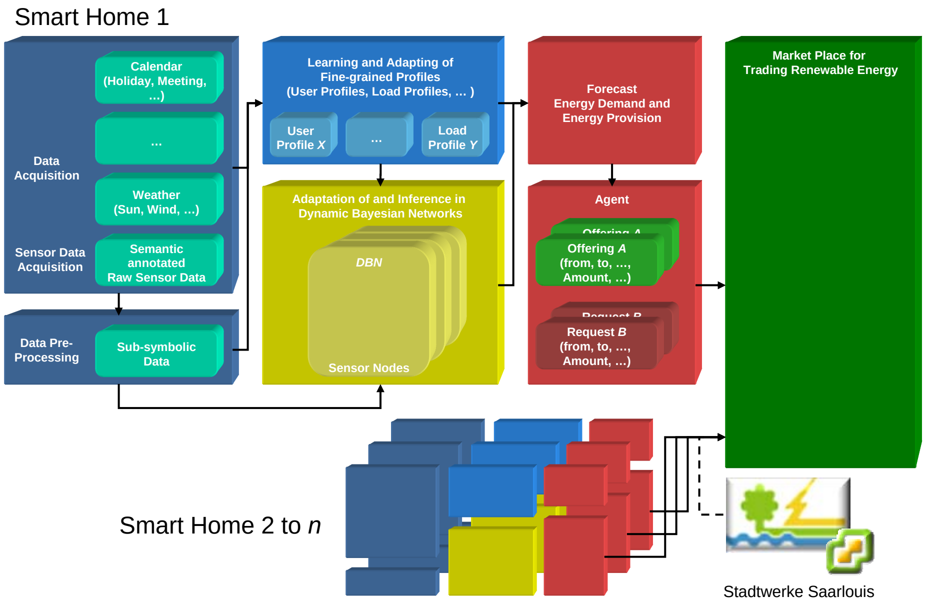

Fig. 1. Data flow in the smart micro grid from a smart house to the market place for trading renewable energies.

a user's energy demand and provision. The long-term and short-term forecast will serve (regularly updated) as input for the user's personal agent which then will deal for him with the personal agents from other smart homes on the civil market place for trading renewable energies.

A **Standard Load Profile (SLP)** is a representative load profile, which helps to predict and balance the load profile of an energy consumer, without to measure and record the current performance. In general most of the households will not show such a consumption pattern. The quality of a forecast (for a group) based on standard load profiles depends on the size of the group. But this standard load profile is not suitable to predict the power consumption of an individual. But this would be necessary to enable a user for trading with renewable energies.

The standard load profile and the actual energy consumption don't have much in common. The curve of the load balance shows many big peaks in both directions. But big peaks in either direction may cause a shutdown of the energy grid and have to be avoided. Hence, this method is unsuitable for energy trading at the civil marketplace.

The **Individual Fine-grained Load Profile (IFP)** overcomes the constraints of the standard load profile. First, it reflects the user's individual power consumption over the day. Second, compared to the standard load profile which consists

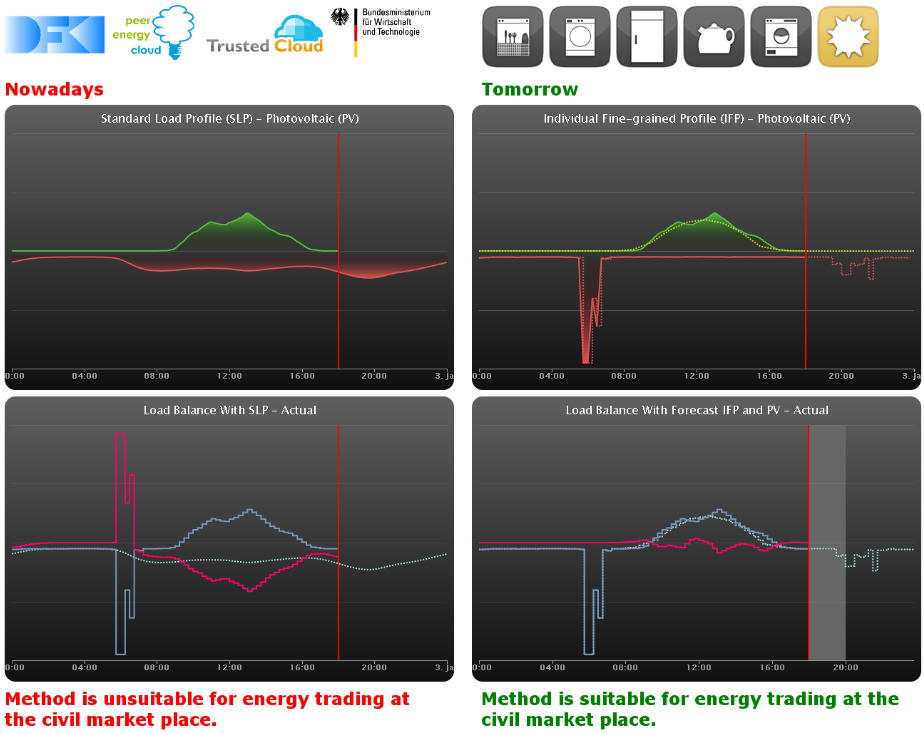

Fig. 2. The standard load profile and the actual energy consumption don't have much in common. The curve of the load balance shows many peaks in both directions. The individual fine-grained load profile and the photovoltaic system are combined and the resulting curve represents the absolute power consumption respectively provision by the household.The resulting load balance shows in both directions only small peaks.

of measurement points every 15 minutes the individual fine-grained load profile consists of measurement points every 1 second which supports the identification of peak consumptions. Additionally, measurement points will be enriched semantically by available sensor data.

Based on such an individual fine-grained load profile and some current sensor data (e. g. weather forecast) a long-term forecast for the next day will be done in the night. The short-term forecast will adapt this long-term forecast for the following two hours based on current context information. Context information will be any available sensor data which will help to foresee a user's activities and therefore his energy demands. For the photovoltaic system – considering its specific parameters and based on a weather forecast – a long-term forecast will be done in the night. The short-term forecast will adapt this long-term forecast for the following two hours based on the local conditions like e. g. just one cloud is covering one part of the photovoltaic system. The resulting individual fine-grained load profile and the photovoltaic system are combined and the resulting curve represents the absolute power consumption respectively provision by the household. This data serves as input for the household's personal agent which then will deal for the household with the personal agents from other households at the civil market place for trading renewable energies. The curve of the load balance shows in both directions only small peaks: this method is suitable for trading renewable energies on the civil market place.

3 Outlook

In addition to load profiling a complementary next step is to realize a mechanism for recognizing activities of daily living (ADL) [3] based on the existing Peer Energy Cloud infrastructure. A relevant factor when dealing with terms like energy awareness and resource efficiency is to understand the motivation of people's actions living in smart houses. To support, influence or even change their behavior we must be able to find out why and under which conditions they are performing those actions. For instance, the problem which monthly energy bills is that people just see the total amount of their energy consumption. Typically there is no logical connections to single daily activities like cooking, heating or watching television.

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