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Cognitive Architectures as Building Energy Management System for Future Renewable Energy Scenarios; A Work in Progress Report

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Abstract- As determined in the EU climate and energy package, until 2020, 20% of energy has to be gained from renewable sources together with a 20% reduction of the overall energy consumption. Today, approx. 40% of the total energy consumption in higher developed countries stems from buildings. Thus, aiming at a reduction of energy consumption in homes and public buildings is an important factor in the fulfillment of these objectives. This requires the development of new building energy management concepts. Accordingly, in this article, a novel cognitive architecture for building energy management based on advanced recognition, decision-making, and control strategies is introduced. Furthermore, a PV supplied, storage augmented, grid connected test bed is presented, which is suitable for flexibly testing the performance of building energy management systems in future renewable energy scenarios. The article shall be understood as the first part of a series of work in progress reports of our research.

Keywords-*building energy management; renewable energy; storage; load shifting; situation awareness; cognitive architecture;*

I. INTRODUCTION

The globally booming demand for (electrical) energy together with the trend of substituting fossil fuels and nuclear power with renewable energy (e.g., solar and wind, which are only intermittently available) brings new challenges to the energy market [1, 2]. In the EU climate and energy package 2009 [3], it has been determined that within the European Union, 20% of energy has to be gained from renewable sources until 2020 and that the overall energy consumption has to be reduced by 20% until this date. For these new energy market constellations, also the employment of novel energy storage technologies and models of variable pricing (time-of-use pricing) – not only for large industrial clients but for all customers – are currently discussed [4].

Today, approx. 40% of the total energy consumption in higher developed countries stems from buildings (heating, cooling, ventilation, lighting etc.). Thus, aiming at a reduction of energy consumption in homes and public buildings has been identified as an important factor in resource saving and is a market with high growth potential [3]. For one part, the development of more energy efficient appliances and better thermal insulation of buildings to reduce heat losses will play an important role in this process. However, due to the high necessary investments, these measures can only be realized over a longer time horizon. In [5], it has been identified that in addition to this, the employment of innovative ICT-technologies together with novel energy management strategies can bring up to 10% of energy savings but needs less investment costs and is realizable within a shorter time horizon. These novel ICT-concepts could furthermore allow for strategies of variable load shifting of energy consumers to times when enough energy is available.

Today, ICT-based energy management in buildings is generally limited to relatively simple HVAC and lighting control mechanisms based on information from thermostats and occupancy sensors [6, 7, 8]. Various research projects (mainly in the field of demand-side management) are currently aiming at developing novel energy management concepts for the efficient scheduling and control of energy consumers in buildings incorporating also local renewable energy producers (e.g., photovoltaic system on the roof top) and storage devices into their consideration [9, 10]. Nevertheless, so far suggested concepts and algorithms for the control of such energy consuming devices and systems aiming at energy saving, peak load reduction, etc. are generally still based on relatively simple and rigid rules [11]. According to the current developments on the energy market described above, novel building energy management concepts will be needed in order to increase energy efficiency and increase the amount of renewable energy consumption.

In this article, the application of a newly developed cognitive architecture as building energy management system in such renewable energy scenarios is discussed. For this purpose, Chapter 2 first gives an outline of the upcoming challenges and needs of future building energy management systems. Afterwards, in Chapter 3, we introduce our novel energy management architecture, basing on advanced situation and user activity recognition and decision-making approaches. In Chapter 4, a hardware test bed modeling a three-phase PV supplied, storage augmented, grid connected household is introduced, which was designed to test the performance of our proposed architecture in various future renewable energy management scenarios. Finally, Chapter 5 provides a conclusion and an outlook.

II. Future Challenges and Needs

In the following, a number of challenges and needs are outlined that come along with the planned shift to renewable energy resources and the targeted reduction of the overall consumption.

- *Limited amount of available energy*

No matter if obtaining energy from fossil fuels, nuclear power, or renewable resources, the energy that can be generated and distributed at reasonable economic expenses is limited. To allow for an optimal usage of available resources, future building energy management systems will have to provide mechanisms to limit the overall energy consumption by detecting and subsequently avoiding the operation of energy consumers not absolutely required (e.g., lights switched on in rooms where nobody is present) or not effective (e.g., heating/air conditioning switched on when window open).

- *Time of production ≠ time of consumption*

One major problem with renewable energy sources is that the times of energy production do not necessarily correspond to the times when energy is ideally consumed. One partial solution to this problem can be provided by a load shifting of energy consumers. However, this has to be done in an adequate way to not block services absolutely necessary and to not limit user comfort. This also includes mechanisms to determine what services are absolutely required immediately/within a certain timeframe by the users and what services are more uncritical for a load shift. Besides load shifting, a second solution can be a temporal storage of the produced energy for later use. However, the affordable storage capacity is still limited due to high investment costs and the energy conversion efficiency is still suboptimal. Furthermore, at least in the case of battery storage, the battery charging and discharging processes significantly influence the lifetime of the storage device. Thus, an optimization of the utilization and charging and discharging strategies of the storage device is important to get the optimum back from the made financial investment.

- *Limited predictability of time of production and time of consumption*

In renewable energy scenarios, the amount of produced energy is dependent on the specific climate and weather conditions, which can only be predicted up to a certain extent.

Similarly, also the energy consumption by the user can currently only be estimated very roughly. Furthermore, climate and weather can influence the amount of energy needed (e.g., for thermal heat pumps). To allow for an adequate scheduling of resources, possibilities are necessary to adequately integrate (uncertain) weather forecast data and user behavior data into the energy management strategies.

- *Variable energy pricing models*

Due to the abovementioned discrepancy between the time of energy production (supply) and desired energy consumption (demand) of renewable energy, it is predicted that “self-regulating” mechanisms will be put into practice via the introduction of variable (daytime dependent) energy pricing models [4]. In the renewable energy scenario, where “clients” can be consumers (e.g. household appliances) and producers (e.g. PV on roof) at the same time, this offers completely new energy trading strategies. For instance a household could attempt a profit maximization by providing energy to the grid at times where energy has a high price and get energy from the net when the price is low and optimize this process by load shifting and storage strategies.

III. Building Energy Management Architecture

In Chapter 2, an overview was given about upcoming challenges and needs for building energy management systems in the renewable energy context. The objective of this chapter is to present a first sketch of a cognitive architecture for the purpose of building energy management capable of handling such scenarios. Fig. 1 gives an overview about the proposed architecture.

The architecture consists of two main modules: the recognition unit and the decision & control unit.

The *recognition unit* is responsible for recognizing the status of different components/devices of/inside the building, of situations going on in the building and of the activity and needs of building occupants. For this purpose, different sensors have to be installed in the building and in/on particular devices. Besides installed *physical sensors* (e.g., cameras, microphones, door, window, and cupboard contact sensors, presence detectors, light barriers, wattmeters, brightness sensors, temperature sensors, pyranometers), information can also be obtained from *virtual sensors* (e.g., status information received from different appliances, status information edited by users, weather data from a central weather station, etc.).

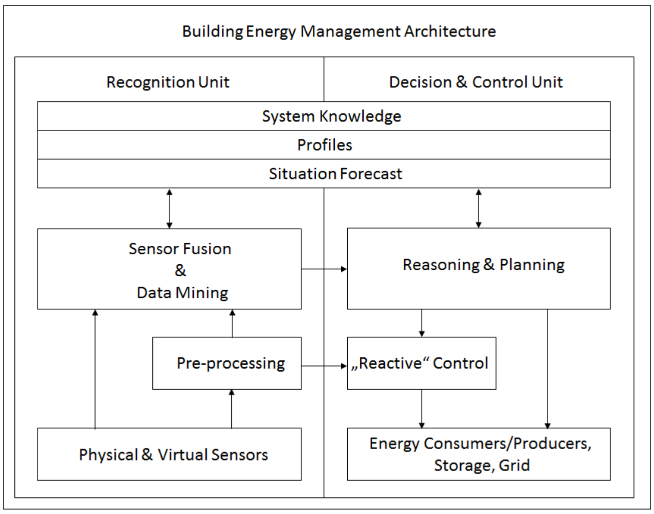


Fig. 1. Building Energy Management Architecture

Based on the current situation, the *decision & control unit* has the task to decide about the activation and deactivation of specific *energy consumers* (e.g., appliances, heating, air conditioning, lighting), about when to charge and discharge *storage* devices, about when to get energy from and provide energy to the *grid*, and when to connect/disconnect local *energy producers* (e.g. photovoltaic system).

Both the recognition unit and the decision & control unit base on a two-level information processing and actuation strategy.

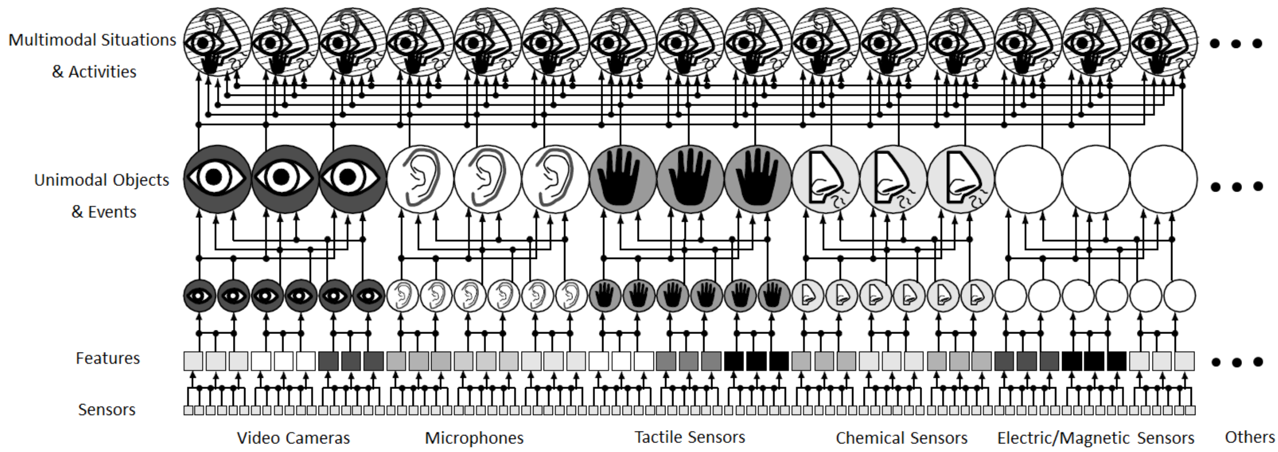


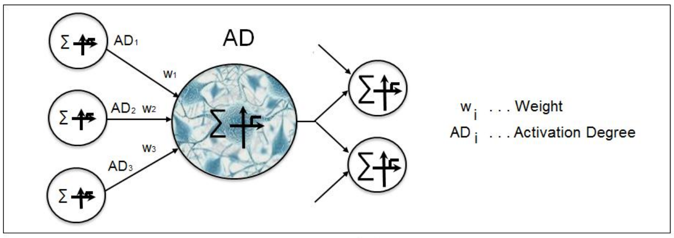
Fig. 2. Basic Structure of a Neuro-Symbolic Network as used in the Sensor Fusion & Data Mining Unit

The lower-level, in Fig. 1 represented by the modules pre-processing and "reactive" control, provides the system with a basic mode of function based on relatively simple, predefined rules in order to avoid system damage or substantial energy losses. In the *pre-processing* unit, simple status information from the building and different devices is extracted. In the "*reactive" control* unit, a simple actuator control is carried out based on this status information. An example for processing and control strategies in this level could be to detect that the battery storage is fully charged and to therefore disrupt the charging process to avoid battery damage. Another example would be to detect that the window is opened in a room and to therefore switch off the heating in order to avoid useless energy losses.

The main modules of the higher-level information processing and actuation strategy are the sensor fusion & data mining unit and the reasoning & planning unit, which provide the system with advanced recognition and situation-aware control mechanisms based on innovative information processing, reasoning, and planning approaches.

The *sensor fusion & data mining* unit receives (partly pre-processes) information from the different physical and virtual sensors and additionally considers *system knowledge* (e.g., relations between objects, events, activities, and situations), specific data defined in *profiles* (e.g., scheduled activities in certain rooms), and information derived from *situation forecasts* (e.g., objects, events, activities, and situations that are likely to occur in specific time intervals or as a reaction to prior situations). Data processing in the sensor fusion & data mining unit bases on a so-called neuro-symbolic information processing strategy originally introduced in [12, 13, 14, 15, 16, 17, 18]. Fig. 2 provides an overview of this neuro-symbolic information processing structure, generally referred to as neuro-symbolic network. Neuro-symbolic networks are structured in a modular hierarchical fashion. Information is processed in consecutive levels starting with the extraction of simple features from sensor data, continuing with a detection of objects and events for each sensor modality separately, and finally resulting in a multimodal recognition of all currently occurring situations and activities.

The basic information processing units of neuro-symbolic networks are so-called neuro-symbols (see Fig. 3), which combine characteristic of neural and symbolic information processing. Neuro-symbols represent and process perceptual information like features, objects, events, sounds, activities, and scenarios. To indicate that the perceptual information they represent has been detected in the environment, they have an activation degree. Each neuro-symbol has a certain number of inputs and one output. Via the inputs, information about the activation degree of connected neuro-symbols, sensors, or other information sources (system knowledge, profiles, and situation forecasts) is received. All incoming activations are weighted (positively or negatively), summed up, and normalized by the sum of the positives weights. If this normalized, weighted sum exceeds a certain threshold, the corresponding neuro-symbol is activated. The information about the calculated activation degree is transmitted via the output to other connected neuro-symbols. For further detailed descriptions about the function principle of neuro-symbolic information processing and examples of its successful application of see [19, 20, 21, 22].



$$AD = \frac{1}{\sum_{i=1}^{n_+} wi_+} \cdot \sum_{i=1}^{n} wi \cdot ADi$$

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if (AD > Threshold)
        Activate Neuro-Symbol
        Transmit 1
else
        Deactivate Neuro-Symbol
        Transmit 0
end
```

Fig. 3. Basic Function Principle of Neuro-Symbols

The *reasoning & planning* unit receives input from the sensor fusion & data mining unit concerning the current status of different components/devices of/inside the building, of situations going on in the building, and of the activities and needs of building occupants. Furthermore, it considers information stored in the modules system knowledge (e.g., information about the building, infrastructure installed, factual knowledge, the outcome of energy management strategies having already been employed in specific contexts), profiles (e.g., energy consumption profiles of appliances and other devices, customized user profiles about comfort ranges of different users), and situation forecasts (e.g., about the weather, likely user behavior, or the electricity price). For the decision making in the reasoning and planning unit, principally, different strategies can be employed. In [23], we introduced an approach based on a simple rule engine. In [10, 24, 25, 26], we introduced a concept based on a complex neuro-cognitively inspired architecture. Due to limitations in space, we would currently like to refer to these publications for further reading. The presentation of a detailed evaluation and performance comparison of different decision-making approaches in the context of building energy management is planned for a separate consecutive publication.

IV. Implementation and Planned Experiments

In prior work, predecessor models of the architecture presented in Chapter 3 have been implemented in AnyLogic/Java [12] and RuleML [23], respectively and successfully tested for a range of applications including building surveillance/alerting systems and autonomous agent control [23, 27]. Suitable test data were generated by different hardware installations and simulation environments [10, 19, 20].

Based on the experience gained in these former projects, we are currently in the course of building up a hardware test bed at our facilities to acquire data and validate the performance of our current architecture for the purpose of building energy management. Fig. 4 presents a schematic overview of the main building blocks of this test bed. For better clarity, the employed sensing and control devices are not depicted. The test bed models a three-phase PV supplied, storage augmented, grid connected household with controllable/ switchable loads. The test bed is designed to allow for maximal flexibility in the testing and validation of a wide range of possible future energy scenarios (see next chapter).

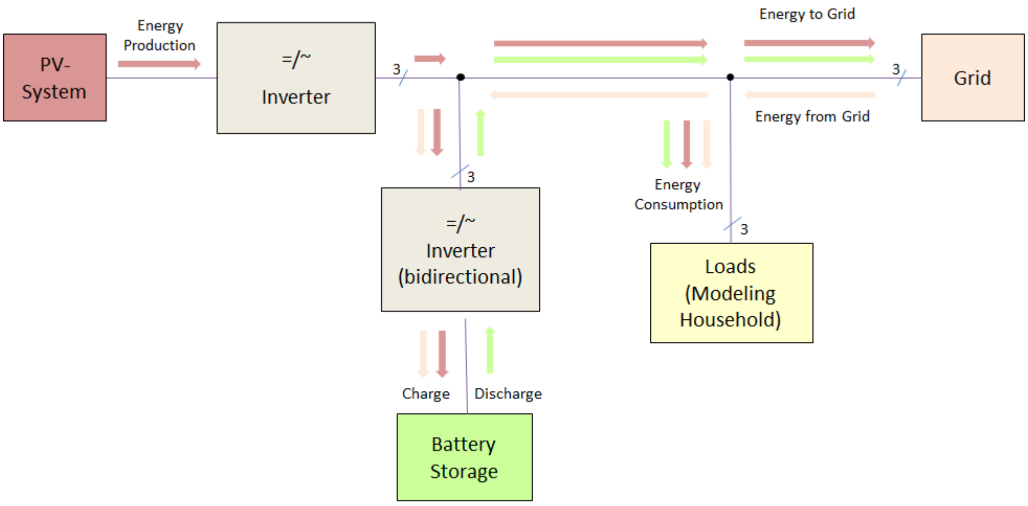

Fig. 4. Schematic Overview of Main Building Blocks of Test Bed and Possible Energy Flows

In the following, a few technical key data of the test bed are summarized: As renewable energy source, a 5.4kWp photovoltaic system consisting of 22 PV modules of the type E-2000|245 is installed on the roof of a building with a tilt angle of 18° and an orientation of 50 south-west. As DC/AC solar inverter, an SMA inverter of the type Sunny Tripower 5000TL-20 is used. For electricity storage, 8 solar lead-acid batteries of the type 12 V SGI 300 are used from which always four are connected in series resulting in two parallel 48V strings with a electricity storage volume of in sum 28,8kWh. To connect the batteries to the AC grid, three bidirectional uniphase Studer battery inverters of the type XTM2600-48 are used together with an ENS31NA as three-phase electrical network monitoring system. The used energy consumers (loads) are switchable/controllable to model different energy consumption scenarios in a household and to allow for the evaluation of different load shifting strategies. In Fig. 4, the arrows indicate the possible directions of energy flow within the system, which are determined and controlled by our energy management architecture implemented on a PC and interacting with the different devices via a Beckoff PLC system. To allow for situation-aware control strategies and performance evaluations, the system is equipped with a range of different sensors and sensing devices including temperature and solar radiation sensors on the PV modules, temperature sensors on the battery inverters, and watt meters in all DC and AC branches. Furthermore, the system obtains information from "virtual" sensors based on event and activity models for different household scenarios and status information from the different devices. Acquired data are stored on a data server.

Energy management strategies to be implemented and validated include but are not limited to (1) weather, situation, and user-behavior dependent resource scheduling, (2) non-user comfort restricting energy saving and load shifting strategies, (3) grid stability support mechanisms via predeterminable load/feed-in curves. (4) profit maximization based on energy trading models with variable price models, (5) "in-house" energy consumption maximization in a multi-parameter setting with secondary goals like user-comfort ensurance and profit optimization, (7) scale-up simulations for energy neighborhood management, (8) combinations of the objectives 1-7.

V. Conclusion and Outlook

In this article, a cognitive architecture for building energy management in future renewable energy scenarios has been introduced based on novel recognition, decision-making, and control strategies. Furthermore, a PV supplied, storage-augmented, grid-connected test bed was designed, which is suitable for flexibly testing the performance of our architecture in different future energy management scenarios. The test bed is currently installed in the facilities of the technology park Villach. Once operational, the test bed will be used to evaluate the performance of our cognitive architecture as energy management system based on real data.

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