Building Energy Management and Data Analytics

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***Abstract*— Energy efficiency in buildings depends on the way the building is operated. Therefore energy management is the key component for efficient operation. Data analysis of operation data helps to better understand the systems and detect faults and inefficiencies. The facility manager benefits from smart analysis that makes use of machine learning algorithms and innovative visualizations. This analysis is part of a bigger review of the current structure of building automation as it is used in today's buildings. The operation targets in energy efficiency are complex, ambiguous and contradictory: indoor comfort, energy efficiency, high availability and low costs cannot be met at the same time. In order to improve building operation, a novel model of automation is discussed. The foundation of this model is in cognitive automation, since each building is unique in its selection of energy sources, architecture, usage and location, which implies that the building's control system has to be adapted individually. This paper connects the data-driven analysis of operation data with a cognitive concept to be used for operating the energy systems in a building and regarding goals on how to optimally operate while considering constraints about the limits of operation, using the complex, dynamic data from building automation.**

Keywords — building automation; energy-efficient systems; cognitive systems; artificial intelligence; bionics; data analytics

I. Introduction

Functional buildings, i. e. buildings that employ building automation, allow monitoring and controlling of their daily operation, have two significant properties with regard to information and communication technology: they are complex systems, which require a control system that is capable of handling the complexity. Secondly they create and collect relatively large amounts of data about their operation, which requires advanced analysis in order to be useful. The first area benefits from advancements in complex control systems architecture, while the second area has a close link to the domain of data analytics and data mining. This paper addresses both areas and brings them together in the energy management of buildings, as successful energy management depends on the integration of all involved systems. We have two topics that we cover in depth in this paper. The cognitive architecture in the second part, which is based on the findings of a functional description of the human mind is the overarching topic. Of the many different functions that are required we have selected to topic of operation data analysis. The building is an interesting field for cognitive science, since it sensory and actuatory equipment is scarce compared to other domains like visual analysis or robotics, where an abundance of sensor data is available. The challenge in buildings is not to harness the huge lot of data, but to identify smart algorithms that are capable of extracting information from data, which is mostly represented as time series of scalar values and which may be incorrect, incomplete or simply contradicting. Therefore the focus can be put on the question how to interpret the data and deduce according actions.

This paper is organized as follows: first we take a look at the work that has been done with regard to data analytics and data mining in energy systems and we examine existing architectures for complex control systems in the area of building automation. In the next section we show the available methods for data analytics in building automation. Then we describe an architecture for the next generation of building automation systems. Finally, a conclusion and outlook close the paper.

II. State of the Art

Automatic condition monitoring, fault detection and fault diagnosis have been studied and successfully implemented in many industrial areas. There are numerous methods for monitoring of wind power plants [1]. In this context Andrew Kusiak et al. used data mining technologies to detect errors in bearings in wind turbines [2]. Also the field of building and system technology profits from data mining approaches to optimize systems and to detect and classify faults. Ammar Ahmed et al. [3] used data mining technologies to model the thermal comfort and the natural light in rooms. They used Naive Bayes, Decision Tree and Support Vector Machine based on sample data sets and compared them with respect to their accuracy and reliability. The work showed the high accuracy and reliability of the methods in the prediction of comfort and energy-efficiency in rooms.

Approaches to modeling and automatic information extraction by data mining also exist in the field of HVAC systems, with most of the work focusing on individual HVAC components. Zhun Yu et al. [4] used Association Rule Mining to extract information from monitoring data. The goal was to identify contexts that allowed deriving energy efficiency improvement measures. The methods also were applied to air

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conditioning data and allowed the identification of inefficiencies and errors in operation. To detect sensor failures especially in heating, ventilation and air conditioning systems the authors of [5] used a combination of Rough Sets and neural networks. By using only a few parameters they predicted residual sensor values during operation. A mismatch to the measured values can generally be taken as an indication of an error. Setu Namburu Madhavi et al. developed a generic scheme for fault detection and fault diagnosis in [6] applicable to chillers. In order to minimize the complexity of the calculations, the cost of the required sensors and to increase the reliability of the prediction a genetic algorithm was used for the selection of sensors. Additionally, an error classification based on previously trained faults and methods of Support Vector Machines, principal component analysis, partial least squares and an error weighting has been implemented. The developed methods were then evaluated using a compressor chiller. Similar approaches were done in [7] and [8] for fault detection and diagnosis in compression chillers, which was extended in [9] towards the detection of several simultaneously occurring errors.

Modern technical systems in building automation grow more complex as they have to handle a large number of distributed sensor data and this problem cannot be solved easily with traditional, centralized systems [10]. In the area of building automation, mostly reactive systems are used, which perform poorly in unforeseen situations [11]. Current technology is reaching its limits and has a long way to compete with human capabilities [12]. This problem was clearly visible in the Smart Kitchen Project at the Institute of Technology at Vienna University of Technology [13]. A normal kitchen was equipped with large number of sensors and actuators connected to field bus systems. The purpose was to assist persons by recognizing the user behavior and reacting on it. A result of the project was that there was a need of new solutions, which can not only compress, filter and abstract perceived information, but also infer it with known situations, in order to be able to act in an appropriate way. This required a more complex processing of sensor data [14].

In the research of building automation, behavior-based systems like [15] have been developed for the automation of user routines. Ontologies are used to describe observed user behavior patterns and task hierarchies model the actions. In [16], a cognitive architecture is developed for usage in demand-side management. While these architectures have been designed specifically for the area of building automation, other general purpose architectures are available. Many of them follow a cognitivist approach [17], which is characterized by a top-down design process with symbolic, rule-based, algorithmic information processing. Sensor data is abstracted to multiple levels of symbols, as shown in [12]. The symbols provide the input to the cognitive architecture, which keeps an internal symbolic representation system. Together with knowledge, the perceived input usually activates beliefs in the agent [18], [19], [20]. Beliefs represent what the agent knows about the current situation. This may be achieved with production rules [18] or memory activation. Based on the beliefs, options are proposed of what is possible to do in a certain situation. A cognitive agent can also have multiple goals, which are represented by motivations [18], [21]. A motivation therefore tells the agent what to do. The options are evaluated based on the motivations and the potential to reach a system goal by taking a certain action, then one of them is selected to be executed [19], [22], [23]. Some well-known cognitive architectures are, among others, SOAR [19], BDI [18], LIDA [20] and ICARUS [24].

Another approach for a building automation system is to use case-based reasoning instead of rule-based reasoning, which many architectures do. In [25] a system used reinforced learning in order to assure comfort and to minimize energy consumption. Different to rule-based systems, this system started without any rules and needed a couple of simulated years of training to learn the correct action to an input state. However, at the end, performance was equal to traditional approaches and flexibility was still maintained.

III. Data Analytics in Building Automation

Data acquisition in buildings and building-related energy systems is primarily implemented for control purposes and for manual examination of historic events. Practical experience with monitoring data of building related energy systems has shown that it is often incomplete and contains different types of errors (e.g. incorrect sensor calibrations, misconfigurations or missing samples). As a result, analysis as found in norms and standards, e. g. EN 15316 can create misleading results [26]. Therefore data sanitation and the validation of the recorded data is an important step that has to be taken before any other analysis. To illustrate the data sanitation approach we use recorded data of a solar driven adsorption chiller. The system uses hot water that is produced by solar power to produce cold water, which is used for cooling incoming air in ventilation systems. Applications are, for example, the air conditioning of meeting rooms or big event facilities, but also cooling facilities for food products. The design of the system is shown in Figure 1, showing the Low Temperature (LT), Medium Temperature (MT) and High Temperature (HT) cycles along with the installed sensors that are used for analysis.

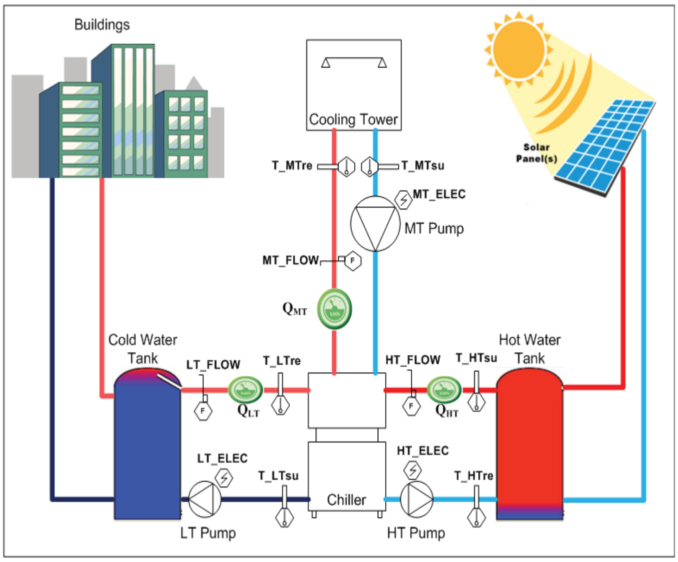

Figure 1 Adsorption chiller system configuration

The first step is an automated detection of outliers. The z-scores [27] has been altered as given in the following Equation 1.

$$\boldsymbol{Z-Score_{cycle}} = \frac{X-\mu_{cycle}}{\sigma_{cycle}} \qquad \text{Equation 1}$$

Here, μ_{cycle} represents the mean of each ON and OFF cycle whereas, σ_{cycle} shows the standard deviation of each cycle. For automatic detection of outliers, the original raw data is normalized using cycle based Z-Score and then automatically clustered using Expectation Maximization [28]. The second row in Figure 2 shows the detected outliers marked with circles with cycle based Z-Score. The benefit of using cycle based Z-Score over the normal Z-Score is the fact that the behavior of machine vary in two states (ON/OFF), therefore there are certain acceptable values in one state which might not be acceptable in the second state. E.g. a sudden change in temperature can be observed in Figure 2 on 17/06/2009 at around 18:00 o'clock. As the change is not that much far away from the normal behavior if we consider the whole data of machine, thus not considered it as outlier by the normal Z-Score, as can be noticed in row one in Figure 2. But the same has been detected with using cycle based Z-Score as it makes these values away from the normal behavior. That helps the EM clustering to identify them in the cluster of outliers. These can be removed and given that they are singleton - interpolated with neighboring values.

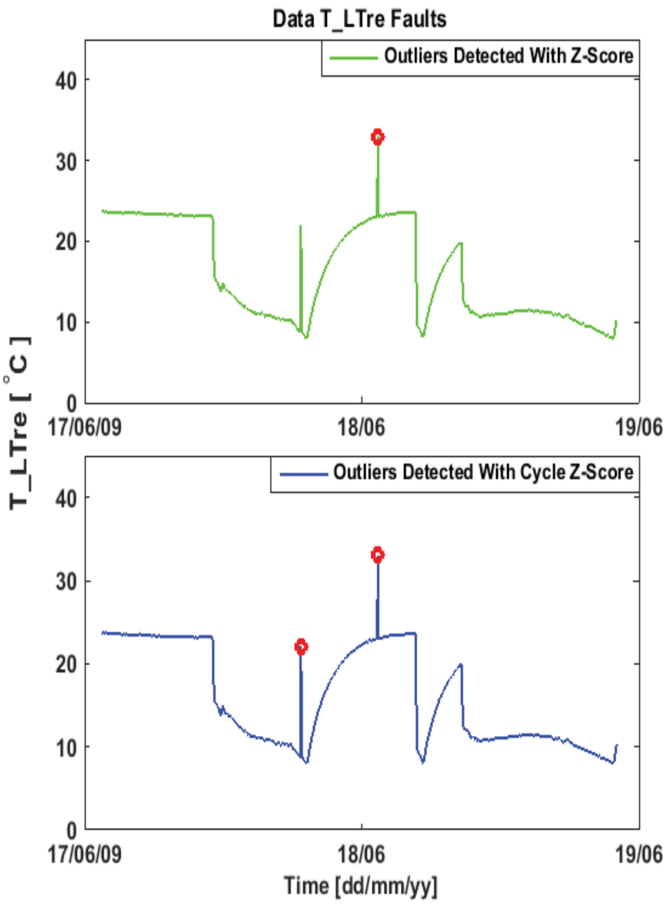

Figure 2 Outlier detection using z-score and cycle based z-score

In a next step the plausibility of data can be checked by including process knowledge into the data analysis. Based on the principle of energy balance, the following statement can be used in the given adsorption chiller: the sum of all thermal power that enters the process needs to match the outgoing thermal power. This represents the law of energy conservation in each point in time, given that there is no thermal storage in the process (which is the case here).

Using this knowledge and regarding the thermal losses of the process, which are not measured but can be estimated from experience to be around 300 W, we can derive that

$$Q_{LT} + Q_{HT} = Q_{MT} + 300W$$

While this will not hold for a precision down to numerical equality, it still allows checking the data points Q_{LT}, Q_{HT}, and Q_{MT} in Figure 1 for plausibility by checking that the formula above holds within a certain ε-environment around equality.

IV. Next Level Building Automation: The ECABA Architecture

Building automation systems of today are rigid with regard to controlling their components, especially the energy systems. Goals like energy efficiency are programmed into the system and are tightly integrated into the control strategies; they are not achieved autonomously, but are implemented upon design phase. Unlike programmable control systems, cognitive systems learn through interaction with data and reprogram themselves in order to adapt to dynamic environments. Within the project ECABA (Energy-efficient Cognitive Autonomous Building Automation), a building automation system shall be able to pursue goals autonomously and to adapt itself to changes in the environment.

For a building automation system, the following are the top goals: 1) Minimize energy consumption over its runtime by maximizing the exploitation of renewable energy sources like solar thermal, 2) maintain user comfort while people are in a building and 3) being able to react to disturbances or changes in the environment.

The human mind is a multiple-input multiple-output (MIMO) system which has the ability to process large amounts of sensory information to solve complex control problems. Such problems still remain out of reach for programmable systems as the processing of data in high dimensional spaces requires simplifications which often lead to suboptimal solutions. Cognitive architectures try to mimic the functional model of the human mind and provide a promising approach to handle complex situations, i.e. a large set of possible input states and several options for actions, by adjusting focus and processing data on demand in order to get from one state to a more desired state [12].

Bionic approaches to developing technical systems are inspired by the way the brain works regarding how information is perceived, represented and transformed in order to make decisions [13], [29]. Such systems are able to sense, learn from experience, predict the consequences of actions and plan in order to achieve goals. As a result they exhibit a proactive behavior since, similarly to humans, they are capable of planning in advance to make a desired state happen or to avoid an undesired state.

Since the human mind is probably the most autonomous and adaptive controller, we follow a bionic approach in using it as an archetype for the ECABA control system. However, in difference to other cognitive systems ([18], [19], [20] [24]) the ECABA model uses embodiment for the generation of motivations and emotions for the system's fine-grained goal evaluation as the basis of decision making and further integrates those into a holistic model. The applied concept of embodiment represents the building's physical properties, sensors and actuators and implements a generative approach to creating the agent's motivations. Emotions in ECABA influence the internal state (motivations) of the cognitive agent and therefore they enable context-based decision making. As such, goal priorities may change and the agent will modify its plans in order to pursue a more urgent goal. Thus when trying to harness human information processing for solving complex problems we have to model such basic decision making processes. In fact, following a human-inspired approach, we believe that only the consideration of such evaluation mechanisms (as a basis of rational cognition) enables technical systems with human-like control capabilities.

Overall we use as starting point the Simulation of Mental Apparatus (SiMA, former ARS) cognitive model [30] and translate it into the domain of building automation. The latter needs the capabilities of human cognition, but strongly deviates from the design of a human body and mind. If we succeed in translating the functions and interfaces of the human mind into an autonomous, cognitive building management system, we open the door for new services in building operation by transferring cognitive capabilities and using them for optimal operation of buildings.

A central aspect of ECABA is the introduction of reinforcement learning for acquiring knowledge. Similar to [25], the system explores different actions for different situations. Each feedback from the system is stored. In that way, the system learns the consequences of actions. The next time the system is confronted with a similar situation, it can choose to act the same way as last time, or to avoid that action, depending on the feedback. The longer the system is trained, the more confident it will be regarding its actions. However, the work of [25] can only cover a part of the system. Following the SiMA approach, the ECABA architecture has extended functionality to evaluate situations depending on the current goals of the system. Further, the system has the possibility not only to use previous experience for making decisions, but also to use external modules like a model based predictive control module to generate an action to execute [31].

The process steps that are taken during execution are described in Figure 3. External stimuli originating from the environment and the body (i.e. the building) are monitored by sensors and are processed in step 1. Sensor inputs are inferred with stored knowledge in order to perceive the current state. An internal representation of the state is thus created which corresponds to the perceived image. The perceived image is compared in step 2 to the target state that the system aims to maintain. When a deviation from this target occurs, motivations are generated. This process is similar to the homeostatic process which regulates stable internal conditions in organisms by changing variables as a response to changes in external conditions (e.g. control of blood sugar levels). System motivations vary in time depending on the perceived image and result in the generation of system goals. Depending on the deviation from the state condition each goal has a different importance.

The evaluation process in step 3 assesses to what degree an action leads the system closer to fulfilling a goal. Goal fulfillment is perceived as a reduction on the intensity of motivations, represented by rewards. A reward is the difference of the intensity of the motivations between two time steps. If an action did successfully lower the intensity of a motivation, the reward from that motivation is positive. The outcome of this evaluation process is the generation of emotions. Rewards can be modified depending on the changes of the motivations. Rules are used as implicit system knowledge in order to introduce external preferences. They further provide a negative or positive reward in order to increase the learning tempo. For example, in order to satisfy the motivation for thermal user comfort the system turns on the heating and the comfort reward in the system increases. An external rule for reducing energy consumption provides a negative reward to the system, with a magnitude depending on how much energy is consumed.

The information available to the system at each time slot is stored in step 4. Here the complete situation is provided including the perceived state, the action performed at the previous time slot and the evaluation results of step 3. The sum of the stored information in the memory is the experience of the system. The system uses the gained experience in order to improve on its decisions. For the detection of similar situations a comparison between the perceived image and other stored images takes place in step 5. If similar images are detected, the whole situation is activated. Here the only criterion for the match is the spatial setup.

At this point, in step 6, the system has to decide which system goals shall be pursued. In general more than one goal can be chosen to be fulfilled. It is decided based on the goal importance. The purpose of the system is to return to a state of balance, where no goal has an importance. After this decision, the most urgent unbalance of the body (building) will be handled. Additionally, the system also has to be able to react on external stimuli, e.g. if sensors values are above their allowed limits. In that case, an emotion will be the top goal.

In a first version of the system, the actions of the system will be based only on previous experience. Therefore, relevant experiences as sequences have to be activated from the storage in step 7. In step 5, images were activated, which were identical or similar to the current perceived state. A more fine-grained selection of similar cases now takes place by comparing the history of these images to the history of the current image. The selected cases activate on their turn state sequences ahead in time of previously experienced states. Each activated sequence is like a prediction a couple of time steps in the future, in order to determine the consequence of actions.

In order to fulfill a goal, in step 8 options for action possibilities are generated. For the decided goal, first the activated sequences are evaluated regarding the possible fulfillment of the goal with the belief “what worked before, will work today too”. Further, experience can also be used to explicitly avoid certain actions, which will bring penalty to the system. If experience is not used as a source, an exploration function or randomly generated options will be used to gain new experiences. In further versions of the application, also external models of e.g. model predictive control can be included for action generation.

After generation of action possibilities, in the next step 9 options are evaluated and compared regarding goal-fulfillment. Alternatively the system may prefer new actions in a certain situation instead of known actions. Finally, in step 10 all options are sorted and the best option is selected. That action is then performed in the system.

By evaluating actions for perceived states, the system is continuously trained to find the best action for each situation. Flexibility is given in that way that rules can still be applied to the system to influence the evaluations of the states as well as the actions taken. If the environment changes, the system automatically updates its behavior as it adds new states and reevaluates its actions.

V. Conclusion and Outlook

The benefits of the presented approach are in the potential savings of energy and maintenance costs in the building and its energy systems. The main benefit is the reduction of user energy costs through automatic, on-demand data analysis and management of energy usage on the basis of data mining and artificial intelligence methods.

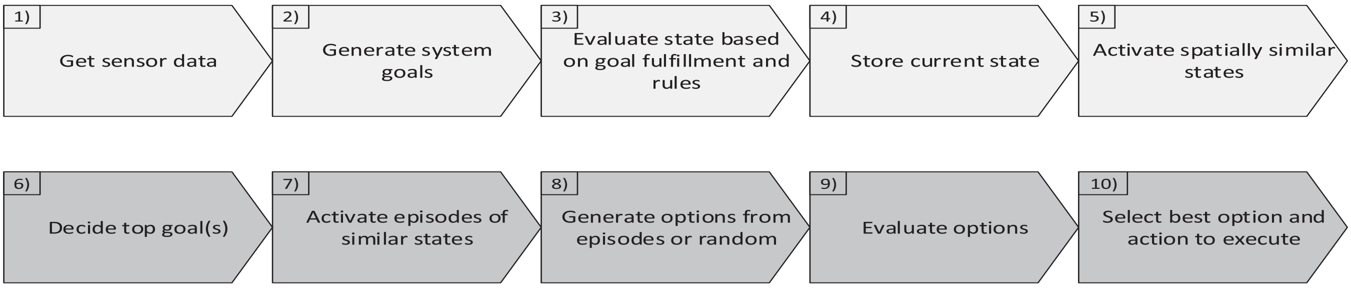

Figure 3 Evaluation process within the cognitive architecture ECABA

This paper shows the current status of the cognitive architecture and covers on particular function dealing with operation data analysis. The impact of an architecture as such is difficult to assess, but indicators are visible: the approach is expected to influence the research of disciplines outside technical disciplines, namely neurology, neuropsychology, psychiatry, pedagogics and the social sciences. And the approached has only recently been acknowledged by the Austrian Funding Agency: an 800 kEUR research project starting in 2015 will continue the research[1]. In particular, following a bionic approach for cognitive control systems, we harness the autonomous and adaptive features of the human mind. Regarding autonomy, the system generates its goals based on its bodily (i.e. building) state. The competition between these goals is handed over to a multi-step evaluation process, which adapts the system’s decision on the external world, the system’s state. Additionally, conflicts between contradictory goals are considered and mediated. User preferences are integrated as rules providing rewards for the system. These features enable the system’s adaption on different demands and make it more robust to disturbances.

Overall, the cognitive layer on top of an existing building management opens a wide area of new services that can be implemented: buildings become autonomous units that can be operated on a goal basis, thus introducing flexibility into daily operation. The available flexibility can be used for new service such as pooling of buildings in virtual power plants. Robustness and the ability to react on changes in the environment are benefits that are highly appreciated due to the achievable increase in uptime and availability and thus higher user comfort.

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