Autonomous Control Strategy Creation for Building Energy Management

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***Abstract*—Building automation and control defines the energy efficiency of a building during its operation phase. Optimization of the underlying control strategies is still mainly done manually. By introducing a cognitive system and providing it with information on the building, its energy systems and the operation goals, this paper shows how to autonomously optimize control strategies for building energy systems. The system architecture consists of the cognitive system, an ontology and a physics simulator that allows to assess the quality of a control strategy. In this paper a first use case for optimization of a ventilation system is presented and the processes in the cognitive system that lead to the creation of control strategies are elaborated.**

Keywords—building energy management; cognitive system; automation and control; energy efficiency

I. INTRODUCTION

Energy systems in buildings are often not operating efficiently, therefore the European Union has declared reduction of energy consumption as one of its main goals and manifested it, amongst others, in the Energy Performance of Buildings Directive (EPBD) [1], buildings account for 40% of the overall energy consumption in the European Union as well as 36% of all greenhouse gases (GHG) [2]. Aside of costly building refurbishment measures, an improvement of the building automation and control system is often a low cost alternative. In this work, the control strategies shall be optimized using a cognitive system. The architecture of the cognitive system mainly focuses on unconscious processes that processes low level symbols and defines the motivations of the system. The building under controls is interpreted as the body of the system, providing sensory information and being subject to actuation. The goal of the system is to create optimized controls with regard to energy efficiency and comfort that are created autonomously based on the description of the building and its energy systems.

The rest of this paper is organized as follows: Section II gives an overview of the state of the art with a special focus on the prerequisites for the cognitive system; Section III covers the methodology of this work and Section IV elaborates the specific approach for creation of control strategies. Section V explains the system architecture and Section VI rounds up the paper with presentation and discussion of results.

II. STATE OF THE ART

Building management operates on a complex system that shall fulfill multiple goals: energy efficiency (i. e. low-energy building design, efficient operation of components, use of renewable energy, etc.) and indoor comfort (i. e. maintaining parameters for temperature, humidity and air quality within the comfort boundaries) are the main focus for energy management, but within the same system also security and safety of both building and inhabitants are important [3]. Energy management itself addresses multiple domains and only operates efficiency, if all domains work together. The challenge in this paper is to optimize the performance of the supervisory control system in a building, which operates on rule-based control strategies. Building automation is based on a mix of control strategies, which are based on finite state machines and process control, which is mostly realized through continuous, linear controllers. Control strategies are widely established although they have certain deficiencies: control strategies are static programs, which are, due to cost constraints, often templates that are applied to various different system, given that the systems have similar structure. After commissioning the optimization of controls is not commonly done, instead they are left as is [4]. If the goal of energy management is energy efficiency, the programmer has to translate the efficiency goal into parameters for the control strategies, a task, which is time intensive and requires highly skilled personnel.

The cognitive system presented in this paper is based on the bionically inspired, cognitive architecture SiMA [5]. It operates on Damasios concept of emotions to model the human foundation of decision making [6]. SiMA aims at engineering the human cognitive process in an ongoing, interdisciplinary research project, following a top-down development approach. In order to reproduce human cognition on a functional level, SiMA uses well established psychoanalytic theories to determine the complex underlying functions of human decision-making and computer scientists then implement these functions as independent modules that come together in the cognitive cycle depicted in Fig. 1.

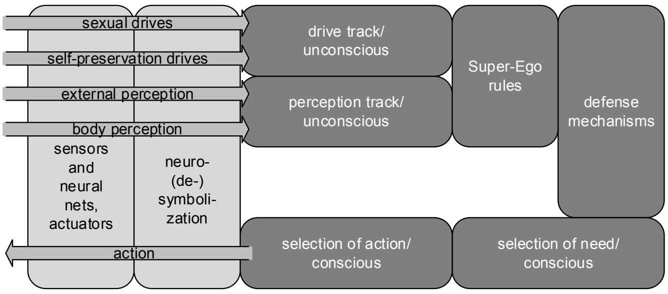

Fig. 1 Functional Model of the Cognitive System [7]

A comprehensive elaboration of Fig. 1 would go beyond the scope of this introduction, but we will shortly outline some basic concepts that are relevant for the work at hand, a detailed explanation of the model is available in [7]. The model is processed from top left to bottom left. Inner- and outer-bodily perceptions traverse the modules in a fixed order and each module can enhance the data with knowledge from the systems' memory and various evaluations. After multiple cycles, the system will come to a decision, based on the evaluations added to the options provided by the systems memory. Central to the decision are the inner-bodily demands, represented by so-called drives. These flexible data structures represent continues bodily demands and the rewards for meeting these demand are an essential driving force in the system.
For the application of energy management in buildings, drives are used in a similar fashion to represent the users demands on the generated solution regarding comport and energy efficiency. SiMA is furthermore a hybrid architecture, meaning that it can combine symbolic and sub-symbolic approaches to artificial intelligence. This is essential for the work at hand, since we consider the possible relationships present in the problem domain, building automation, to be too complex for sub-symbolic approaches, like neural networks. The combination of higher level, symbolic, representation and lower level pattern matching and learning has the best chance of solving the problem of control strategy creation for energy management.
Different research groups have already used the SiMA framework in different settings. The base research project implements SiMA in cognitive agents within an artificial life simulation, with the expressed goal to reproduce human behaviour, with its strengths as well as its flaws, during psychoanalytically inspired use cases [8]. [9] introduces a SiMA based framework called SiMA-Compact (SiMA-C) and uses it to simulate and predict decision making in humans within the context of switching energy providers. The project especially emphasizes the role of emotions and social interaction in the decision-making process. [10] presents a recommendation system for marketing in the field of consumer simulations. The research project ECABA [11] researched a theoretical approach for transferring the functions specified in SiMA to the building control domain. The project developed a hypothetical controller for managing a centralized heating system that can utilize fossil based and alternative heating methods. Its goal was the optimization of the heating process to minimize cost and environmental footprint, while still meeting the building's comfort demands.

III. General Methodology

The cognitive controls system presented in this paper creates flexible controls, but at the same time maintain the established structure of control strategies and is based on the research in project KORE (funded by the Austrian Research Agency, project number 848805), which develops methods for autonomous optimization of controls in the energy management of buildings. The cognitive system operates on an ontology, which delivers meta-data on the building's energy systems and its semantic properties, as well as on indoor comfort criteria.
The cognitive system is responsible for establishing control strategies for the operation of the energy systems. It evaluates the achievement of the given goals, which are energy efficiency and indoor comfort.
In order to allow a seamless integration into existing building automation systems, the result of the cognitive system is a classic rule-based control strategy that can be coupled with existing building automation systems. This allows to continue using existing structures and systems, but at the same time enables the link to a cognitive system. In regular intervals (i. e. once or twice per year) the control strategies can be re-evaluated and optimized and, if a better solution is found, re-commissioned to the building automation system.

IV. Creation of Control Strategies

The system currently uses two cognitive processes in different areas of the application. The first cognitive process controls the execution sequence of the cognitive components, e.g. it decides if it should re-use an existing control strategy and adapt or re-parameterize it, or if it should generate a completely new strategy that fits the problem. This cognitive process is not subject to this work but is discussed in [12].
The second cognitive process is responsible for generating a valid control strategy that optimizes the buildings energy efficiency while maintaining comfort. To achieve this, the system traverses a problem definition that consists of a definition of the building, its energy systems and the specific constraints and goals of the problem. It applies the cognitive cycle presented in Fig. 2 to each zone in the building (whereas "zone" is used as an umbrella term for rooms, floors, areas or combinations thereof). After multiple cycles, the cognitive process generates a control strategy using a library of basic control blocks (e. g. PID controllers or time schedulers that define when a system is switched on or off) that are required to fulfil the user goals for the zone. As mentioned above, goals are the main driving force for choosing the central block but not all zones have explicit goals, e.g. the buildings top zone, in most cases. The cognitive cycles in these zones are driven by the demands of their connected zones and therefore have their first cognitive cycles after all goal driven zones had theirs. This way, the essential blocks are distributed and the non-goaled-zones can then provide necessary inputs and outputs where appropriate. The stop condition for traversing the

building is a valid rule spanning all zones. Remember that the cognitive cycle always aims to provide the best solution for the current situation, i.e. if the neighbouring room changes, the previously chosen approach might not be the best solution anymore and is replaced by a different approach. Detecting and managing loops in this process is an open topic and currently avoided by providing building blocks that minimize the occurrence of such loops.

The control strategy generation was developed by by adapting and simplifying the SiMA model outlined in Section II, since the SiMA model is intended to perform decision making in a real time system, which is addressed by starting out with a quick solution that is refined by various functions but could still be used unrefined if there are not enough resources. Control strategy creation, on the other hand, has no hard time constraints and therefore simplifies the process by integrating the refinement steps into a single activation step. Similar considerations removed the separation of primary and secondary process (as described in [5]) or details on these concepts, and combined various rule application functions into a single step.

Fig. 2 shows the resulting cognitive cycle, consisting of Problem Translation, Activation, Semantic Rule Application, Evaluation and Reality Check and Solution Storage. The rest of this section will explain how each step provides additional evaluation for the available control blocks in order to decide how to combine them into a beneficial control rule.

A. Problem Translation

The process starts with the problem description; this description includes the building structure and energy systems, the goals (energy efficiency and indoor comfort) and the target period for the control strategy (e.g. summer).

The cognitive system generates internal goals based on the relation between comfort and energy and uses them in the next step for goal based activation, while the building structure provides the cognitive system with perception of the current situation, which is later used for reality checking activation. The target period is also used during activation to increase the matching efficiency for the case based reasoning.

B. Activation

The activation step provides an initial evaluation value for each control block that reflects the block's expected performance under a given goal constellation. At the current stage, this is implemented as fuzzy cognitive maps to represent this information (Fig. 3). To increase flexibility and control within the net an additional abstraction layer called "Strategies" has been added that can be used to specify alternative blocks for the same purpose.

Fig. 3 shows an example of an activation map for a ventilation use case. The associations between goals and strategies in Fig. 3 represent how well we expect a strategy to perform for a goal and are intended to be updated based on experience with the quality of the developed solutions. The relations between strategies and blocks represent the suitability of a block to a given strategy and allows specifying multiple options for implementing a strategy. The system uses separate maps for different contexts (e. g. summer operation vs winter operation).

C. Semantic Rule Application

This phase combines the SiMA concepts of defence mechanisms and social rules as described in [5]. It allows the system to integrate classical production rule aspects into the cognitive system, which is beneficial for some specific use cases. The building experts can define rules directly in a simple IF-THEN format e. g. "IF a block is tagged 'control' AND has an input tagged "enable" THEN connect a follow-up block to that input".

D. Evaluation and Reality Check

This phase matches the current dominant control blocks, clustered by strategies, against the building structure, i.e. the system checks if the required inputs and outputs of the blocks can be connected to the available sensors and actuators in the building structure. Central aspect of this phase is type based port matching. In order to avoid taxonomical haywire, we use standardized port types as specified in VDI 3813-2 [13], which we extended on demand. To increase flexibility, hierarchical port types covered in VDI 3813-2 were defined. This reality check is potentially very calculation expensive, which is why it is situated at the end of the cognitive cycle. The reason for this high demand is that control blocks do not match zones perfectly. This can be solved by using other blocks to connect the target block to the room, e.g. a sum block, or provide artificial inputs, e.g. by using a constant demand block. The complexity is increased further by the fact

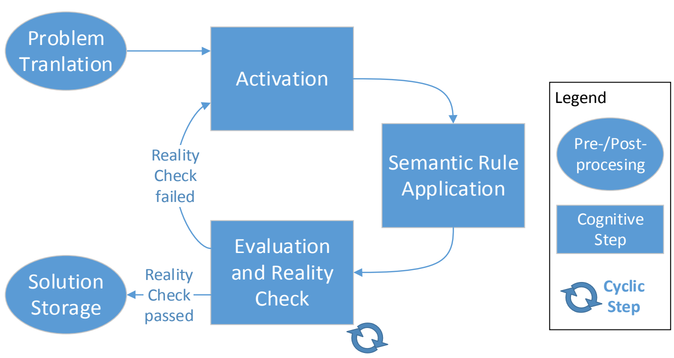

Fig. 2 Cognitive Cycle

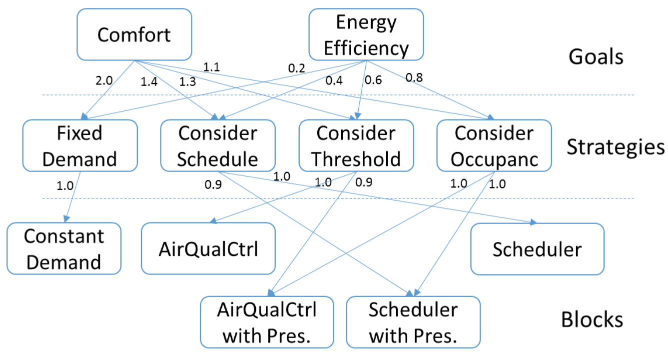

Fig. 3 Activation map

that some blocks will need to be connected to other rooms, e.g. a local scheduler that needs to connect to a global clock. This can result in multiple attempts before the blocks proposed by the previous cognitive steps can be connected or discarded. This is why the step is marked cyclic in Fig. 2. We attempt to minimize the number of attempts by using a similar mechanism as during the activation step, i.e. similarity based activation currently implemented as fuzzy cognitive map. We use an additional map to encode, which blocks are most successful when connecting a given block to a given zone (in this case the similarity is based on the goal block ports and the zone ports). It might still require the system to repeat the port matching several times, so previous tries are tracked in case a search does not converge and the system has to retrace. If a block is not connectable in this step, the system will exclude it from the list of possible blocks (for the current application run only) and the cognitive cycle restarts in order to find the next best block for a given strategy, or drop the strategy entirely. If the reality check is passed, the cognitive system will accept the rule as implementable and store it (see Section V). Due to the nature of the problem the cognitive cycle can fail to reach a conclusion. In such a case, the last attempt of the cognitive system will be a rule that consists only of the sensors and actuators present in the building structure, fully or partially connected, in such a case the cognitive cycle will interrupt and report a failed attempt.

V. System Architecture

The main components of the system are the cognitive system, an ontology for knowledge representation and storage of results, and a simulator (Fig. 4). The assessment of the quality of a control strategy is done by evaluating the simulation results with a fuzzyification approach that uses fuzzy membership functions to aggregate and assess the energy and comfort goals. The sequence of execution is coordinated by a director, the operation of the system can be observed by a user interface (GUI).

A. *Cognitive System*

The cognitive system described in the previous chapter is the first component in the system architecture. Fig. 4 shows that the cognitive system connects to the Director component and the knowledge base over a HTTP-based interface. The knowledge base contains the ontology that stores the episode memory and semantic knowledge for the cognitive system and is used as central component for sharing data in the system. The director component triggers other components with commands sent via HTTP. The control flow to the cognitive system (labeled “signaling” in Fig. 4) is limited to simple triggering command, implemented over RESTful interfaces. Currently the cognitive system only accepts the commands “Optimize”, with configuration parameters that identify the settings outlined in beginning of Section IV and “Cancel” for interrupting the current process prematurely, for example to prepare it for another optimization request. Any other data flow to and from the cognitive system, is directed over the knowledge base and is performed over a SPARQL[1] based interface (labeled “store data” in Fig. 4), implemented on a FUSEKI server[2].

The cognitive system was built using graph-based data structures that represent the various valuations generated during the steps outlined in the previous section. We chose this representation for its flexibility in modelling relations in data, as well as the fact that it reflects the way the ontology organizes its data (which is a collection of data triples). The cognitive cycle organizes its steps as a cyclic pipeline of functions that operate on the evaluation graphs and attempt to find the best overall strategy, in respect to the current problem definition.

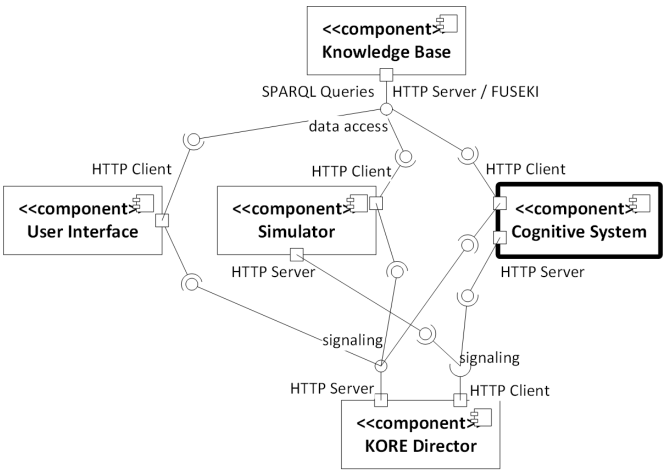

Fig. 4 Communication architecture of the system

B. *Ontology*

The knowledge representation, which is needed to create new control strategies, is an ontology of relevant building parameters and elements, which builds upon the ThinkHome ontology [14]. It contains the knowledge about actuators and its capabilities, about sensors and their placement, but also represents the information about the building and the energy systems that shall be controlled.

It is also used to provide the problem descriptions described in Section IV) and the resulting solution that the cognitive system identifies.

C. *Simulator*

The assessment of control strategies is done with the help of a physical simulator. The simulator couples MathWorks Simulink® and the thermal simulation tool TRNSYS[3] using the co-simulation framework Ptoemly II[4]. A simulation run is triggered by the cognitive system, i. e. once the cognitive system has found a solution, it is communicated to the simulator, which then triggers Simulink and TRNSYS to run for the specified simulation period. The results are time series data of physical values and control signals (e. g. CO_2 levels, temperatures and presence signals). Once the simulation is

[1] https://www.w3.org/TR/rdf-sparql-query

[2] https://jena.apache.org/documentation/fuseki2

[3] http://www.trnsys.com

[4] http://ptolemy.eecs.berkeley.edu

finished, the results are committed to the ontology and linked to the solution. The fuzzification processes uses the time series data and creates the fuzzified variables for energy efficiency and comfort.

D. Simulink Control Strategies

The control strategies that are built by the cognitive system have two properties: first, it not intended to implement real-time optimization of the system; problems in this domain are covered by model predictive controllers. Instead, the cognitive system is used to find control strategies that are committed to the building automation system and then left unchanged for a certain period (e. g. half a year). This way the solution fits to the way that buildings are operated today and is therefore expected to have a higher acceptance in the field. The second main property results from the first one: the building blocks used to create a control strategy are blocks that are found in today's control strategy as, for example, in sequential function charts defined in IEC 61131-3 [15]. The cognitive system has a set of controller blocks at its disposal that it can and connect to create a control strategy. These include air quality controllers, fan controllers, time scheduler, general linear PID controllers and other basic blocks. By limiting the solution space to these blocks, the identified solution will always consist of blocks that are by themselves easy to comprehend by control engineers that are working in the field of building energy systems.

VI. Results and Discussion

To validate our approach, we implemented the steps described above in a Java prototype and applied it to the problem description depicted in Fig. 5. This test aims to show the systems' ability to generate a valid rule structure for a given problem description, i.e. a provided building structure including sensors and actuators. By showing how our approach automatically provides a valid Simulink rule structure, we offer proof-of-concept for this fundamental step in automated rule generation using a cognitive system. Our prototype simplifies the essential step of parameter optimization for the rule, by using pre-defined default parameters. Due to the flexibility of the presented approach, we do however believe that the same concepts we applied during rule structure generation will be applicable for the parameter optimization process as well. The exemplary building used in our example application, its' structure is shown in Fig. 5, consists of four lecture rooms and an open office space. Lecture rooms 1-3 are equipped with CO_2 sensors and presence detectors that provide binary information about room occupancy. Lecture room 4 contains only a CO_2 sensor without presence detection. All four lecture rooms are equipped with volume flow controllers that allow regulating the supply air into each room. The open office space contain no sensors and actuators at all, but require a constant supply of air during office hours. The lecture rooms and the office areas are connected to a central ventilation system that requires demand information (i. e. volume flow) from all connected rooms to determine the necessary airflow it has to provide.

In our current development stage, we do not yet translate the created strategies into a Simulink-compatible format automatically, but instead interpret the results directly in the ontology. For the purpose of this paper, we visualized the information by manually placing Simulink function blocks, according to the ontology representation of the generated strategy, as shown in Fig. 6.

To enable the automated rule generation we first extend the problem definition manually by two goals for each zone (i. e. room or open space): comfort and energy efficiency. These goals represent a hypothetical user's demands on the expected strategy. The cognitive system now has to identify, which control strategy is feasible for each zone and the supply fan. The process described in Section IV, successfully determined the correct control blocks for each zone depending on the

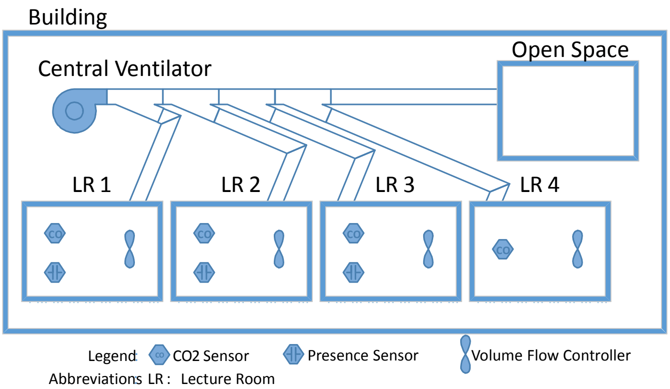

Fig. 5 Ventilation System for four lecture rooms and an open space

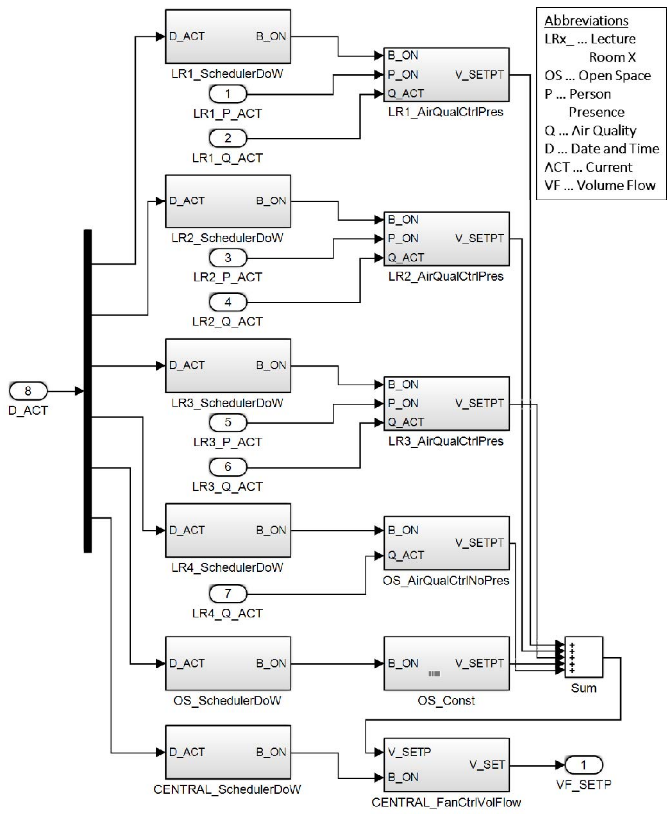

Fig. 6 Mock-up solution for control strategy in Simulink

available equipment in the room and the specified goals. For lecture rooms 1-3 the algorithm chose volume flow control-blocks to satisfy the comfort goals and day-to-day scheduler blocks for the energy efficiency goals. It also regarded the presence sensor, since the comfort goal only needs to be met if the room is occupied. For lecture room 4 the system correctly chose a scheduler block without presence sensor. Since the open spaces provide no sensors and actuators at all, the algorithm rejected all other blocks and used a control block that only provides constant volume flow demand to the central ventilator, which was communicated to the cognitive system as a possible fallback solution if no other strategy can be applied in a zone. The empty room still uses a schedule, which ensures that the empty office space does not generate a volume flow demand outside of regular office hours.

The connection of the four volume flow controller blocks to the central ventilation presented the algorithm with a n:1 connection problem since the supply fan needs the total volume flow demand of all zones as an input. A semantic rule was provided for 1:n and n:1 problems. The rule takes into account what kind of signal participates in the problem; in this example, the signals represented volume demands, thus allowing to sum up the demands (in case of temperature, this would not be the sum, but the maximum of all controllers). The semantic rule, therefore, promotes a generic sum block for combining signal of the given type and the algorithm use this to connect the room demands to the central ventilator. As shown in Fig. 6, the algorithm in its current form would propose separate schedulers for each room and another scheduler for the central ventilation. This can be viewed as a flaw due to unnecessarily high complexity caused by so many schedulers, but considering the fact that all schedulers will be configured by the cognitive system automatically and the fact that this constellation provides high flexibility, the solution is considered viable. It would, however, be possible to avoid this problem by introduced another semantic rule that specifies if and how to combine multiple schedulers connected to the same system.

As mentioned in the beginning of this section, this example solution is only intended as proof-of-concept. The system currently only generates rule structures with default parameterization for each control block, but even in this version, the system could already be used to simplify the initial setup of rule-based control systems. As explained in Section III, the main benefit of using rule-based control strategies, as generated by our approach, is the seamless integration into existing building control structures.

The main advantage of the approach is the savings in engineering effort. Today the engineering of control strategies has to be done under considerable time and resource constraints. Once it is possible to generate control strategies automatically and assess their performance, these costs are reduced; additional engineering effort can then be invested in manual adaptations or optimization, but the tedious repetitive tasks of, for example, room control, have already been solved cost efficiently.

The final version of our system, including experience based parameter optimization, which we will introduce in future publications, will also allow for the periodic optimization and adaption of the rule-based strategy during the lifetime of the building.

Acknowledgements

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