Evolutionary Optimization of Smart Buildings with Interdependent Devices

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Abstract. To enable a more efficient utilization of energy carriers, energy management systems (EMS) are designed to optimize the usage of energy in future smart buildings. In this paper, we present an EMS for buildings that uses a novel approach towards optimization of energy flows. The system is capable of handling interdependencies between multiple devices consuming energy, while keeping a modular approach towards components of the EMS and their optimization. Evaluations of the EMS in a realistic scenario, which consists of a building with adsorption chiller, hot and cold water storage tanks as well as combined heat and power plant, show the ability to reduce energy consumption and costs by an improved scheduling of the generation of hot and chilled water for cooling purposes.

Keywords: Energy management · Smart building · Evolutionary Algorithm · Combined heat and power plant · Adsorption chiller

1 Introduction

The transition from fossil energy carriers towards renewable energy sources is one of today's most important challenges for society. To support this transition, the European Union has defined ambitious goals for the year 2030: A reduction of greenhouse gas emissions by at least 40 %, an increase of the share of renewable energy to at least 27 %, and an increase of energy efficiency by at least 27 % [1]. Apart from new technologies, a better usage of existing systems is a promising factor to achieve these goals. Considering the increasing usage of volatile renewable energy sources, an efficient utilization of energy carriers is getting increasingly complex [2]. Among other cases, this applies to energy usage in commercial and private buildings. To ensure efficient energy carrier utilization, sophisticated *energy management systems* (EMS) have been introduced [3].

In this paper we extend an EMS that is based on a modular approach for optimization. It uses a customizable, run-time based phrasing of the optimization problem, because the problem instance varies with respect to the devices that have to be optimized and the constraints to be considered from one building to another. The actual optimization utilizes a dynamically assembled and

A.M. Mora and G. Squillero (Eds.): EvoApplications 2015, LNCS 9028, pp. 239–251, 2015.
DOI: 10.1007/978-3-319-16549-3_20

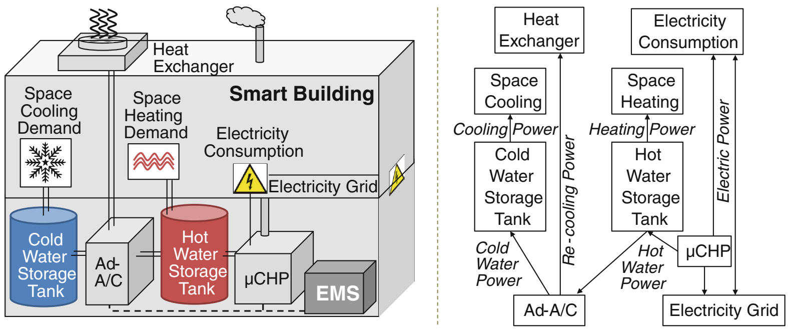


Fig. 1. Smart building scenario with EMS (left) and schema of power flows (right)

parametrized *Evolutionary Algorithm* (EA) [3,4], which can be adapted to the current optimization problem at run-time of the system.

The major contribution of this paper is the consideration of interdependencies between the devices. In particular, a flexible approach is presented for the optimization of interdependent devices with non-linear behavior. The term interdependency refers to the nature of energy consumption: The actual energy consumption of an interdependent device depends on the state of at least one other device and may also be non-linear in its energy consumption. The approach presented and evaluated in this paper is able to optimize diverse setups of buildings with different devices. Typical examples for interdependent devices in buildings can be found in the *heating, ventilating, and air conditioning system* (HVAC). To evaluate the EMS, a simulation of an EMS-controlled building has been carried out that is based on data of a real building.

Details about the energy management scenario and the EMS extended in this paper are given in Sect. 2. The major contribution of this paper—the *Energy Simulation Core* that enables the customizable optimization of interdependent energy-consuming devices—is presented in Sect. 3. In order to demonstrate the effectiveness of the presented approach, simulations with the setup shown in Sect. 4 have been conducted. The results are then discussed in Sect. 5. The paper is concluded with a summary and an outlook to further work.

2 Scenario and Energy Management System

2.1 Energy Management Scenario

This paper focuses on energy management and optimization of multiple energy carriers, such as electricity and hot water, in intelligent *smart buildings* (SB). The presented scenario (see Fig. 1) is based on a real SB environment and consists of a building with a *small combined heat and power plant* (μCHP), an *adsorption chiller* (Ad-A/C), as well as storage tanks for hot and chilled water. The chilled water, which is produced by the Ad-A/C, is used to cool a meeting room. The Ad-A/C is powered by the hot water that is generated by the μCHP. This hot

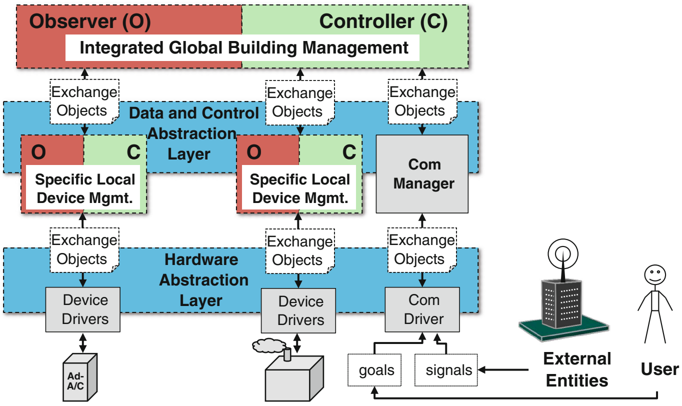


Fig. 2. Overview of Organic Smart Home

water is a secondary product of the μCHP in addition to electricity. Generation of electricity and production as well as consumption of chilled respective hot water are decoupled by the storage tanks. Such a system is called *trigeneration* or *combined cooling, heat and power* system.

2.2 Related Work

Similar systems with have been optimized using linear programming [5], non-linear programming [6], or Evolutionary Optimization [7–10]. However, these publications focus either only on optimization of the technical setup of the system [7,8], do not respect interdependencies or non-linearities [6,8,10,11], or perform only a scheduling that is exact to the hour [5,10,11]. In contrast, this paper schedules devices exact to the minute with respect to interdependencies and non-linearities of the devices, such as the non-linear interdependence of hot water input and cold water output of the Ad-A/C, using an EA.

2.3 Organic Smart Home

The *Organic Smart Home* (OSH) is an EMS that has been designed following the principles of *Organic Computing* [12] by using the generic *Observer/Controller Architecture*. This architecture constitutes one way to achieve controlled self-organization in technical systems utilizing a regulatory feedback mechanism [12]. An overview of the general system architecture is shown in Fig. 2. Major advantage of the OSH is its usability in both, real world energy management and simulations of buildings with different sets of devices in diverse scenarios [3].

The OSH utilizes different kinds of sensors and actuators to monitor and influence the *System under Observation and Control* (SuOC), in the present case a smart building. Every sensor and actor is assigned to a Local *Observer/Controller-unit* (O/C-unit). Every Local O/C-unit forms a closed control loop around the specific local device. To enable a global interaction between the devices, every Local O/C-unit is connected to a Global O/C-unit, responsible for the global building energy management. This hierarchical structure enables expedient responses to behavior, status, and interaction of different local agents, representing the physical or simulated devices in the building, as well as the global system, representing the smart building. Interaction with users or external entities is handled by a *Com Manager*, analogous to the handling of devices.

A *Hardware Abstraction Layer* (HAL) and device-specific drivers realize the abstraction from distinct devices, protocols, and communication media of components into generic exchange objects [3]. The Local O/C-units pass abstracted data to the Global O/C-unit, which aggregates the data of all Local O/C-units to the current state of the SuOC. Based upon this state, the energy management predicts the future global state and optimizes its control sequence in order to influence the SuOC with respect to given external and internal constraints as well as objectives defined by the user. The resulting schedule of planned actions and procedures, i.e., the control sequence, is then communicated back to the Local O/C-units, which apply it to the devices.

3 Energy Simulation Core

In the present paper, the OSH, which has a configurable, modular Optimization Algorithm [3], is enhanced by an additional component: the *Energy Simulation Core* (ESC). This component, which is depicted in Fig. 3, simulates the local electricity and thermal grids, i.e., the local electrical wiring and water pipes, as well as the energy consumption of interdependent devices while keeping a modular approach to the optimization. This modular approach is necessary, because the concrete operational scenarios in SBs with different setups of devices and characteristics of these devices, as well as the objectives of the users are widely unknown a priori to the installation of the EMS. Furthermore, these properties may change over time, when additional devices are being added to management and optimization. Moreover, the ESC enables the reuse of the abstracted models of the devices, which are already used for prediction purposes in the EMS.

3.1 ESC: General Architecture

The ESC is used in two parts of the EMS (see Fig. 3): the calculation of energy flows in every simulated time step, which in the present EMS is at every second, and the simulation of energy flows in the optimization process, which is done in time steps of 60 s. The calculation of energy flows is necessary to determine the actual electrical and thermal power consumption, when different producing and consuming devices are considered. For instance, active power generated by a photovoltaic system has usually a different payment scheme for feed-in than power generated by a μCHP.

Characteristics and control of thermal devices, such as water heaters and Ad-A/Cs, usually depend on the current state of the overall system, i.e., indoor and

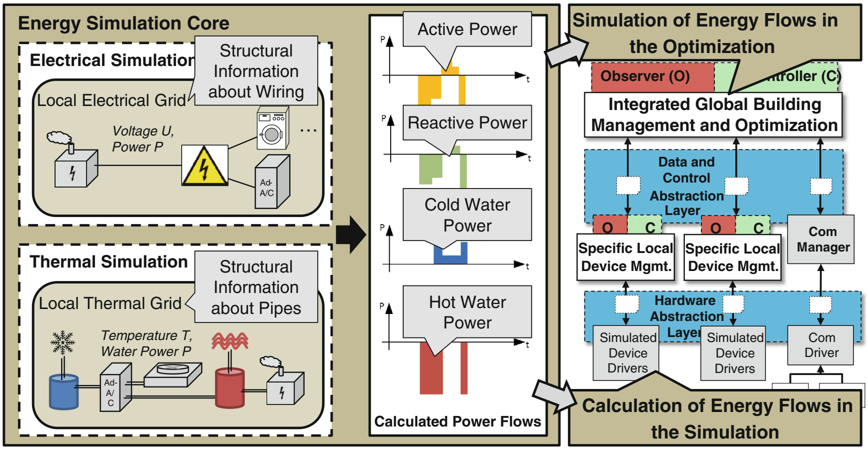


Fig. 3. Overview: Energy Simulation Core in the Organic Smart Home

outdoor temperature, as well as the water temperatures of hot and chilled water in the storage tanks. Additionally, these characteristics often include non-linear dependencies. For example, the required thermal energy in terms of hot water consumption of an Ad-A/C is non-linear with respect to the generated thermal energy in terms of chilled water. Therefore, the simulation of energy flows in the optimization requires a step-by-step approach when determining the future control sequence of the devices.

The ESC consists of two main components: the *Electrical Simulation* and the *Thermal Simulation*. Both sub-modules simulate their respective local grid with its different energy carriers. The local electricity grid consists of the wiring, i.e., the electrical connections between all devices consuming or producing electricity in a building. To be able to take their different payment schemes into account, active power produced by a photovoltaic system is regarded as a different *commodity* than active power produced by the μCHP.

Similarly, the local thermal grid contains all information about the physical interconnections, i.e., pipes, between devices consuming different thermal commodities, such as hot and chilled water. In addition to the power flows between the devices, the temperatures are communicated between the devices. Thus, devices can react on states of other devices: The μCHP starts producing hot water when the water temperature of the hot water storage tank falls below a certain threshold level. Furthermore, devices can determine their current power consumption or production based on the temperatures of other devices, such as water temperatures. For example, the hot water power consumption of an Ad-A/C depends on the hot water temperature in the storage tank.

The ESC handles the information exchange between all simulated devices, i.e., the actual power consumption and productions as well as the additional information, such as water temperatures or voltages. These simulated devices (see Fig. 3) are for one thing the simulation agents, i.e., simulation drivers, and

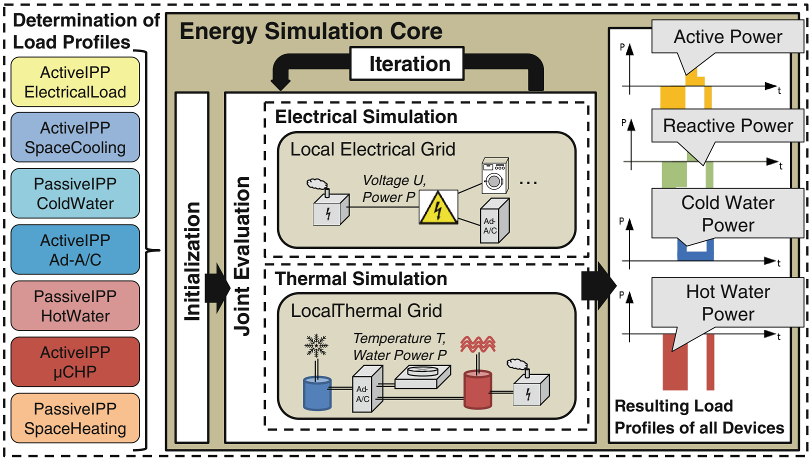


Fig. 4. Determination of load profiles using Interdependent Problem Parts

for another the *Interdependent Problem Parts* in the optimization, which are more closely described in the next subsection.

3.2 Interdependent Problem Parts

The modularity of the approach is further enabled by the introduction of *Interdependent Problem Parts* (IPP). These IPPs are an extended version of the *Problem Parts* presented in [3], which are provided by the Local O/C-units to handle the optimization of devices. Every device managed by the EMS provides an IPP that contains information about characteristics, behavior, predicted future states, such as the predicted power consumption, and possible control sequences of the device, as well as interdependencies with other devices. The IPPs are used in the ESC to determine load profiles of the devices with respect to their interdependencies (see Fig. 4).

There are two fundamentally different properties of an IPP: *controllability* and *activeness*. Controllability (see also [3,4]) refers to the the property whether a device offers the possibility of control, i.e., in the case of a *non-controllable* device the respective IPP has zero bits, whereas a *controllable* device has at least one bit in the optimization. Activeness refers to the property of whether the device is determining the power flow to other devices (*active*) or not (*passive*).

Depending on the optimization target, the same device may be handled alternatively with different IPPs. For instance, one IPP may be non-controllable and active, whereas another may be controllable and active. This means that in the first case the device controls itself, e.g., by using an on-off control, while in second case it receives an optimized control sequence by the global optimization. In both cases, the device determines actively its power flows.

3.3 Interdependent Problem Parts of the μCHP

The μCHP simulated in this paper is controllable, because it can be controlled using a signal that switches it on or off. In order to show the effect of optimization, it can also be run unoptimized using an IPP that is non-controllable by the optimization. Therefore, it uses two different types of IPPs: one IPP is non-controllable another is controllable.

Both IPPs implement an on-off control ensuring that the water temperature in the hot water storage tank remains within an upper and a lower temperature threshold. This thermal management ensures that every solution determined by the optimization leads to a valid solution: the μCHP is forced on or off in cases of violations of the threshold, even if the control sequence by the optimization would originally lead to a violation of the thresholds. In both cases, the μCHP is actively participating in the energy simulation, because its state, i.e., being switched on or off, and therefore its power generation of hot water and electricity, depends on at least one other device: the hot water storage tank. The encoding of the μCHP uses a sequence of bits that is interpreted as the control sequence, i.e., sequence of being switched on or off, and is more closely described in [4].

3.4 Interdependent Problem Parts of the Ad-A/C

The Ad-A/C uses IPPs that are similar to those of the μCHP. Other than that, it consumes hot water from the storage tank and produces chilled water that is stored in the chilled water storage tank. Additionally, it considers the outdoor temperature that determines the efficiency of the heat exchanger for the re-cooling process. Both IPPs, non- and controllable, implement an on-off control for ensuring that the chilled water temperature remains within its thresholds.

3.5 ESC and IPPs: Optimization Process

The optimization process in the OSH and its usage of the ESC are depicted in Fig. 5. Analogously to the optimization process in [3], the IPPs are constructed periodically and in case of certain special events in their relative Local O/C-units. Every IPP is initialized with information about the current device state and the current possibility of control.

In the scenario presented in this paper, the control sequences of an Ad-A/C and a μCHP have to be determined with respect to states of the storage tanks, predictions of future hot and chiller water power consumptions as well as outdoor temperature and price signals. The present example requires three bits for both, the Ad-A/C and the μCHP, for every five minutes in the optimization horizon. Among the IPPs for the controllable devices, the states of the storage tanks and the predicted power consumptions are handled as non-controllable IPPs.

All these IPPs are communicated to the Global O/C-unit and aggregated to represent the global optimization problem in the building for the current optimization period. They determine the length of individuals in the optimization

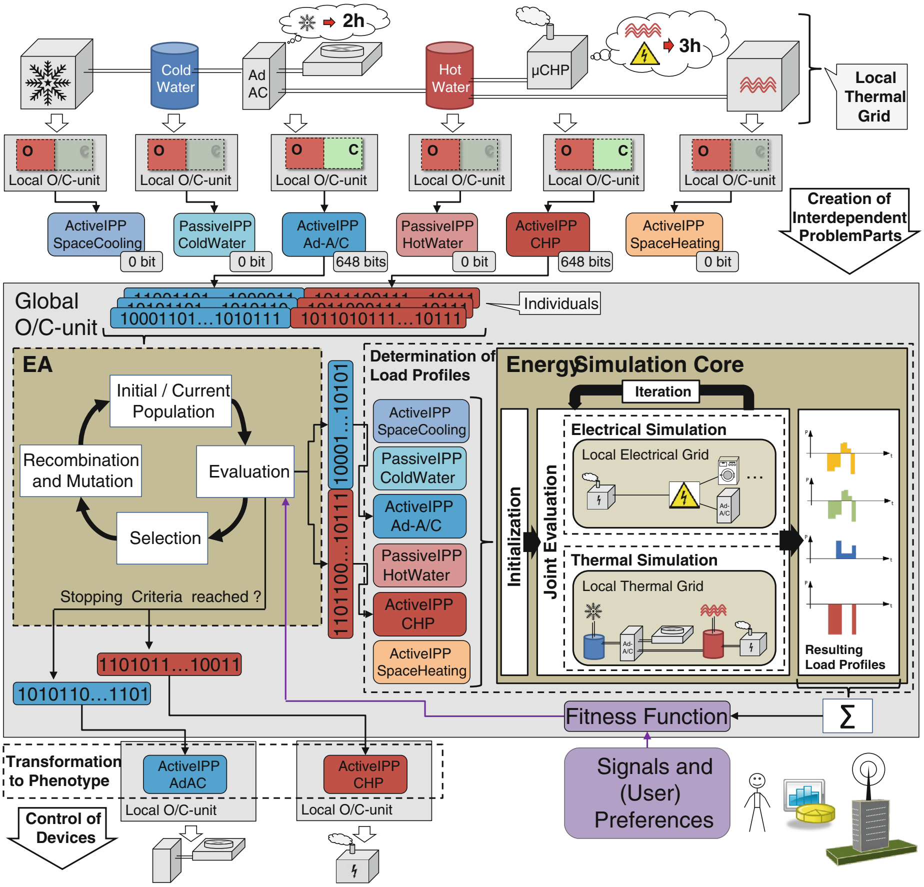


Fig. 5. Energy Simulation Core in the optimization process

process and its EA by defining an adequate number of bits required for the optimization of every device. Thus, every individual consists of sub-strings of bits, which have to be interpreted by their relative IPP in order to determine the load profile of the related device. This joint evaluation with the determination of load profiles is done using the ESC. The load profiles are combined to expected total future load profiles for the building, which are then evaluated to a fitness value using external signals, such as the costs of electricity and natural gas, or the feed-in tariff for electricity.

The EA runs until the stopping criterion, which in the present case is the maximum number of generations, has been reached. The sub-strings of the best individual are then transformed to their phenotypes, i.e., the control sequences for devices that can be controlled. In the scenario of this paper, these are the future periods when the Ad-A/C respective the μCHP are scheduled to be switched on or off.

Table 1. Experiments: combinations of Interdependent Problem Parts

Experiment	IPP of Ad-A/C	IPP of μCHP	Appointments
A	Non-controllable	Non-controllable	Real, simulated
B	Non-controllable	Controllable	Real, simulated
C	Controllable	Non-controllable	Real, simulated
D	Controllable	Controllable	Real, simulated

Table 2. Experiments: specifications of devices

Device	Specification	Real device
Ad-A/C	Cooling power: 9 kW	*InvenSor LTC 09*
μCHP	Hot water power: 12.5 kW	*Senertec Dachs G 5.5 standard*
	Electric active power: 5.5 kW	
	Natural gas power: 20.5 kW	
Hot water storage tank	3250 liters	Custom-made tank
	Min. temperature: 57 °C	
	Max. temperature: 78 °C	
Chilled water storage tank	3000 liters	Custom-made tank
	Min. temperature: 10 °C	
	Max. temperature: 15 °C	

4 Experimental Setup

To evaluate the performance of the implemented ESC and to demonstrate its capability of handling interdependent devices, a simulated SB has been used. The specifications of the simulated SB and its devices are based on a real SB, the *FZI House of Living Labs*[1]. The EMS—the OSH—uses a sub-problem based EA for optimization purposes, which applies binary tournament selection, single-point-crossover with two offspring and bit-flip-mutation using an elitist (μ,λ)-strategy with a rank based survivor selection [3]. Parameters of the operators have been calibrated manually (see Fig. 6) and set to a crossover probability of 0.7, a mutation probability of 0.005, and 200 generations with 100 individuals.

4.1 Simulated Devices

The simulated SB consists of a simulated Ad-A/C, a μCHP and simulated storage tanks for hot and chilled water. These have been modeled according to specifications of real devices (see Table 2). The efficiency of the Ad-A/C, which depends on the tank and outdoor temperatures, has been interpolated from the

[1] http://www.fzi.de/en/research/fzi-house-of-living-labs/.

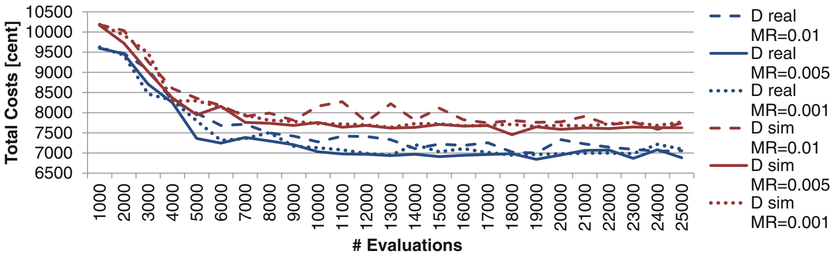


Fig. 6. Total Cost with different Numbers of Evaluations and Mutation Rates (MR)

technical specification. Standing loss P_{loss} in kW of the storage tanks, depending on the current tank temperature T_{tank} in °C and the ambient temperature T_{ambient}, which has been set to 20 °C, has been modeled based on measurements with $c = 0.040$ for the cold water and $c = 0.011$ for the hot water storage tank:

$$P_{\text{loss}}(T_{\text{tank}}) = -c \cdot (T_{\text{tank}} - T_{\text{ambient}}).$$

Optimization using the EA is triggered at least every four hours or when a temperature threshold of either the hot or the cold water storage tank has been violated. Optimization horizon is the next 18 h.

4.2 Test Scenarios and Experiments

In the simulations, eight different experiments with 30 random seeds each have been tested. All simulate four weeks in July 2013 with real outdoor temperatures. The experiments are presented in Table 1 and consist of the four combinations of controllable and non-controllable IPPs of the Ad-A/C and the μCHP as well as two different sets of appointments determining the cooling demand: *Simulated* cooling demand refers to simulated appointments in the meeting room, *real* cooling demand refers to real appointments in the meeting room pulled from the *Microsoft Exchange Calendar*. The simulated appointments are randomly generated using the following constraints based on the typical key data of appointments in the meeting room of the real building:

$$\begin{gathered} \#appointments\ per\ day \in \{1, 2\}, \\ \#appointment\ duration\ in\ h \in \{2, 3, 4\}, \\ pause\ between\ appointments\ in\ h \in \{2, 3, 4\}. \end{gathered}$$

Cooling demand P in kW as a function of the outdoor temperature T in °C is calculated using the an empirical formula that is based on measurements in the real building. Above an outdoor temperature of about 21.9 °C, this model leads to a cooling demand that increases linearly with the outdoor temperature:

$$P(T) = \max(0;\ 0.4415 \cdot T - (0.4415 \cdot 21.8831)).$$

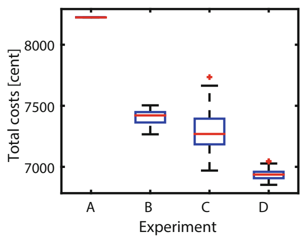
5 Results and Discussion

Simulation results (see Fig. 7 and Table 3) show an average improvement of the total monthly costs by up to 15.6 %. This improvement is realized in experiment D with real appointments in comparison to experiment A. The results of a t-test confirm the significance of improvements by the optimization with IPP in comparison to the non-optimized reference scenario.

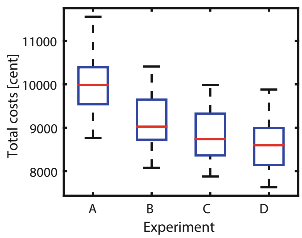
Optimization of the Ad-A/C only (experiment C) leads to better results than the sole optimization of the μCHP (experiment B). Nevertheless, a higher volatility of the achieved total costs is observed. This can be explained by a surplus of hot and chilled water that remains in the storage tanks at the end of the simulation. In case of an optimized μCHP and Ad-A/C, the optimization ensures that the tank temperatures are kept at a low respective high temperature at any time without an appointment. Thus, the tank is not unnecessarily heated up respective cooled down to prevent standing loss. Especially when using real appointments, the volatility is higher. This is due to the nature of the real appointments, which are less often but longer than the simulated ones. Therefore,

Table 3. Simulation results: statistical values of the absolute total costs and the improvement over the non-optimized experiment A.

		Abs. Electricity Costs				Improvement wrt. A [%]				t-test
Experiment	Appointments	Min	Max	Avg	s_n	Min	Max	Avg	s_n	p-value
A	Real	8224	8224	8224	0	-	-	-	-	-
	Simulated	8762	11555	9974	659	-	-	-	-	-
B	Real	7266	7504	7410	54	8.75	11.64	9.89	0.65	0.000
	Simulated	8078	10410	9100	578	3.76	14.24	8.70	2.90	0.000
C	Real	6969	7734	7304	213	5.94	15.25	11.18	2.59	0.000
	Simulated	7878	9984	8818	544	2.69	17.42	11.48	4.02	0.000
D	Real	6853	7046	6939	49	14.31	16.67	15.63	0.60	0.000
	Simulated	7631	9880	8589	551	7.87	19.90	13.82	3.12	0.000



(a) Experiments with real appointments



(b) Experiments with simulated appointments

Fig. 7. Boxplot of the average costs in the experiments

on the last day of the simulation, the remaining hot water in the storage tank is not used to produce chilled water for an appointment in the meeting room.

6 Summary and Outlook

This paper presented an approach towards flexible and modular energy optimization in smart buildings using an EMS. The approach has been implemented as an additional module for an existing EMS that can be used in both, simulations and real-world control. The formulation of the problem instances at run-time of the EMS has been extended to cope with interdependent devices, such as trigeneration systems consisting of a combined-heat and power plant combined with an adsorption chiller as well as hot and chilled water storage tanks.

The implementation of the presented module has been tested in simulations of a scenario that is based on the characteristics of a real building. Results of the simulation show the ability of the system to manage and optimize such buildings. The energy costs of the building can be reduced by the optimization using the EA on average by up to 15 %. This improvement is mainly due to the better coordination of the adsorption chiller and the combined heat and power plant as well as the generation of chilled water in the morning, when the outdoor temperature allows for a better efficiency.

Future work shall verify the simulation results with additional data from real buildings. Furthermore, the approach presented in this paper will be extended to the optimization of a battery storage and hybrid household appliances that may use hot water from the storage tank, too, while substituting electricity.

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