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Proactive Control for Solar Energy Exploitation: a German High-Inertia Building Case Study

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***Abstract*—Energy efficient passive designs and constructions have been extensively studied in the last decades as a way to improve the ability of a building to store thermal energy, increase its thermal mass, increase passive insulation and reduce heat losses. However, many studies show that passive thermal designs alone are not enough to fully exploit the potential for energy efficiency in buildings: in fact, harmonizing the active elements for indoor thermal comfort with the passive design of the building can lead to further improvements in both energy efficiency and comfort. These improvements can be achieved via the design of appropriate Building Optimization and Control (BOC) systems, a task which is more complex in high-inertia buildings than in conventional ones. This is because high thermal mass implies a high memory, so that wrong control decisions will have negative repercussions over long time horizons. The design of proactive control strategies with the capability of acting in advance of a future situation, rather than just reacting to current conditions, is of crucial importance for a full exploitation of the capabilities of a high-inertia building. This paper applies a simulation-assisted control methodology to a high-inertia building in Kassel, Germany. A simulation model of the building is used to proactively optimize, using both current and future information about the external weather condition and the building state, a combined criterion composed of the energy consumption and the thermal comfort index. Both extensive simulation as well as real-life experiments performed during the unstable German wintertime, demonstrate that the proposed approach can effectively deal with the complex dynamics arising from the high-inertia structure, providing proactive and intelligent decisions that no currently employed rule-based strategy can replicate.**

***Index Terms*—High-inertia buildings, Energy-efficient climate control, Large scale systems control, Real-life building control application.**

Nomenclature:

BCS: Base Case Scenario	MPC: Model Predictive Control
BOC: Building Optimization and Control	PCAO: Parameterized Cognitive Adaptive Optimization
BEPS: Building Energy Performance Simulation	PVP: Photovoltaic Panel
HJB: Hamilton-Jacobi-Bellman	RB-BOC: Rule-based BOC
HVAC: Heating ventilating and air conditioning	TABS: Thermally Activated Building Systems

I. INTRODUCTION

Motivated by the fact that around half of the energy produced on the planet is used for the daily needs of building systems,

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especially for climate-control purposes (heating/cooling), during the past decades a significant amount of research effort has been concentrated on energy efficient designs and constructions [1][2][3]. Energy efficient building design and construction techniques go under the name of “passive” designs, since they do not involve the use of literally “active” mechanical and electrical devices for climate control. Examples of passive design includes: passive solar building design, where windows, walls, and floors are made to store, cage and distribute solar energy in the form of heat in the winter and reject solar heat in the summer; passive cooling with different forms of ventilation and earth coupling; passive day-lighting to most effectively capture sunlight; superinsulation techniques [4][5]. Despite their heterogeneity, passive design techniques share the common goal of increasing the thermal mass of the building. A building with high thermal mass, also referred to as *high-inertia* or *heavy-weight building*, is able to store heat, providing thermal "inertia" against temperature fluctuations: transient thermal behavior and thermal storage capacity as a function of building inertia have been investigated and are still under investigation, e.g. [6][7][8]. High-inertia buildings are in principle low-energy buildings where active devices like heating, ventilation, and air conditioning (HVAC) units require little energy for space heating or cooling [9][10]. However, this does not directly imply improved thermal comfort conditions for the occupants. In fact, in order for thermal mass being effective in improving thermal comfort and energy consumption, especially during climates and seasons with high daily temperature fluctuations, a *delicate coordination among the passive and the active layers is necessary*, otherwise all the advantages given by the passive design will be lost, with undesirable results in the indoor comfort of the occupants [11][12][13].

In high-inertia buildings the *Building Optimization and Control (BOC)* task resides in the development of a series of control strategies or algorithms aiming at harmonizing the active devices with the passive structure of the building. The development of such strategies is more challenging than in conventional buildings. The control strategy must be *proactive*, in order to cope with the high thermal memory of the building, and *optimal*, so as to fully exploit the peculiar structure of the building. For these reasons, the simple rule-based control strategies which typically escort passive designs are not able to guarantee energy efficiency: any attempt to increase the performance of rule-based control strategies requires a tedious, time-consuming and rough manual rule tuning, which typically leads to complex networks of cooperating rules based on specific field observations, experience and common control practice. In addition to the complexity of the tuning task, other factors might influence the quality of control. For example, in high-inertia buildings equipped with heating or cooling systems based on distribution of water, the quality of control is also determined by the hydronic circuit [14], i.e. on the process of optimising the distribution of water to provide the intended indoor climate at optimum energy efficiency and minimal operating cost: a complex networks of cooperating rules is necessary for any hydronic circuit control to function properly. A similar elaborate ruled-based tuning task is necessary in high-inertia buildings utilizing thermal storages for demand side management applications [15]. Motivated by the difficulty of implementing complex networks of cooperating rules, more elaborate control techniques are required so as to fully exploit the advantages of a design with high thermal storage mass.

1. Related work and contribution of the paper

In the current state-of-the-art several approaches to rule-based BOC, such as intelligent comfort and predictive weather-data based controllers have been suggested to tackle and exploit the slow dynamics of thermal systems in buildings [16][17][18][19][20]. Unfortunately, most of these techniques require a tedious and "expensive" design and calibration phase in order to provide the aforementioned savings. The reasons are e.g. the design of an accurate Building Energy Performance Simulation (BEPS) model, the extended optimization phase, the prolonged operator training. Progress in building technologies, weather forecasting and low-cost embedded computing systems pave the way for implementation of intelligent strategies with “proactive” and “optimal” capabilities for BOC applications. Advanced state-of-the-art implementations of BOC systems mostly rely on Model Predictive Control (MPC) [21][22][23], Co-simulation [24][25][26], popular optimizers [27][28] or neural networks [29][30][31][32][33][34]. Despite the recognized improvements over rule-based control strategies, such methods do not efficiently scale to large high-inertia BOC designs. In fact, in such high-inertia building applications additional challenges must be faced. Due to the large time constants which are involved, it is more than evident that the prediction horizon has to be several hours so as to “predict” in an effective manner the model behavior and furthermore generate optimal control decisions. In most cases BOC schemes rely on simplified linear models that make prediction over several hours unreliable. Such simplifications are a necessary consequence of making calculations implementable in real-time. In general, in order to “predict” in an efficient manner the model behavior and generate optimal control decisions increased complexity and calculation are necessary, which, due to the high dimension of the arising optimization problems, put at stake most current state-of-the-art modern BOC methodologies (cf. Table I in this paper).

On the other hand, several adaptive control optimization methodologies developed by the authors showed the ability to automatically provide optimal control strategies in large-scale systems [35][36][37][38][39][40]. The most recent of these methodologies [40], referred to as Parameterized Cognitive Adaptive Optimization (PCAO), has been shown to possess adaptive self-learning abilities. In this paper we applied the PCAO methodology to the design of a BOC strategy for a low-energy, high-inertia building in Kassel, Germany. The advantage of the PCAO method over the mentioned state-of-the-art techniques is the fact that it is assisted by an elaborate simulation model of the building in order to attain energy efficient control of the building. The simulation model is able to model the effect of *high-inertia, advanced insulation techniques and very slow dynamics* involved in the building: thus the simulation model is able to provide reliable predictions for the model behavior and for the future effect of BOC decisions. The proposed PCAO approach thus employs a simulation-assisted control methodology. The simulation model of the German building is used to develop a strategy that proactively optimizes, using both current and future information about the external weather condition and the building state, a combined criterion composed of the energy consumption and a thermal comfort index. The main attributes of the presented PCAO approach are its ability to handle the large-scale nature of the optimization problem and provide efficient BOC schedules and policies. Both extensive simulation experiments as well as real-life experiments performed in the high-inertia building demonstrate the aforementioned attributes of the PCAO approach.

2. Test Case Building

In order to test and evaluate PCAO, an office building, comprising 22 offices, is implemented for the BOC design. The test case building, built in 2001 in the campus of the Kassel University, Germany is an exemplary low-energy building. The energy consumption is highest during the winter period for heating of the interior offices. The test case building falls under the category of heavy weight buildings with thick and well insulated external walls and massive concrete floors. Furthermore the building presents a large glass façade oriented South-East (Figure 1 and Figure 2). Some other features of the building:

- The net heated floor area is 1332 m² and the main floor space is 892 m². The annual heat demand is approximately 30 kWh/m² or 5.3 kWh/m³; the annual electricity consumption based on the heated net floor area is approximately 20 kWh/m².
- The building has three Thermally Activated Building Systems (TABS): (i) a basement slab or ground heat exchanger for cooling; (ii) radiant floors, and; (iii) radiant ceiling systems. For heating purposes, floor and ceiling TABS utilize district hot-water in the winter [41]. Cooling is realized through ground cold through the basement slab during summer, although the available cooling power is very low (see Figure 3). The TABS may be operated independently. Thermostats are used for the activation of the radiant slabs while the valve-tab position is always set to the maximum available setting. Therefore the slabs

are operated using a simple if-then-else rule which energizes the water flow only when the respective zone temperature is below the thermostat set point which is between 15 ºC and 30 ºC.

- A huge base of real life measurement data is available for this building, as is an extensively validated BEPS model (see Appendix) implemented in TRNSYS [42][43].

Both passive construction techniques and an active system composed of concrete core activation slabs are combined in the building design. As a result of these features, the high inertia and slow dynamics involved make proactive control mandatory [44]. One of the main problems faced by the building is that a few sunny days during winter time will expose the building to excessive solar radiation that, combined with a bad schedule of the concrete core activation slabs, will cause the building to overheat and reach uncomfortable temperatures over very long periods, with wasted energy consumption and undesirable results in the indoor comfort of the occupants. To avoid this drawback, a careful balance between exposition to solar radiation and setting of the slabs thermostats must be achieved. Despite the extensive tuning efforts, no existing set of rule-based control strategies has shown the ability to cope with this problem: every year, temperature excesses, and thus thermal discomfort, are measured over many days during winter. High inertia and slow dynamics make the design of an efficient BOC system for the test case building more complex than in a conventional building. More details on the building and on the associated challenges may be found in [44] [45] [46]. The rest of the paper is organized as follows: Section II presents the main ideas behind the proposed PCAO methodology applied to BOC system design; Section III focuses on the control objectives in the high-inertia building; in Section IV the PCAO BOC system design is extensively tested using both simulation experiments as well as real-life experiments; finally, Section V concludes the paper, while in the appendix more details regarding the TRNSYS simulation model of the building are given.

II. MODEL-ASSISTED PCAO FOR BOC SYSTEM DESIGN

The basic structure of the BOC employed within the PCAO approach is shown in Figure 4. The depicted BOC system comprises of three basic elements: the optimizer (PCAO), the simulation model (TRNSYS model) and the real building plant. The presented Building Energy Performance System (BEPS) PCAO is based on *co-simulation schemes* used in building applications and simulations. The BEPS model of the system is connected to the controller and PCAO modifies/updates the parameters of the controller by evaluating them through the use of the BEPS model by employing a co-simulation approach. More precisely: (a) for each PCAO’s choice of controller parameters, the closed-loop system on the right, is simulated under different scenarios (e.g., simulating the controller for many days with different weather characteristics) so as to make sure that the optimized controller is able to efficiently handle many different possible real-life situations; (b) a quantitative performance measure (defined as the close-to-optimality error index) is provided by the BEPS model so as to be able to evaluate the efficiency of the closed-loop system under the aforementioned choice; (c) such a quantitative measure is then used by PCAO in order to update the controller parameters (d) using the updated control parameters and based on current plant measurements the closed control loop on the left is used for control signal actuation/realization. Steps (a)-(c) are repeated until no further improvement in the BOC system performance is obtained. Step (d) is repeated as many times as defined by the control frequency within/in-between one iteration of steps (a)-(c).

An interesting feature of the PCAO approach is the exploitation of L different *linear controllers,* whose action is combined in a mixing (or smoothly switching) architecture, enabling complex dynamics of the system to be recognized. In fact, each of these linear controllers is responsible for implementing the BOC actions for different *exogenous building operating conditions* (e.g., for different values of the ambient temperature and/or total solar radiation). The mixing scheme is used to smoothly mix the control signals from the different controllers. In such a way, smooth operation of the overall BOC scheme is ensured during changes in the exogenous operating conditions. Moreover, the use of different linear controllers around different operating conditions reduces substantially the complexity of BOC system design: mathematically speaking, it suffices to design each controller to be efficient within an operating area and, moreover, to make sure that the transition from one operating point to another is efficiently performed [47].

Moreover, for the vast majority of BOC systems, extensive theoretical, simulation and real-life investigations established that it suffices to choose the number L in the range 1-5 (i.e., to employ up to 5 different linear controllers), while to choose a mixing scheme that depends only on the ambient temperature (T_{amb}). Using the above logic the hybrid nature of the building dynamics can be exploited while the optimization problem is discretized to L smaller ones. It has to be emphasized that, even with such architecture, the BOC system design remains extremely challenging, as it consists of the solution of a high-dimensional and complex optimal control problem. For instance, for a building with 10 offices, the number of optimization parameters for each of the gain matrices is in the range of 200-1000 [40]. In other words, efficient BOC system design requires optimization of several hundred or, even, thousands of parameters affecting the building dynamics in a very complex, nonlinear manner. PCAO achieves to successfully deal with such a high-dimensional, complex optimization problem by suitably combining two different "ingredients":

- The so-called CAO approach [38], an adaptive optimization approach which is capable of rapidly and with minimum computational burden provides solutions to high-dimensional, complex control-related optimization problems. It is emphasized that the CAO approach has been successfully implemented in a variety of real-life control-related optimization problems including automated fine-tuning of large-scale traffic control systems and control of swarms of unmanned aerial or underwater vehicles [35][38].
- A new control design approach [40] whose key-idea is to use the well-known in optimal control theory Hamilton-Jacobi-Bellman (HJB) equation [48] which, for each set of control parameters, can provide with a measure of how far these parameters are from their optimal values. Using such a measure and by appropriately enhancing CAO, the PCAO approach has been developed and analyzed in [36][40]. Contrary to existing control design approaches which update the control parameters so as to improve the overall performance of the system, PCAO updates the control parameters so as they "come" closer to their optimal values as dictated by the Hamilton-Jacobi-Bellman equation. By doing so and as shown in [36][40], PCAO not only achieves to very rapidly "catch" the optimal control parameters but also to be able to efficiently self-adapt in order to compensate for system variations and modeling inaccuracies.

The reader interested in more details regarding PCAO and its properties is referred to [40]. In the sequel, we describe how PCAO can be implemented and used in the case of BOC system design.

For comparison purposes, and in order to highlight the challenges of the BOC system design, in Table I the PCAO performance was tested among several algorithms taken from the Matlab Optimization Toolbox: `fmincon`, `patternsearch`, `ga` (genetic algorithm) have been chosen. Because of the formulation of the BOC problem, the optimization algorithms must be *derivative-free* as, in the absence of the analytical form of the building model; it is not possible to calculate analytically the gradient of the BOC performance. It has to be emphasized that in all cases the optimization algorithms used in the evaluation have been extensively fine-tuned so as to make sure that they perform the best they can. A *maximum number of iterations* of 10000 were chosen for all the algorithms. Table I summarizes the findings of the comparison, where it is shown that PCAO attain quickly an energy-efficient BOC system design, while the other optimization algorithms fail to produce any improvement. It has to be emphasized, that the computational time required for each of PCAO's iteration is the same – and in some cases less – than that of popular optimization algorithms.

III. CONTROL OBJECTIVES OF THE GERMAN BUILDING

Due to the fact that most of the energy of the German building is consumed in winter, this section focuses on the heating case and the control problem under consideration is one of energy-efficient heating the German building, while guaranteeing a satisfactory thermal comfort index. In the German building (and in High-inertia buildings in general) an efficient BOC system must be such that it pre-actively schedules the operation of the HVAC system over very long-periods. The energy storing capacity of the building's thermal mass has two effects on a building; it moderates internal temperatures by averaging diurnal (day/night) extremes and it delays the time at which peak temperatures occur. The temperatures experienced in a heavyweight building will peak lower and later than those in a lightweight building and temperatures will not drop as much over the course of the night. Thermal mass offers the opportunity to manage the thermal energy flows of a building to the advantage of its occupants, without the need for large amounts of high-grade energy. The energy saving potential of the thermal mass exploitation and indirect utilization can be fully realized if the ability to adapt to temperature and/or solar radiation changes throughout the day is efficiently exploited.

In addition, the quest of saving energy through heating using dynamic control elements is challenging owing to the combination of TABS with huge response times, a very low energy building and cold but unstable winter weather conditions. A large glass facade making the buildings thermal behavior highly sensitive to solar radiation makes the task even more complicated. As a consequence, a very complex network of interconnected subsystems with different response times and constants defines the building behavior under different circumstances and periods of the year. It is more than evident that control schedules able to utilize all of the energy savings potential of such building, *in a proactive way*, have to be considered in order to achieve energy efficiency.

1. Cost Function

The cost function to be minimized by the BOC system is a combined criterion taking into account the energy consumption and the user comfort. In principle, the comfort index derived by "Fanger" would be the standard metric [49]: however, in real-life this index is very difficult to measure. It requires sensors and measures that depend on metabolic rates, clothing factors and appliance usage, which are very complicated even to model. The comfort definition for the specified building (see Figure 5) based on/complying with the PMV method as described within ANSI/ASHRAE Standard 55-2013 standard, could be measured in real-life as it depends on temperature and humidity measurements only. The used cost function considers energy consumption and the level of comfort:

$$Total\_score = t*Energy\_score + (1-t)*Comfort\_score$$

where $0 < t < 1$ regulates the importance of one term with respect to the other. The *Energy_score* is evaluated by reading the actual heating energy supplied to each respective office (heat exchange between radiant slabs and indoor air volume for each office). The *Comfort_score* is the user comfort index discussed before defined as the distance of the current state point [Temperature, Humidity] and the center point as defined [21°C, 55%] for each office. As t increases in the cost function, energy savings become more important than comfort conditions.

2. Base Case Scenarios

For performance comparison purposes, the PCAO strategy is compared with base case BOC system. Two different control strategies were tested and evaluated. The first one considers as control period the office working hours only and the second the whole day. These base case BOC systems correspond to the best rule-based controllers in each control case respectively. The

Base Case Scenarios (BCS) are as follows:

- **BCS PULSE:** BCS that operates the set points at 21 °C during office hours (8.00-17.00) is the best among all BCSs. This BCS was used for comparisons and as an initial point of the respective PCAO application.
- **BCS FREE:** BCS that operates the set points at 21 °C during the entire day is the one that is currently employed in the building. The set points equal to 21 °C were chosen based on German heavy and most of the times cloudy winter. This BCS was used for comparisons and as an initial point of the respective PCAO application.

That is one has to distinguish between two different BCS strategies used to compare against **PCAO_PULSE** and **PCAO_FREE**, respectively. Respective sets of simulations and real-life experiments were performed and evaluated separately for such purpose. In addition three different control policies considering three different values for the weight exchange factor in the cost function as described previously were tested and evaluated both for *PULSE* and *FREE* tests. Thus $t=0.5$, $t=0.7$, $t=0.9$ were considered for each office respectively.

3. Closed-Loop Feedback Vector

In the Base Case Scenario (BCS) strategy each zone is considered as independent from the other as the set point in one room is selected independently of what is happening in the other rooms.

Such assumption/consideration though is one of the main reasons for obtaining an inefficient control performance (see section IV for more details). As a matter of fact, thermal fluxes between rooms are very important, and cannot in general be neglected, especially in cases where neighboring offices are considered.

In the PCAO control strategy each zone is not considered independent of the others, as every controller’s action depends on the whole state vector. This approach, although increases the complexity of the control scheme, is able to identify and respond to inter-zone heat exchange. The feedback information for the control scheme include *forecasted information*, allowing PCAO approach to fine tune an efficient controller enhanced with *pre-active control properties*, taking advantage of future system and ambient “knowledge”. Summing up, the PCAO feedback vector is composed of the following components:

- 3 measurable external weather conditions: outside temperature, outside humidity and solar radiation.
- 12 forecasts for the mean outside temperature in the next 48 hours (divided into prediction four-hour periods).
- 12 forecasts for the mean outside solar radiation in the next 48 hours (divided into prediction four-hour periods).
- The internal temperatures of the offices.
- The internal humidities of the offices.

IV. EXPERIMENTS

This section provides details on the simulation and the real-life experiments conducted for the test case building. Simulations are conducted using historical data collected in winter 2010 using an elaborate, validated BEPS [42] model for the building established in TRNSYS [43]. Note that in all the figures, occupancy period is shown using a solid horizontal black line**:** this means that outside the occupancy period no people are present and the thermal discomfort is automatically set to zero.

1. Simulation Experiments

An elaborate available model [50] is shown in red highlighted area Figure 2. Simulation results presented in this paper are focused only on this building slice. For the sake of compactness, only the results relative to a particular *zone* (Office 207) of the building will be shown in the simulation section. The representative zone located on the second floor is presented in the simulation results, since real life experiments were performed only on second floor offices (see common green and red highlighted areas office on the second floor Figure 2).

Finally due to building management restrictions and maintenance policy of the real building during the real experiments period, the available offices for tests were 3 and all located on the second floor as shown in Figure 2 and the available period for tests was considered from 23rd of November 2013 until the 26th of December 2013.

Simulations are conducted using historical data collected in winter 2010. A period of two winter days was selected for performing BEPS-based BOC design, which corresponds to the days 12th (Monday) – 13th (Tuesday) of January 2010. The respective outdoor temperature and solar radiation for these days, used in the building simulation, are shown in Figure 6. It has to be emphasized that weather conditions during this period are unstable (from subzero ambient temperatures to over +4 °C) and significant solar radiation is not available (cloudy weather most of the time). PCAO controls the slabs by varying the set points during each simulation day.

1) PCAO vs BCS: Working period ***PULSE*** *control policy*

PCAO HVAC usage is varying every day depending on building usage policy and weather conditions (see Figure 7b). PCAO is maintaining internal temperatures between 20ºC and 22ºC, where comfort cost is very small, when occupants are present by using the slabs in an intelligent and effective way so as to consume less energy, taking advantage of weather conditions and solar radiation thermal gains. Moreover, different occupancy weights for each zone contribute to increase the complexity of the BOC system design. Table II shows the simulation results for PCAO PULSE case as compared to its respective BCS PULSE for such a s*lice*, considering the total score index. As mentioned above, due to space limitations control set points and temperatures are presented for one representative office located on the second floor, where real life experiments took place also.

It can be seen that the PCAO PULSE set points are lower than the respective BCS's, especially during the second day of the simulation. Energy consumption savings take place during both simulation days. The reason that this phenomenon occurs is due to the available solar radiation especially during the second day of the simulation period (see Figure 6).

It is reasonable to consider that each office requires a certain amount of energy every day to maintain the comfort conditions between satisfactory bounds, depending every day on the initial office state - stored energy in building's thermal mass. PCAO achieves to avoid overheating the building (office temperatures never exceed 22ºC) while consuming less energy. As can be seen from the results, the stored energy within the thermal mass combined with a small portion of energy from the slabs together with the amount of the available solar energy are efficiently utilized from PCAO, towards reducing the energy demand of the building.

PCAO PULSE is able to realize, through weather prediction data feedback, that a free resource of heating energy – solar radiation internal office gains and thermal mass "energy-charge" – can be utilized sensibly for such purpose while at the same time prevent from overheating. Therefore PCAO PULSE activates the radiant slabs in an intelligent manner so as to avoid discomfort costs during early office hours (higher set points when no solar energy is available) and in parallel to avoid thermal over charging both in energy and discomfort terms, when solar radiation will be available (lower set points). During the second day it can be seen that even less energy is necessary to maintain acceptable comfort levels since more solar radiation is available. *PCAO not only intelligently distributes the usage of radiant slabs but activates them for an optimal time period since combined thermal-mass stored energy, solar radiation and radiant slabs energy never lead to temperatures outside the acceptable comfort area [20ºC, 22ºC] (see Figure 5) as shown in Figure 7a*. On the other hand since no intelligence is included in the BCS control scenario and no logic able to act pre-actively is included, spare/more than necessary, energy is used during both simulation days. Such strategy besides increasing energy cost, it leads to undesired comfort conditions since it slightly overheats the offices during midday period.

PCAO PULSE efficiently takes advantage of the available free solar energy, even when low amounts are available, through two different energy flow “paths”: (a) directly as heat gains internally in the offices (b) indirectly through charging building thermal-mass. *PCAO presents a demand shaping behavior which is almost the inverse curve profile of solar radiation* (see Figure 6b and Figure 7b). It can be said that PCAO control presents similar behavior to a strategy that would consider *a locally installed, fictitious, photovoltaic panel (solar gains through window facades) accompanied by a thermal storage “battery” (thermal-mass) able to exploit both heat energy sources efficiently*, while in the same time slightly improving the internal comfort conditions of the offices during office hours.

*2) PCAO Vs BCS: Whole day **FREE** control policy*

The same simulation experiments were performed by applying control during the entire day, this time, both for the BCS and the PCAO approaches. The set point behavior and the control strategy followed by PCAO FREE are similar to PCAO PULSE. The only difference is that PCAO FREE, since slabs are available for control during the whole day, achieves to avoid early office hours comfort costs by pre-heating the building before working period starts. The distribution of the slabs activation differs but the total energy consumption is similar to PCAO PULSE (see Figure 8).

This behavior underlines again the fact that the necessary amount of energy the building demands, so as to have the same thermal comfort conditions, is nearly the same for all PCAO control strategies. *The intelligence of PCAO control appears in the exact distribution of the needed energy, for heating the building.*

Table III shows the total improvements of PCAO FREE strategy with respect to BCS FREE. The improvements are quite impressive taking also into account that this BCS strategy is used in practice in the real building.

2. Real-life Experiments

As mentioned before, an offline controller tuned and generated using the available TRNSYS model of the building was applied to the real life building – based on the previously presented simulation experiments.

1) Directly comparable results

Due to different weather conditions and initial states of the three zones all located on the second floor, in each experiment, not all results could be directly evaluated and post processing of raw data was necessary. However two representative and directly comparable sets of PULSE policy experiments are presented below to show the potential of PCAO idea.

a) Experimental set 1

Two comparable days (weather conditions wise) among the test results could be extracted for more detailed analysis and comparison. The experimental days PCAO PULSE #3 and BCS PULSE #1 were selected as shown in Figure 9.

The respective actual weather conditions for these two experimental days are shown in Table IV below. As shown in Table IV the weather conditions of these two days were quite similar therefore the comparison between these two experiments can be considered reasonable since the initial temperatures of all three rooms were quite similar too.

Considering very similar weather conditions for these two experiments it can be seen from the energy consumption figures that PCAO PULSE is able to outrun the BCS PULSE performance by far and take advantage of the available amount of solar radiation during the day. It can be seen that after midday where solar radiation takes significant values that slabs for all three rooms are deactivated since the rest of the necessary energy will be gained from the solar energy which is free of cost – as expected from the weather forecasted data. It is also important to mention that both BCS PULSE and PCAO PULSE achieve the same comfort conditions for all three offices by keeping the internal temperatures between the acceptable bounds as shown in Figure 5. The improvements in energy consumption of PCAO approach under real-life circumstances are shown in Table VI.

b) Experimental set 2

The second set of comparable experiments considers PCAO PULSE #1 and BCS PULSE #4. This is an extreme example of the intelligence PCAO incorporates in the control decisions. The weather conditions for these two days are shown in Table V. It can be seen that the weather conditions are much more beneficial to the BCS PULSE control. Thus someone, reasonably, would expect less energy consumption in the BCS PULSE case.

However PCAO PULSE again is able to outrun the BCS PULSE performance following the same logic and taking the optimal decisions in a smooth and intelligent manner, as thoroughly described in previous examples. Even in cases where low amounts of solar radiation are available PCAO is able to utilize the available free solar energy in a beneficial way so as to save energy while keeping the thermal comfort conditions between satisfactory levels. The following figures (see Figure 10) of the PCAO PULSE detailed performance in all three offices underline in an emphatic manner the efficiency of PCAO against the BCS.

2) Fair comparison metrics

For fair comparison reasons the experimental results should be post processed so as to make sure that the comparison between BCS and PCAO experiments is fair enough. A metric for projection and fair comparison between all experimental days was designed based on [50][51], taking into account solar radiation, ambient temperature and the difference between 22°C and initial zone temperature at 8.00am.

All these measures were normalized and weighted evenly (*w1=w2=w3=0.33*) to produce a more detailed metric that combines the significant information about the system thermal behavior as follows:

$$EASE\ COMFORT\ INDEX\ = w1\frac{AmbientTemp}{\max(MeanAmbientTemp)} + \\ + w2\frac{SolarRadiation}{\max(SolarRadiation)} + w3\left(1-\frac{22-ZoneTemp@8.00}{\max(22-ZoneTemp@8.00)}\right)$$

The logic for such metric is simple: increased available solar radiation gains, combined with high ambient temperature should lead to a less energy demanding control strategy to achieve same comfort levels. In addition the difference between the initial office temperature and 22°C has a two-fold meaning: (a) acts as index that shows how close the initial state is to the maximum available comfort-wise accepted temperature (b) acts as a metric regarding the heat energy stored within the building's body thermal mass. If the initial temperature is close to 22°C then much less or even zero energy should be necessary to maintain satisfactory comfort levels during occupancy period. Therefore this metric indicates *"how easy is the problem of consuming less energy to achieve the same comfort conditions".* Figure 11a, Figure 11b and Figure 11c depict the trend and the improvements of the two PCAO (PULSE & FREE) approaches with respect to their BCS (PULSE & FREE) control schedules. Linear fitting was conducted and is presented within these figures, so as to have a rough idea of the performance comparison for each office. Finally, Table VII summarizes, for all investigated real-life experiments, the achieved energy savings. The choice of the even weights (*w1=w2=w3=0.33*) in multiobjective optimization can indeed be always open to discussion. We point out that we performed comparisons also with different weights ranging in [0.25, 0.6] and we found always that PCAO (PULSE & FREE) improve with respect to BCS (PULSE & FREE), of course with different percentages. The full comparisons are not shown for lack of space and for better readability. The conclusion of the comparisons is that for a wide range of weights the proposed solution is optimal (specifically Pareto optimal) with respect to the control strategy currently adopted in the building.

V. CONCLUSIONS AND FUTURE WORK

Complex systems, such as buildings, require more intelligent control decisions than rule based strategies for optimal performance. Rules and experts on facility operation may control such systems more or less efficiently, but not in an optimal manner. Efficiency in highly nonlinear, complex, large scale, systems can be achieved through optimization algorithms.

PCAO proved to be able to utilize free solar energy directly – solar heat gains - and indirectly – mass stored energy - and decrease the slabs heat consumption even during winter periods and in highly complex systems with very good thermal construction and extremely slow dynamics. For the test case building under consideration such control solution would lead to relevant energy savings [~50%], while avoiding the installation of photovoltaic panels (or a solar thermal system) to collect solar energy for direct or indirect heating purposes. Both simulation and real-life experiments demonstrate the intelligence pattern followed by PCAO in exploiting solar radiation, deciding when to activate, when to deactivate and for how long to activate the slabs so as to guarantee reduced energy consumption in an energy building which is meant to be already energy-efficient. Such a delicate and intelligent behavior cannot be realized by employing rule-base logics, which are used in the German building as well as in the vast majority of BOC systems today.

Future work will include additional and extensive real-life experiments in the real building (e.g. including more rooms and more variable weather conditions) in order to obtain stronger and more complete results and to quantify with more precision the achievable improvements (also with respect to other criteria like emissions and energy costs).

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VII. REFERENCES

[1] A. Costa, M. M. Keane, J. I. Torrens, and E. Corry, “Building operation and energy performance: Monitoring, analysis and optimisation toolkit”, *Applied Energy* 101, (2013), pp. 310-316.

[2] M. Karmellos, A. Kiprakis, and G. Mavrotas, “A multi-objective approach for optimal prioritization of energy efficiency measures in buildings: Model, software and case studies”, *Applied Energy* 139, (2015), pp. 131-150.

[3] C. Li, T. Hong, and D. Yan, “An insight into actual energy use and its drivers in high-performance buildings”, *Applied Energy* 131, (2014), pp. 394-410.

[4] C. Barreneche, M. E. Navarro, A. I. Fernández, and L. F. Cabeza, “Improvement of the thermal inertia of building materials incorporating PCM. Evaluation in the macroscale”, *Applied Energy* 109, (2013), pp. 428-432.

[5] A. Mahdavi, C. Pröglhof, M. Schuss, and K. Orehounig. “Passive Cooling in existing buildings: an innovative approach”, *REHVA Journal* 47(4), (2010), pp. 42–47.

[6] K. A. Antonopoulos and E. P. Koronaki. “Effect of indoor mass on the time constant and thermal delay of buildings”, *International Journal of Energy Research* 24, (2000), pp. 391–402.

[7] J. A. Orosa and A. C. Oliveira, “A field study on building inertia and its effects on indoor thermal environment”, *Renewable Energy* 37(1), (2012), pp. 89-96.

[8] J. Karlsson, L. Wadsö, and M. Öberg, “A conceptual model that simulates the influence of thermal inertia in building structures”, *Energy and Buildings* 60, (2013), pp. 146-151.

[9] D&R International Ltd., “2011 Buildings Energy Data Book”, *Buildings Technologies Program Energy Efficiency and Renewable Energy U.S. Department of Energy*, (2012).

[10] N. Aste, A. Angelotti, and M. Buzzetti, “The influence of the external walls thermal inertia on the energy performance of well insulated buildings”, *Energy and Buildings* 41(11), (2009), pp. 1181-1187.

[11] T. Olofsson and T. M. I. Mahlia. “Modeling and simulation of the energy use in an occupied residential building in cold climate”, *Applied Energy* 91, (2012), pp. 432–438.

[12] K. W. Roth, D. Westphalen, J. Dieckmann, S. D. Hamilton, and W. Goetzler, “Energy Consumption Characteristics of Commercial Building HVAC Systems Volume III: Energy Savings Potential”, *Building Technologies Program*, Contract No.: DE-AC01-96CE23798 (2002).

[13] L. Yang, H. Yan, and J. C. Lam. “Thermal comfort and building energy consumption implications -- A review”, *Applied Energy* 115, (2014), pp. 164 – 173.

[14] B. Lehmann, V. Dorer, M. Gwerder, F. Renggli, and J. Tödtli,”Thermally activated building systems (TABS): Energy efficiency as a function, of control strategy, hydronic circuit topology and (cold) generation system”, *Applied Energy* 88, (2011), pp. 180–191.

[15] A. Arteconi, N. Hewitt, and F. Polonara. “State of the art of thermal storage for demand-side management”, *Applied Energy* 93, (2012), pp. 371-389.

[16] Oldewurtel, F.; Parisio, A.; Jones, C.N.; Morari, M.; Gyalistras, D.; Gwerder, M.; Stauch, V.; Lehmann, B.; Wirth, K., "Energy efficient building climate control using Stochastic Model Predictive Control and weather predictions," *American Control Conference (ACC)*, (2010), pp. 5100-5105.

[17] M. Gwerder, D. Gyalistras, C. Sagerschnig, and R. S. S. D. Sturzenegger, “Final Report: Use of Weather And Occupancy Forecasts For Optimal Building Climate Control – Part II: Demonstration (OptiControl-II)”, 2013.

[18] J. Bai, S. Wang, and Z. Xiaosong. “Development of an adaptive smith predictor-based self-tuning pi controller for an hvac system in a test room.” *Energy and Buildings* 40(12), (2008), pp. 2244 – 2252.

[19] M. Gwerder, D. Gyalistras, F. Oldewurtel, B. Lehmann, K. Wirth, V. Stauch, and J. Tödtli. “Potential assessment of rule-based control for integrated room automation”. *Proc. 10th REHVA World Congress, Sustainable Energy Use in Buildings – Clima 2010*, (2010).

[20] J. Liang and R. Du. “Design of intelligent comfort control system with human learning and minimum power control strategies”, *Energy Conversion and Management*, 49(4), (2008), pp. 517 – 528.

[21] F. Oldewurtel, A. Parisio, C. N. Jones, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, and M. Morari, “Use of model predictive control and weather forecasts for energy efficient building climate control”, *Energy and Buildings* 45, (2012), pp. 15-27.

[22] J.D. Álvarez, J.L. Redondo, E. Camponogara, J. Normey-Rico, M. Berenguel, P.M. Ortigosa, “Optimizing building comfort temperature regulation via model predictive control”, *Energy and Buildings*, (57), (2013), pp. 361-372.

[23] M. Avci, M. Erkoc, A. Rahmani, S. Asfour, "Model predictive HVAC load control in buildings using real-time electricity pricing", *Energy and Buildings*, (60), (2013), pp. 199-209.

[24] M. Trcka, J. L. M. Hensen, and M. Wetter. “Co-simulation of innovative integrated HVAC systems in buildings”, *Journal of Building Performance Simulation (2)*, (2009), pp. 209–230.

[25] T. Nghiem and G. H. Pappas. “Receding-horizon supervisory control of green buildings”, *American Control Conference*, San Francisco, CA, (2011).

[26] M. F. Pichler, A. Dröscher, H. Schranzhofer, G. I. Giannakis, E. B. Kosmatopoulos, and D. Rovas, “Simulation-assisted building energy performance improvement using sensible control decisions”. In: Build-Sys’11 Proceedings. Seattle, WA, USA (2011).

[27] J. Wright, H. Loosemore, and R. Farmani, “Optimization of building thermal design and control by multi-criterion genetic algorithm”, *Energy and Buildings* 34, (2002), pp. 959-972.

[28] M. Gruber, A. Trüschel, J.-O. Dalenbäck, “Model-based controllers for indoor climate control in office buildings – Complexity and performance evaluation”, *Energy and Buildings* 68, (2014), pp. 213-222.

[29] S. H. Kim, “An evaluation of robust controls for passive building thermal mass and mechanical thermal energy storage under uncertainty”, *Applied Energy* 111, (2013), pp. 602-623.

[30] E. Žáčeková, Z. Váňa, and J. Cigler, “Towards the real-life implementation of MPC for an office building: Identification issues”, *Applied Energy* 135, (2014), pp. 53-62.

[31] A. E. Ben-Nakhi and M. A. Mahmoud. “Energy conservation in buildings through efficient A/C control using neural networks”, *Applied Energy* 73, (2002), pp. 5–23.

[32] J. Siroky, F. Oldewurtel, J. Cigler, and S. Prívara. “Experimental analysis of model predictive control for an energy efficient building heating system”, *Applied Energy* 88, (2011), pp. 3079–3087.

[33] A. Kusiak, M. Li, and F. Tang. “Modeling and optimization of HVAC energy consumption” *Applied Energy* 87, (2010), pp. 3092–3102.

[34] M. Aydinalp-Koksal and M .Ugursal, “Comparison of neural network, conditional demand analysis and engineering approaches for modeling end-use energy consumption in residential sector”, *Applied Energy* 85, (2008), pp. 271–296.

[35] E. B. Kosmatopoulos and A. Kouvelas. “Large-scale nonlinear control system fine-tuning through learning”, *IEEE Transactions Neural Networks* 20, (2009), pp. 1009–1023.

[36] C. Korkas, S. Baldi, I. Michailidis, and E. B. Kosmatopoulos. “Intelligent energy and thermal comfort management in grid-connected microgrids with heterogeneous occupancy schedule”, *Applied Energy*, (2015), in print.

[37] D. Kolokotsa, D. Rovas, E. B. Kosmatopoulos, and K. Kalaitzakis. “A roadmap towards intelligent net zero- and positive-energy buildings”, *Solar Energy* 85, (2012), pp. 3067–3084.

[38] E. B. Kosmatopoulos, “An adaptive optimization scheme with satisfactory transient performance”, *Automatica* 45, (2009), pp. 716-723.

[39] S. Baldi, I. Michailidis, E. B. Kosmatopoulos, A. Papachristodoulou, and P. A. Ioannou, “Convex Design Control for Practical Nonlinear Systems”, *IEEE Trans. on Automatic Control* 59(7), (2014), pp. 1692-1705.

[40] S. Baldi, I. Michailidis, E. B. Kosmatopoulos, and P. A. Ioannou, “A “Plug-n-Play” Computationally Efficient Approach for Control Design of Large-Scale Nonlinear Systems using co-Simulation”, *IEEE Control Systems Magazine* 34(5), (2014), pp. 56-71.

[41] CEN, “Ergonomics of the thermal environment – Analytical determination and interpretation of thermal comfort using calculations of PMV and PPD indices and local thermal comfort criteria”, *Österreichisches Normungsinstitut*, (2006).

[42] A. Dröscher, M. Pichler, H. Schranzhofer, A. Constantin, N. Exizidou, G. Giannakis, and D. Rovas; PEBBLE FP7-ICT-2009-6.3, Deliverable D2.2: Validation Results of the Models, available at www.pebble-fp7.eu, (2011).

[43] S. Klein, W. Beckman, and J. Duffie, “TRNSYS - A Transient Simulation Program”, *ASHRAE Transactions* 82, (1976), pp. 623--633.

[44] H. Gerd, K. Jan, and S. Dietrich. “Technical measurement investigations of an office building characterized by low energy use and high thermal comfort”, *7th Nordic Building Physics Symposium, Proceedings*, (2005) p. 8.

[45] M. De Carli and G. Hauser, “AN INNOVATIVE BUILDING BASED ON ACTIVE THERMAL SLAB SYSTEMS,” *58th ATI National Conference San Martino di Castrozza, Italy*, (2003) p. 12.

[46] D. Schmidt, “The Centre for Sustainable Building (ZUB) A Case Study,” *Sustainable Building* (2003), p. 7.

[47] M. Johansson and A. Rantzer. “Computation of piecewise quadratic lyapunov functions for hybrid systems”, *IEEE Trans. on Automatic Control* 43, (1998), pp. 555–559.

[48] R.E Bellman: *Dynamic Programming*, Princeton (1957).

[49] ASHRAE, ANSI/ASHRAE Standard 55-2013: “Thermal environmental conditions for human occupancy”, *https://www.ashrae.org/resources--publications/bookstore/standard-55* (2013).

[50] J. R. Santiago, M. Krause, and J. Adnot, Project PEBBLE Deliverable D7.3 Results of On-Site Evaluation, available at www.pebble-fp7.eu, (2013).

[51] “Methodology and Technical Report for Scenarios of the Climate Severity Index” By Trevor Murdock and Rick Lee with contributions by Elaine Barrow, Francis Zwiers, and Ian Rutherford.

[52] Stephenson, D. & Mitalas, G.Calculation of heat conduction transfer functions for multi-layer slabs. ASHRAE Transactions, 1971, 77(2), 117-126

[53] Lechner, T.Berechnung des Wärmestromes durch ebene geschichtete Wände, Mathematische und physikalische Grundlagen der Transfer Function – Methode, Institut für Thermodynamik und Wärmetechnik Universität Stuttgart, 1992

[54] Delcroix, B.; Kummert, M.; Daoud, A. & Hiller, M., CONDUCTION TRANSFER FUNCTIONS IN TRNSYS MULTIZONE BUILDING MODEL: CURRENT IMPLEMENTATION, LIMITATIONS AND POSSIBLE IMPROVEMENTS, SimBuild, 2012

[55] Koschenz, M. and Lehmann, Thermoaktive Bauteilsysteme TABS, EMPA, 2000

[56] Koschenz, M., Dorer, V. Interaction of an air system with concrete core conditioning Energy and Buildings , 1999, 30, 139 - 145

Appendix A. BEPS – the TRNSYS building model

The TRNSYS building model is realized with the Version TRNSYS 17. The geometrical construction is drawn with Google SketchUp – this is required if one wants to make use of the full 3D functionality concerning the radiation mode that is provided with TRNSYS 17. The geometric model is then imported within TRNBUILD – the provided GUI for editing the building parametrization – and the construction of each wall, floor and ceiling and the window properties are defined. Construction specific details on the building model may be found in the PEBBLE project reports, see e.g. [42]. A few modelling aspects related to the energy demand, especially the heating system and the air exchange, are described in the following.

Any wall in TRNSYS is modelled by means of the transfer function approach. This approach considers only the heat conduction in orthogonal direction (the shortest path from one side of a wall to the other), lateral heat conduction is neglected. The transfer functions are obtained through Laplace transformation of the one-dimensional heat equation and discretization, the details are provided in [52-54]. The model for the thermally activated building system (TABS) takes a special role. The so called active layers (AL) in each floor are incorporated into the layer definition of a wall, floor or ceiling. As for the floor the whole floor area is then divided into four segments – this division leads to spatially better resolved simulation results and it is necessary to obey mass flow rate limit values as required by the TABS-model implemented in TRNSYS. The TABS model implemented in TRNSYS is well documented in [55] but also in [56] and [43] and it has been validated using FE-simulations and real measurement data.

The natural air exchange to the ambient (infiltration) is a typical property of the building, this interaction with ambient is realized through a constant. Ventilation losses are modelled as a function of the current CO2 concentration in the building, which depends on the occupancy schedule. The ventilation itself is realized through automatic window opening – it is assumed that the occupants would react similarly according to the defined CO2 threshold. The air exchange between the three air-nodes of the atrium are parametrized such to fit the real measurement values concerning the vertical temperature stratification in the atrium. The air-exchange between office rooms is not modelled in TRNSYS. Experimentally such losses have been found to be negligible: this is because in practice the doors open automatically only for transit. The office occupants are also advised not to leave the doors open. Solar to air factors are considered being zero. This is only an approximation, but the real construction is extremely heavy weight and there is not too much lightweight furniture in the offices.

Figure 1.Test Case Building, Kassel Germany.

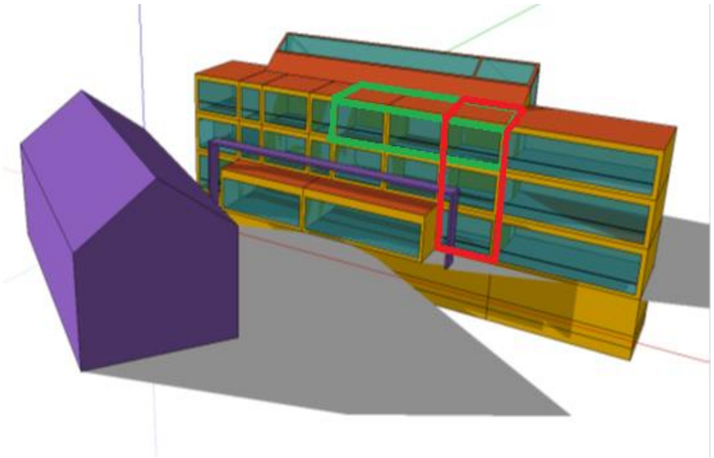

Figure 2. FIBP TRNSYS building model - Reduced "slice" model: **red** highlighted offices / real-life tests: **green** highlighted offices.

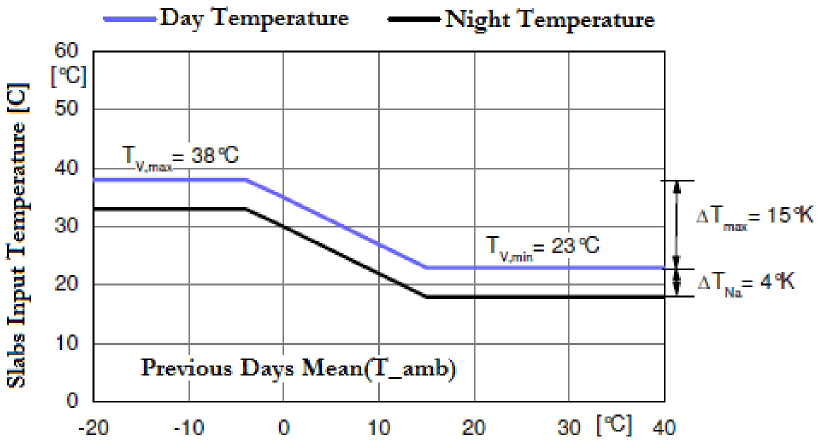

Figure 3. TABS supply water temperature as a function of the ambient temperature

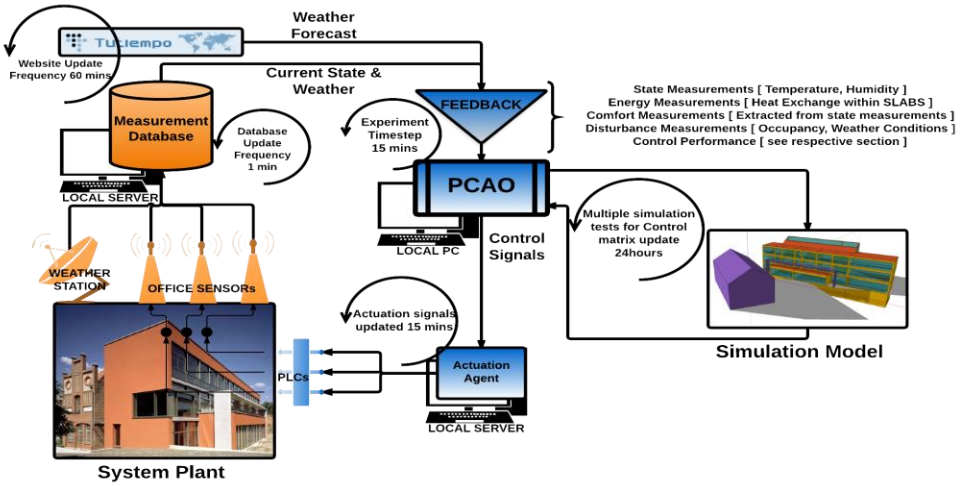

Figure 4. PCAO simulation-based approach for BOC design.

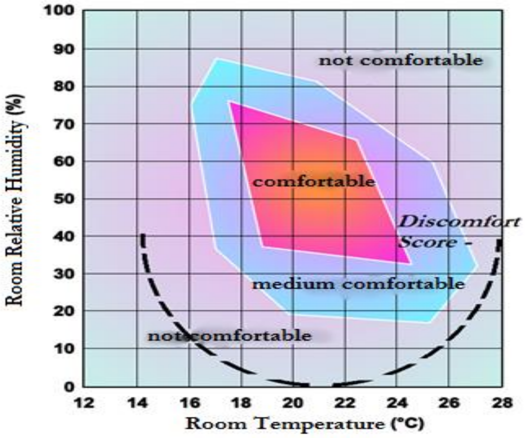

Figure 5. Discomfort score model based on ANSI/ASHRAE-55 standards.

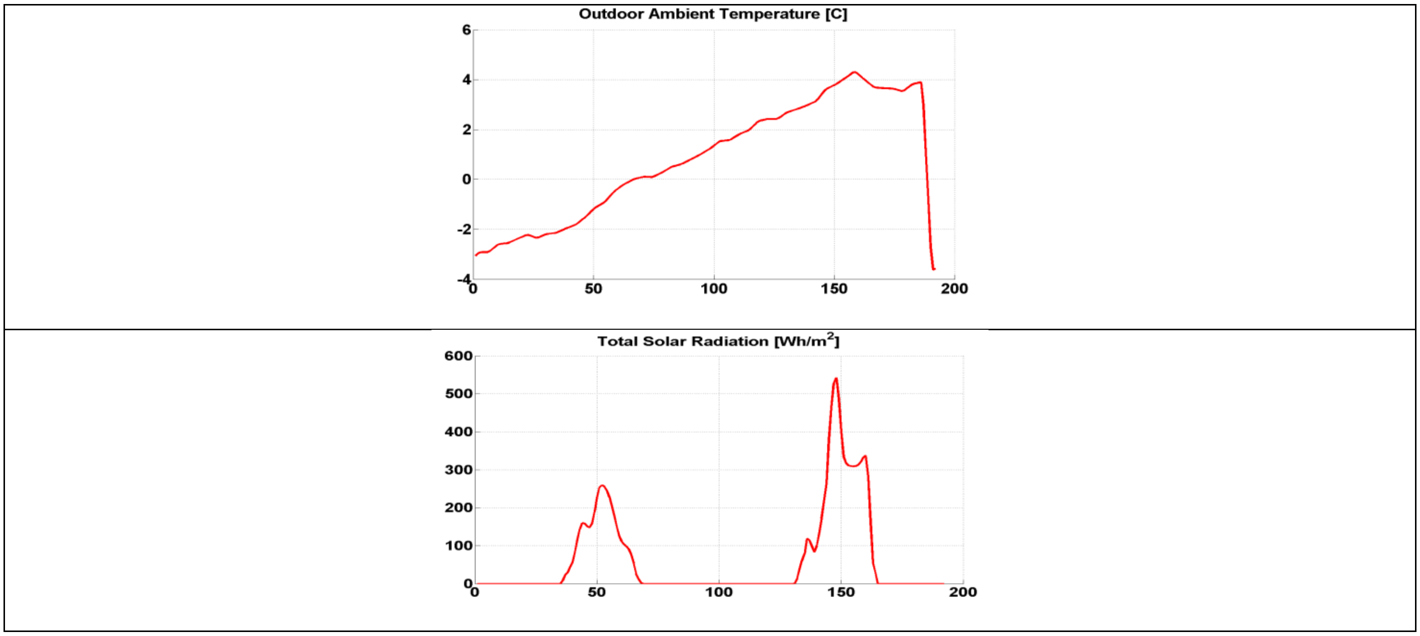

Figure 6. Weather conditions during simulation period (x-axis corresponds to simulation timesteps: 1 timestep = 15mins)

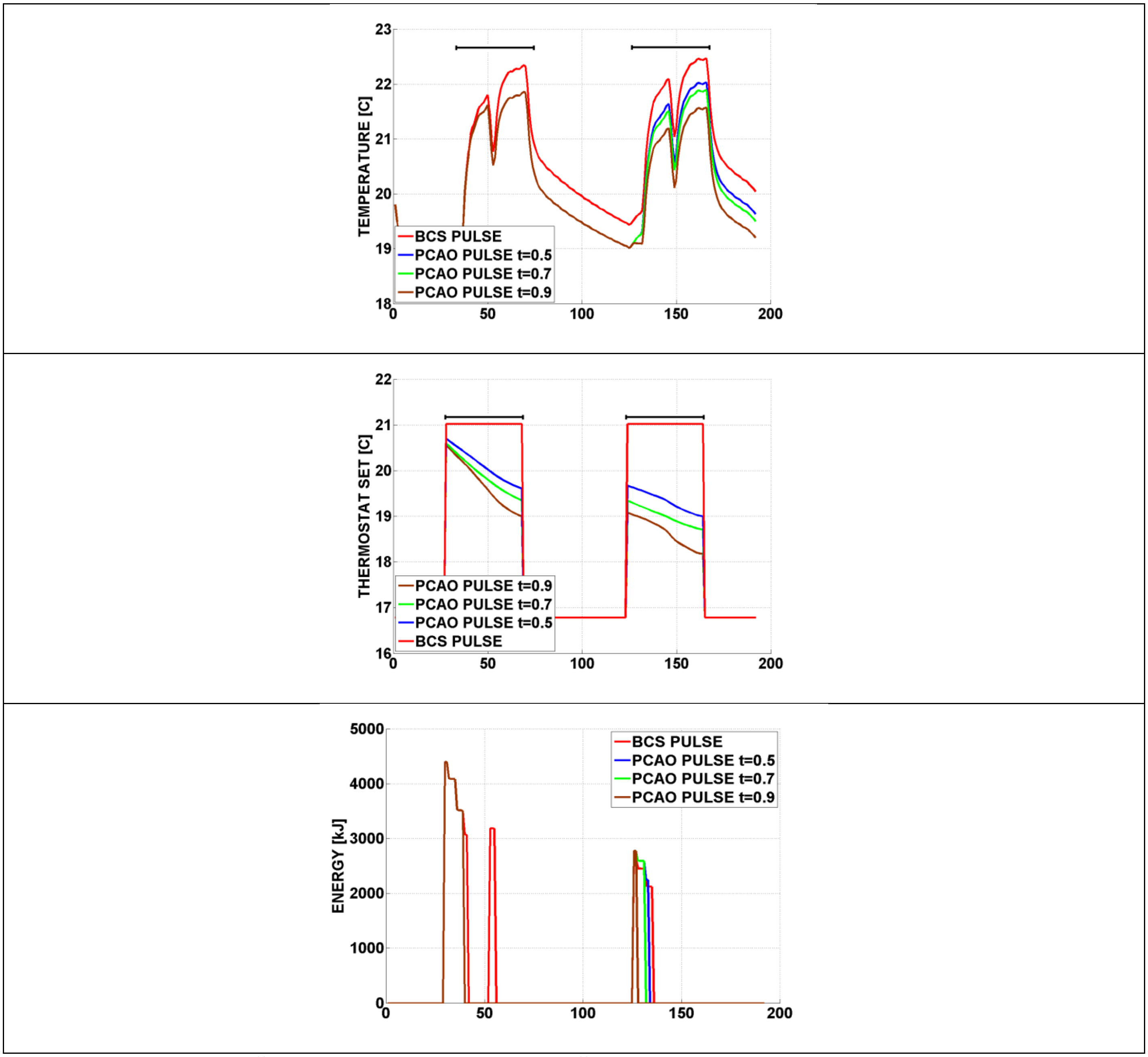

Figure 7. (a-top) Second Floor Office Temperatures (b-middle) Second Floor Office Thermostat Set points (c-bottom) Instantaneous Energy Consumption. (x-axis corresponds to simulation timesteps: 1 timestep = 15mins), legend: BCS PULSE (red), PCAO PULSE t=0.5 (blue), PCAO PULSE t=0.7 (green), PCAO PULSE t=0.9 (brown)

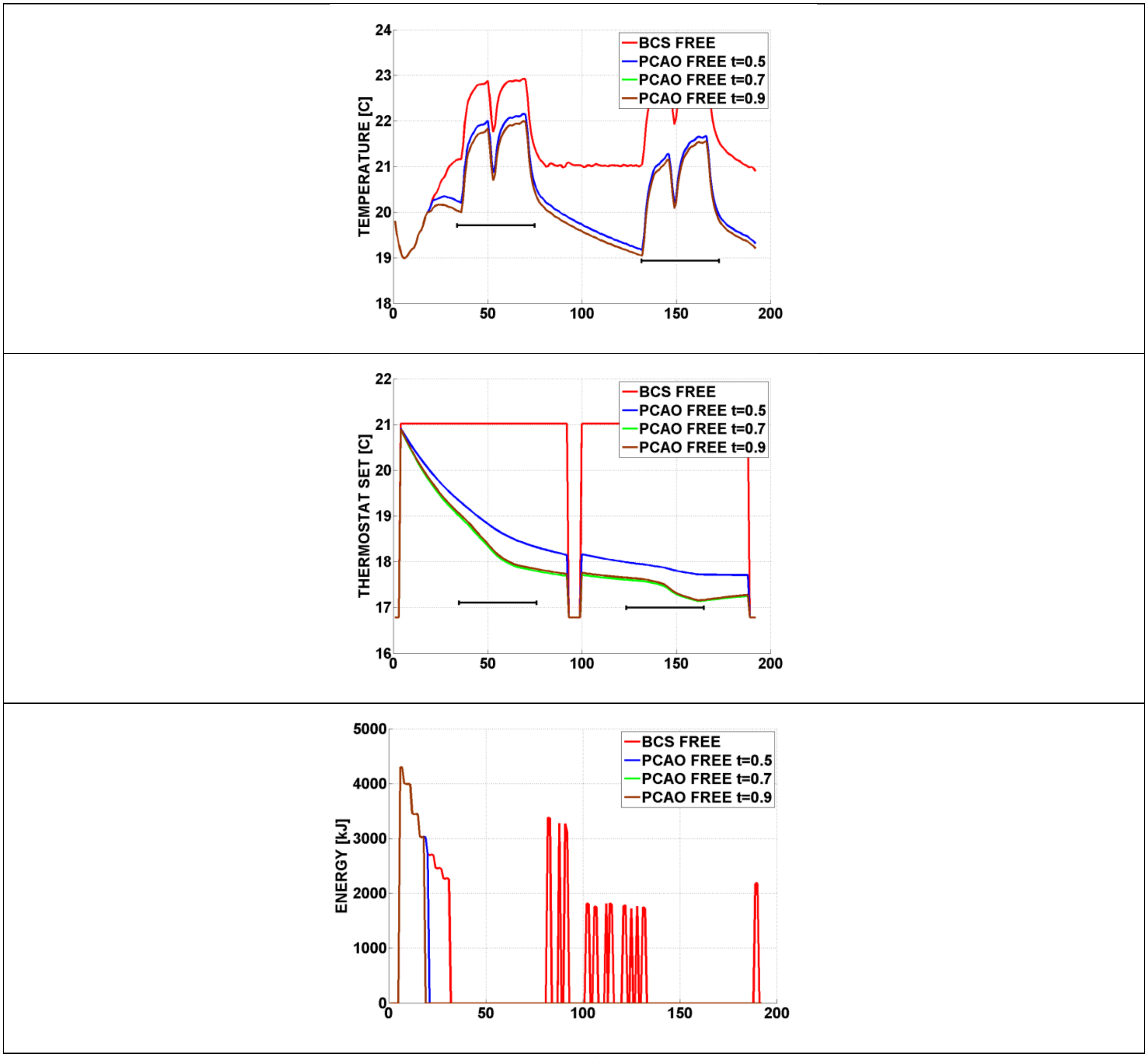

Figure 8. (a-top) Second Floor Office Temperatures (b-middle) Second Floor Office Thermostat Set points (c-bottom) Instant Energy Consumption. (x-axis corresponds to simulation timesteps: 1 timestep = 15mins), legend: BCS PULSE (red), PCAO PULSE t=0.5 (blue), PCAO PULSE t=0.7 (green), PCAO PULSE t=0.9 (brown)

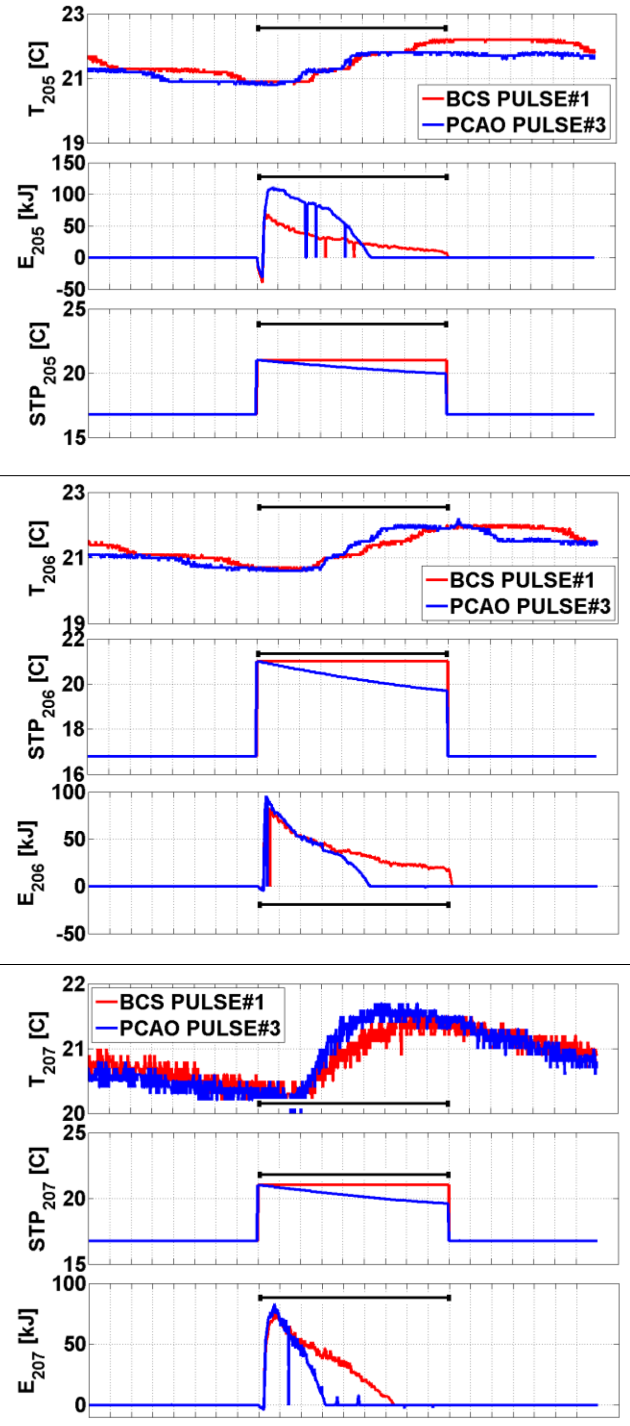

Figure 9. PCAO Vs BCS PULSE Performance – 1st experimental set. Internal office temperature, Thermostat set points and Energy consumption are shown respectively for (a-top) Office 205 (b-middle) Office 206 and (c-bottom) Office 207 during a 24h horizon.

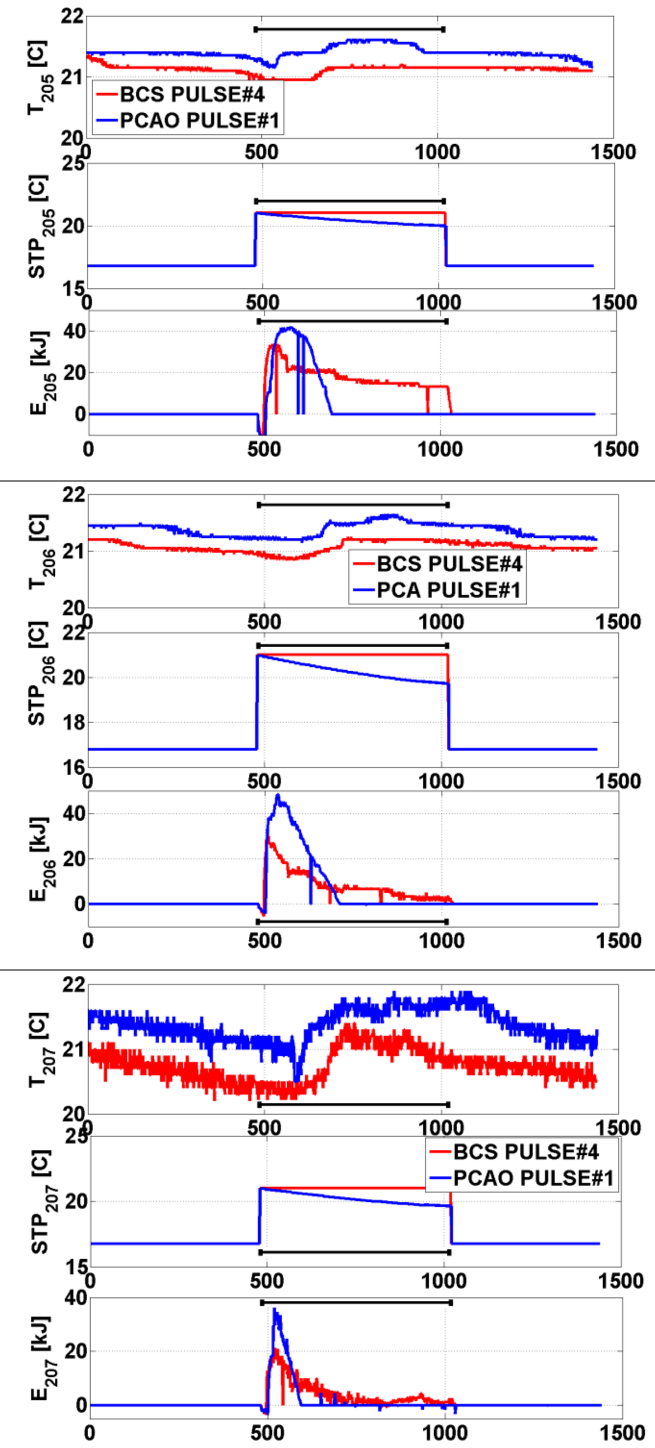

Figure 10. PCAO Vs BCS PULSE Performance – 2nd experimental set. Internal office temperature, Thermostat set points and Energy consumption are shown respectively for (a-top) Office 205 (b-middle) Office 206 and (c-bottom) Office 207 during a 24h horizon.

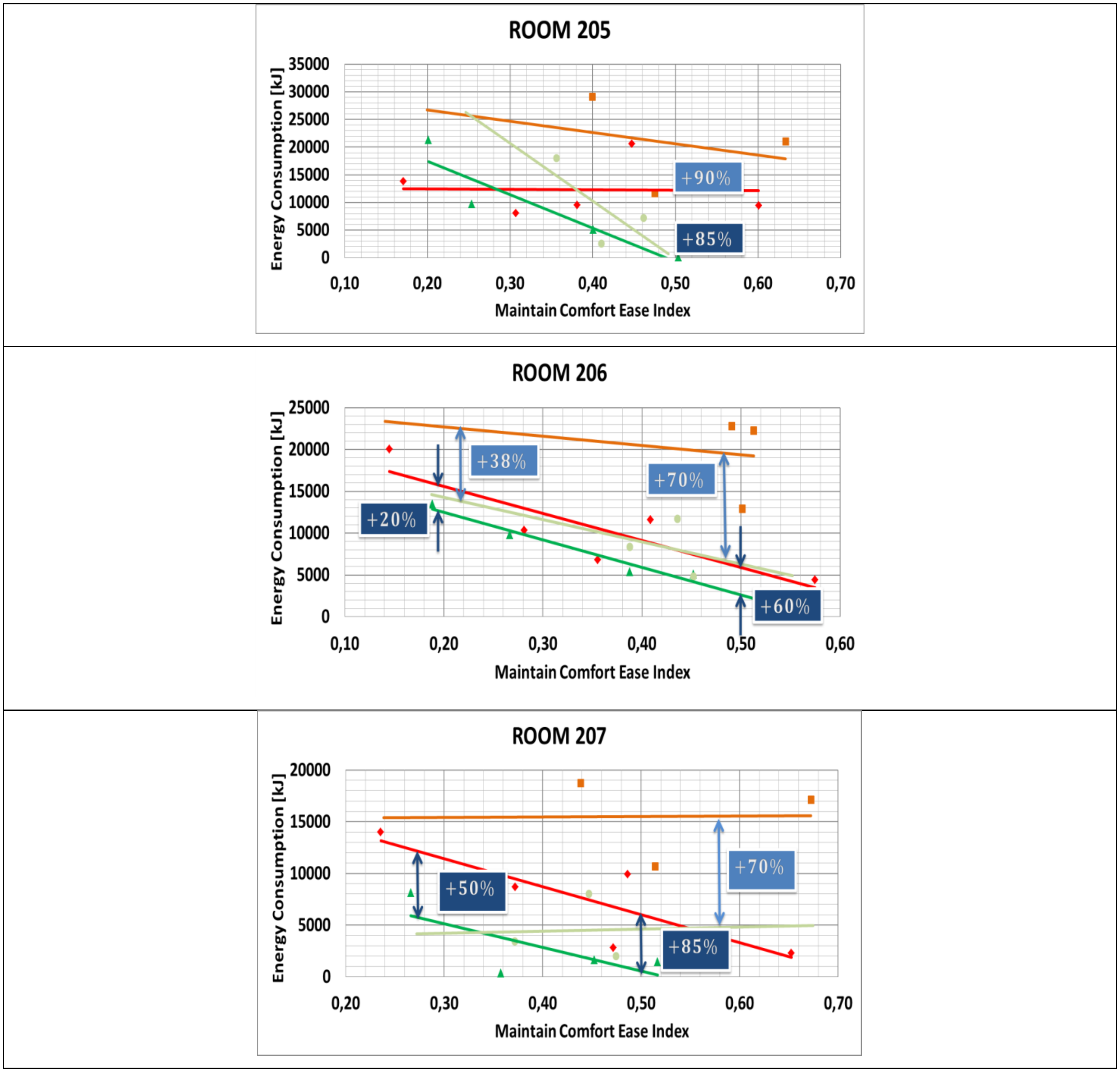

Figure 11. PCAO PULSE (green) Vs BCS PULSE (red) and PCAO FREE (light green) Vs BCS FREE (orange) performances for Office (a-top) 205 (b-middle) 206 (c-bottom) 207.

Table I. Comparison of BEPS-based, PCAO and modern Optimization algorithms on BOC design.

Test Case (BEPS using TRNSYS)		
Methodology	*Iterations*	*Energy Savings wrt the Best Practice (for the same user comfort conditions)*
PCAO	~50	30%-50%
Popular Optimization Algorithms	>10000	0%-5%

Table II. Simulation PCAO PULSE Total Score Improvements

Weight Factor	**Simulation PCAO PULSE Total Score Improvement**
t = 0.5	38%
t = 0.7	40%
t = 0.9	50%

Table III. Simulation PCAO FREE and BCS FREE Total Improvements using different optimization weights between User Comfort & Energy Consumption

Weight Factor	**Simulation PCAO FREE Improvement**
t=0.5	54%
t=0.7	56%
t=0.9	57%

Table IV. Weather conditions of 1st PULSE comparative experiment set

Experiment	*Average T_{amb}*	*Average Solar Radiation*
PCAO PULSE #3	2,53°C	37,03 kJ/m^2
BCS PULSE #1	2,05°C	25,90 kJ/m^2

Table V. Weather conditions of 2nd PULSE comparative experiment set

Experiment	*Average T_{amb}*	*Average Solar Radiation*
PCAO PULSE #1	6,02°C	39,17 kJ/m^2
BCS PULSE #4	11,54°C	86,56 kJ/m^2

Table VI. Total energy consumption and savings in real application

	Office 205 [kJ]	*Office 206 [kJ]*	*Office 207 [kJ]*	*Total [kJ]*	*[%]*
BCS PULSE#1	13850	20020	13993	47863	+23%
PCAO PULSE#3	15322	13472	8119	36913	
BCS PULSE#4	9461	4420	2269	16150	+26%
PCAO PULSE#1	5021	5358	1638	12017	

Table VII. Summary of real life application savings w.r.t. BCS strategies

	PCAO	Energy Savings [%]
OFFICE 205	PULSE	0-80
	FREE	0-90
OFFICE 206	PULSE	20-60
	FREE	40-70
OFFICE 207	PULSE	50-80
	FREE	~70