THE POTENTIAL OPAQUE ADAPTIVE FAÇADES FOR OFFICE BUILDINGS IN A TEMPERATE CLIMATE

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ABSTRACT

A large amount of non-renewable resources is used in buildings. A façade, as an interface between the internal and external environment, has crucial impacts on the energy demand and of the indoor environmental quality in a building. Adaptive façade technologies represent a valuable opportunity to reduce the impact of energy use in buildings while improving the environmental quality. This paper presents the implementation of an inverse method to evaluate the potential of adaptive insulation materials. The method is implemented within a bespoke tool that combines multi-objective optimisation coupled with building performance simulation (BPS). A possible configuration of an adaptive insulation wall is proposed, adopting an actively controllable thermal transmittance on the outer and inner surface of an opaque construction. The energy saving and thermal comfort improvements of adopting the adaptive insulation is evaluated with a south-oriented reference cellular office room in a temperate climate. It is found that the proposed adaptive insulation construction could save 25-35% of energy, and improve the indoor thermal comfort by 40-60%, compared to static insulation solutions. This method and the bespoke tool are also useful for evaluating the performance of other adaptive technologies.

INTRODUCTION

The large amount of non-renewable resources consumed in buildings to maintain a comfortable indoor environment is a major contributor to CO_2 emissions and climate change and has therefore become a global matter of concern. A study by McKinsey (2009) showed that insulation retrofit for buildings is much more cost-effective than other energy saving technologies such as solar photovoltaic and geothermal. Traditional insulation materials have relatively high thermal conductivity, such as mineral wool (0.03-0.04W/mK), expanded polystyrene (0.03-0.04W/mK), extruded polystyrene (0.03-0.04W/mK), etc. They tend to lead to thick and costly building envelopes. Additionally, their thermal conductivities vary with temperature, moisture content, etc (Jelle, 2011). In comparison, high-performance insulation materials or technologies could achieve much lower thermal conductivities (Jelle, 2011). Available VIP products can achieve conductivities as low as 0.003-0.004 W/mK. This is currently the best performing static insulation technology in terms of thermal conductivity. Problems associated with VIP involve degradation, thermal bridges and vulnerability to penetration. Some alternative insulation materials including VIM, GIM and NIM have been proposed with a theoretical thermal conductivity lower than 0.004 W/mK. Although these products are still under development, they could potentially mitigate the problems of VIP technology.

Apart from minimising the thermal conductivity of a material, insulation solutions that are able to modulate their thermal conductivity can be even more promising for reducing the total energy use of the building (heating and cooling) while improving the indoor environmental quality. These kind of solutions are classified as Responsive (or Adaptive) Building Elements (Perino et al, 2007), as they have the ability to adapt to ever changing outdoor/indoor boundary conditions and/or occupant preferences, in order to maximize a certain performance of the building. Therefore, ideally, an insulation construction should not only be capable of achieving a low level of thermal conductivity, but it should also offer the opportunity to control it within a desirable range, in order to transfer/block desirable/undesirable heat as required.
Early versions of dynamic insulation were achieved by integrating a facade with a system based on heat convection through air (Brunsell, 1995) or liquid (Buckley, 1978). The theoretical U-value of the former could be reduced to close to zero (Brunsell, 1995). The latter, so called bi-directional thermodiode, is capable of transferring heat in one direction and providing insulation in the other. One variation developed by Varga et al (2002) for cooling season achieved switchable apparent conductivity from 0.07W/mK up to 0.35W/mK. Some other adaptive insulation technologies control thermal conduction by varying gas pressure, the mean free path of gas molecules or gas-surface interaction in an insulation panel. In (Xenophou, 1976) a system is devised to vary the thermal conductivity by controlling pressure in a wall with a cell structure. Another example is found in (Benson et al., 1994), in which a variable thermal transmittance is achieved by changing the pressure of hydrogen gas by means of absorption/desorption

process of the gas itself. Berge et al. (2015) developed a system to modulate the thermal conductivity of the air in the nano-porous fumed silica structure of a VIP, by means of controlling the air pressure. In (Kimber et al., 2014) the thermal transmittance of a wall is modulated by controlling the distance between a multi-layered polymer membrane. The adaptive ranges of the above-mentioned technologies are summarised in Table 1.

Table 1 Adaptive Insulation technologies

TECHNOLOGY	ADAPTIVE RANGE
Bi-directional thermodiode	Thermal conductivity 0.07-0.35W/mK Varga et al (2002)
Variable Conductance Insulation	Thermal transmittance 1-8 W/m^{2}K (Benson et al, 1994).
Adaptive VIP	Thermal conductivity 0.007-0.019 W/mK (Berge et al., 2015)
Adaptive Aerogel blanket	Thermal conductivity 0.011-0.017 W/mK (Berge et al, 2015).
Adaptive Multilayer Wall	Thermal transmittance 0.2-8 W/m^{2}K (Kimber et al, 2014).

The performance of these adaptive technologies (in terms of total energy use and indoor environmental quality) when integrated into a building has not been attempted to-date, largely due to limitations of building performance simulation (BPS) tools. In this paper, an integrated optimisation and design tool that can evaluate the performance of adaptive/responsive building envelope elements is presented, and the tool is used to evaluate a case study of a building integrated adaptive insulation. The method to evaluate the performance of adaptive building envelope elements is first introduced, together with the proposed simulation framework. Then the performance of a cellular office room located in Shanghai with an adaptive insulation on its south facade is evaluated with the tool.

METHODOLOGY

Description of the simulation framework

In order to evaluate the potential of adaptive insulation, an inverse approach is adopted by evaluating the optimal time series of dynamic building envelope properties required to achieve a certain performance (Kasinalis et al. 2013) (Favoino et al., 2015). The implementation of this approach is constrained by limitations of existing BPS tools: (a) simulation of varying building envelope properties; (b) implementation of receding horizon control (RHC) (Mattingley et al., 2011); (c) capability of explicitly setting initial conditions of building constructions (i.e. surface and internal constructions temperatures), as the initial boundary conditions of subsequent simulations.

RHC is a feedback non-linear control technique, solving an optimization problem at each time step to determine the control sequence (sequence of optimal adaptive building envelope properties) over a certain time horizon (planning horizon), by minimizing a certain cost function. This takes into account the effect of varying material properties on the energy balance of the building for a certain time frame (the cost horizon). It comprises a planning horizon, time frame in which the adaptive building envelope properties are optimized, together with a future time horizon (in respect to the planning horizon), required to assess the effect of varying material properties on future energy balance. These different time frames (horizons) and the optimisation logic of RHC is summarized in Figure 1.

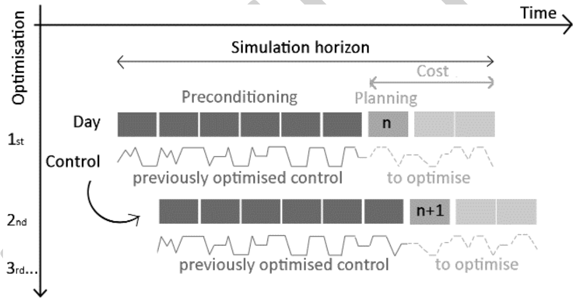

Figure 1. Optimisation horizons management.

A simulation framework was specifically developed to overcome the above-mentioned limitations of BPS tools and to implement RHC for adaptive building envelope properties. This tool (Figure 2) comprises: (a) an *evaluation layer* for calculating the cost functions (i.e. energy use and comfort), making use of the building energy simulation software EnergyPlus (LBNL, 2011); (b) an *optimisation layer* for the optimisation of the control of adaptive thermo-optical properties, making use of Matlab (Matlab, 2013) for multi-objective optimisation problems and GenOpt (Wetter, 2011) for single-objective optimisation problems; (c) a *control layer* developed in Matlab (Matlab, 2013) to overcome the three afore-mentioned issues in the specific BPS tool adopted.

The *evaluation layer* based on EnergyPlus is capable of simulating different dynamic materials and technologies. The embedded Energy Management System (EMS) (NREL, 2013) is employed to accomplish four tasks in the simulation horizon: (a) varying the thermo-optical properties of a material or a construction during simulation runtime according to a pre-determined control strategy; (b) computing the variables used for building services integration in the EMS (i.e. illuminance levels and glare); (c) integrating the control of the dynamic building envelope with the artificial lighting system, if needed

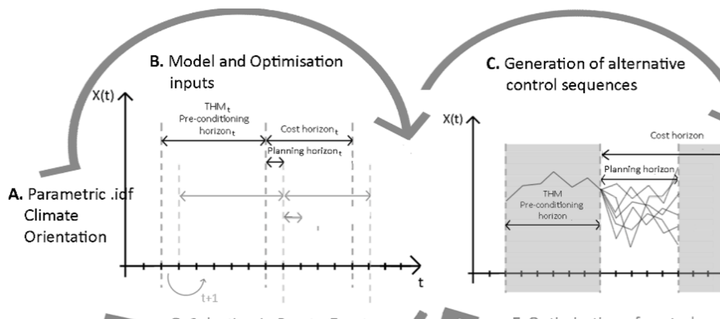

Figure 2 Software framework architecture. The arrows represents the flow of inputs/models (continuous line) and of outputs/results (dashed line).

(Favoino et al., 2015); (d) computing the objective functions and the constraints used by the *optimisation layer* (i.e. total primary energy, thermal comfort etc.).

The *optimisation layer* consists of two sub-modules: a single-objective optimisation sub-module, and a multi-objective optimisation sub-module. The single-objective optimisation sub-module is based on GenOpt, a few different optimisation algorithms are available including Generalised Pattern Search (GPS), Particle Swarm Optimisation (PSO) (Wetter, 2011), Genetic Algorithms (GA), and hybrid optimisation algorithms (GA + GPS, PSO + GPS). The multi-objective optimisation module is based on genetic algorithm scripts in Matlab, developed by the authors. In the control layer the inputs of the optimisation and the evaluation layers are defined. These include: the building envelope adaptive properties, their modulation ranges and modulation time; the parameters to perform RHC, such as length of the planning horizon and length of the cost horizon (Corbin et al., 2013); the optimisation algorithm; the seeding strategy for optimisation (known solutions, i.e. simpler control strategies or previously optimized states, are introduced in the initial population for the optimisation); the selection criteria for the solution in the Pareto Front of the optimised control sequences (sequences of optimised adaptive properties), if multi-objective optimisation is performed.

In order to set the initial boundary conditions of the building according to the ending boundary conditions of the previous optimisation, the Thermal History Management method is adapted from (Corbin et al., 2013) to deal with adaptive building envelope properties. Explicit state update in EnergyPlus is not possible, therefore with this method the building is simulated for a certain period (pre-conditioning) with the previously optimised control strategy for the adaptive building envelope properties, until the start of the planning horizon.

The workflow of the optimisation tool

The simulation process of the bespoke tool is shown in Figure 2. Continuous arrows indicate that the model is modified and exchanged between the different layers, while dashed arrows indicate results passed from one layer to the other. The first part of the workflow (A) and (B) is performed only once at the beginning of the simulation, while step (C) to (I) occur iteratively throughout the simulation period. The tasks performed in the different steps by the different layers are: (A) a parametric model (EnergyPlus in this case) with variable orientation, climate, material properties and control strategy is created; (B) the coordination layer (Matlab) is used to set the different parameters of the model and the inputs for the optimisation (including the selection criteria of the solutions in the Pareto Front); (C) the parametric model and the seed for the optimisation are automatically fed to the optimisation layer (GenOpt or Matlab), which generates alternative control sequences for the adaptive properties to be evaluated; (D) each specific control sequence for the adaptive façade system and the constraints of the cost functions are implemented into the model (EMS system of EnergyPlus); (E) the cost functions are evaluated by the evaluation layer (EnergyPlus) and the results are returned to the optimisation layer in an iterative way until convergence of the optimisation is reached; (F) the optimisation layer defines the optimal control strategy (single objective optimisation problem) or the Pareto Front of optimal control strategies (multi-objective optimisation), which is the time sequence of optimal façade properties; (G) if in multi-objective optimisation the coordination layer selects one solution from the current Pareto front, which will be used as control strategy for the following optimisation period, and generates seeds for the following optimisation period, according to the optimised control of the future time horizon of the current optimisation; (H) the optimisation horizon is shifted forward for a period equal to the control horizon by the coordination layer; (I) THM is performed by the evaluation layer, i.e. the building is re-simulated using the optimised control sequence found in (F) or (G) until the start of the control horizon for the previous optimised period; steps (C) to (I) are repeated until the optimisation horizon reaches the end of the simulation period and all the results are stored. The optimisation process described requires the construction of the parametric EnergyPlus model in (A) and the set-up of the initial parameters and optimisation inputs in (B), while the rest of the process (C to I) is fully automated.

A CASE STUDY

Description of the cellular office room model

A cellular office room in Shanghai (Figure 3) is simulated using the tool described above, to evaluate the effects of dynamic insulation panel on energy use and thermal comfort. The model was constructed using the evaluation layer. This model was adapted from an experimentally validated model of a climatic chamber (Jin and Overend, 2012). The room size is 4m high x 4.5m wide x 3m deep. All the internal surfaces are assumed to be adiabatic, apart from the south façade. The assumption of boundary condition is made according to a typical cellular office room surrounded by similar rooms in a multi-storey commercial building.

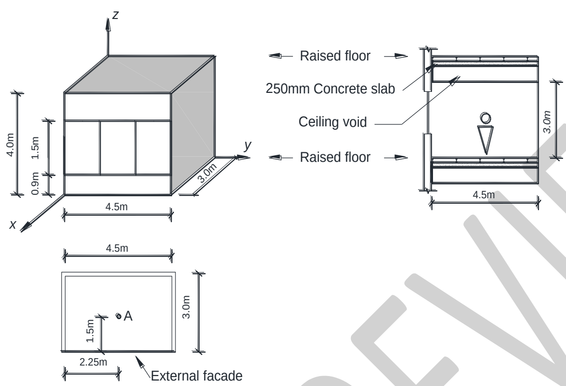

Figure 3 Geometry of office room in Shanghai

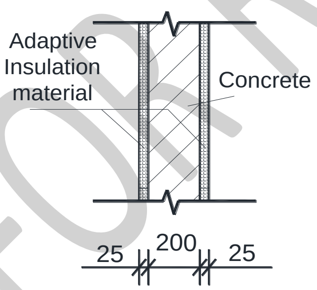

Figure 4 Section through the adaptive insulation panel (Unit: mm)

The external facade is partially glazed (window-to-wall ratio WWR= 40%) with double glazing (*U*-value = 1.1W/m^{2}K, *g*-value =0.62, visible transmittance = 0.79). The room is mechanically ventilated with 2ac/h. Other parameters used in the building energy simulation are summarised in Table 2.

The opaque portion of the facade consists of a sandwich panel that has three layers (Figure 4). The external and internal layers can modulate their thermal conductivity every 3 hours to adapt to the internal and external conditions, while the middle layer is used as a (static) thermal storage. With this wall configuration, three different cases are compared: un-insulated (UN-IN, the inner and outer layer of the wall have high thermal conductivity), insulated (IN, the inner and outer layer have low thermal conductivity), adaptive insulation (AD, inner and outer layer have a transient thermal conductivity). The configuration of the wall is not very common in the construction industry (insulation layer on both the inside and outside surface), but this case study is chosen in order to generate a relatively higher number of variables for the optimisation problem, thereby testing the capability and computational efficiency of the tool. More common wall configurations will be analysed in future.

Table 2 Parameters for building energy simulation.

PARAMETER	**VALUE**
Metabolic rate (office activity)	1.2 met (CIBSE, 2006)
Work efficiency (office activity)	0 (CIBSE, 2006)
Indoor air velocity	0.137m/s
Clothing level	0.5 (May - Sep), 1.0 (Jan – Apr, Oct - Dec) (EN ISO 7730, 2005)
Occupants	2 persons
Lighting Power Density	18 W/m^2(MOHURD, 2005)
Equipment Power Density	13 W/m^2(MOHURD, 2005)
Façade air permeability	5m^3/hm^2 at 50 Pa
Heating set point	20 °C (6am - 10pm weekdays, 13°C set back) (MOHURD, 2005)
Cooling set point	25 °C (6am - 10pm weekdays, 30°C set back) (MOHURD, 2005)
HVAC system	Variable air volume: heating supply temperature 50°C, cooling supply temperature 13°C
Shading system	Exterior horizontal blind with medium reflectivity slats (0.5 reflectivity). Slat angle adjusted to block direct solar radiation
Lighting system	Automated continuous dimming control, illuminance set point 500 lux. Reference points at mid-point room depth (height 0.8m).

Formulation of the optimisation problem

The decision variables for the optimisation are the thermal conductivity of: the external layer of the wall on day D_n; the internal layer of the wall on day D_n; external layer of the wall on day D_{n+1}, the internal layer of the wall on day D_{n+1}. The maximum modulation ferquency of the thermal conductivity is one every every 3 hours, therefore 8 decision variables per day per layer are present (32 decision variables in total, Table 3). The thermal conductivity ranges from 0.003W/mK to 220W/mK to cover an available range as wide as possible. These limits were chosen in order to explore the maximum potentials of adaptive insulation at reducing energy use and improving indoor environmental comfort. The decision variables are log spaced distinctive, i.e., the possible values for each decision variable is 0.0030, 0.0494, 0.8124, 13.3690, and 220. While thermal conductivity of 220W/mK is used for the UN-IN case, and 0.003W/mK is used for the IN case.

Two optimisation objectives (cost functions) are evaluated:

(i) Objective One is to minimise the primary energy use. The heating, cooling, and lighting energy use E_h, E_c, E_l of the office room is calculated by EnergyPlus.

Table 3 List of decision variablesfor each optimisation

	D_n		D_{n+1}	
Time	External layer	Internal layer	External layer	Internal layer
0:00-2:59	λne1	λni1	λ(n+1)e1	λ(n+1)i1
3:00-5:59	λne2	λni2	λ(n+1)e2	λ(n+1)i2
6:00-8:59	λne3	λni3	λ(n+1)e3	λ(n+1)i3
9:00-11:59	λne4	λni4	λ(n+1)e4	λ(n+1)i4
12:00-14:59	λne5	λni5	λ(n+1)e5	λ(n+1)i5
15:00-17:59	λne6	λni6	λ(n+1)e6	λ(n+1)i6
18:00-20:59	λne7	λni7	λ(n+1)e7	λ(n+1)i7
21:00-23:59	λne8	λni8	λ(n+1)e8	λ(n+1)i8

The fuel factors for natural gas f_{NG} and electricity f_{El} are 1.0012 and 1.0005, respectively. They were calculated according to GB/T 2589 (ERINDRCC, 2008). The equipment efficiencies in EnergyPlus are assumed to be 100%, and the conversion is performed after obtaining the results from EnergyPlus. The HVAC efficiency for heating η_h is 0.89 and the seasonal energy efficiency ratio (SEER) for cooling is 3.8 (MOHURD, 2005). The objective function value is calculated according to Eq (1):

$$E_{tot}= \eta_h \cdot E_h \cdot f_{NG} + (\frac{E_c}{SEER} + E_l) \cdot f_{El} \quad (1)$$

(ii) Objective Two is to minimise the thermal discomfort of the office room. The thermal discomfort is evaluated according to European Standard ISO 7730 (2005), by means of the PPD weighted hours, consisting of the time, $t_{PPD,}$ during which the actual PPD exceeds the comfort boundary ($PPD_{boundary}$=10% in this case), weighted with a factor *wf* which is a function of PPD calculated as follows:

$$wf = \frac{\mathrm{PPD_{actual}}}{\mathrm{PPD_{boundary}}} \quad (2)$$

$$t_{PPD}=\sum_{t=0}^{t} wf \cdot t \quad (3)$$

Three typical weeks (Jan 8-14, Apr 23- Apr 29, July 19-25) that represent the winter, mid and summer seasons in Shanghai are selected for simulation, representing the widest possible variation in outdoor air temperature and solar radiation for each season.

The optimisation progress and algorithm settings

Each solution in the Pareto Front resulting from the optimisation indicates a possible optimal control of the adaptive insulation wall, but only one of them is required from day D_n to be used as control strategy for the next day to be optimised D_{n+1}. Different criteria for selecting this solution could be used (i.e. lowest energy use, lowest thermal discomfort, lowest distance from the origin, weighting between the two objectives etc…). In this paper we show and discuss results from one criterion for brevity, i.e., to select the one with minimum E_{tot} .

Non-domination Sorted Genetic Algorithm NSGA_II (Deb et al. 2002) is adopted for performing the multi-objective optimisation, because it is suitable for problems without explicit mathematical objective functions, and has been successful in solving similar problems (Jin & Overend. 2014).

A convergence test was carried out to identify the appropriate population size *Pop* and number of generation *Gen* for running the optimisation. *Pop*s of 160, 320, 640 and *Gen*s of 10, 20, 30, 50 (Figure 5) were tested. *Pop*=320 and *Gen*=30 were selected as these provided a reasonable balance between the obtaining a good approximation of the Pareto Front and computational time. The simulation was carried out with a Windows-based PC with one 2.3 GHz processor and 8GB of RAM. The computational time for optimising one horizon (1 day) is 7.5 hours.

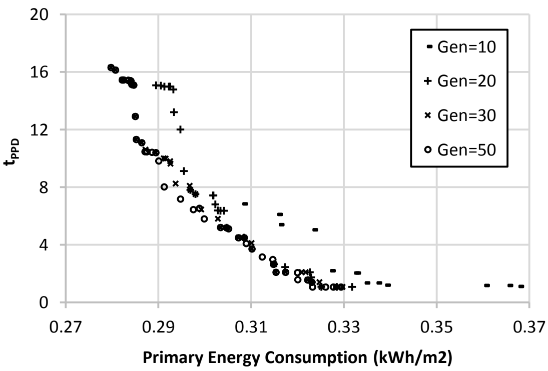

Figure 5 Selection of Gen (Pop=320) simulation of Apr 23.

RESULTS AND DISCUSSIONS

The results are presented in two ways. Firstly the typical Pareto Fronts calculated in the optimisations are presented. Secondly, a comparison of the energy demand and thermal comfort of the optimal adaptive insulation panel and the two static references is discussed.

Optimisation progress and Pareto Fronts

Each season shows a different typical pattern of Pareto Fronts. These can be classified according to the type of energy required to optimise the indoor environment, i.e. heating or cooling dominated condition (only heating or cooling required), or mixed condition (both heating and cooling required in the same period). The former condition is typical of winter or summer seasons, while the latter of the mid-season.

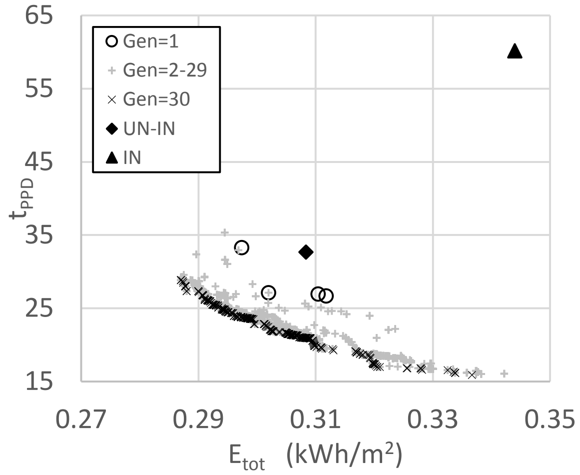

Figure 6 Pareto Fronts of Gen=1, Gen=2~29, and Gen=30 for Apr 24.

For mid-season, the Pareto Front of t_{PPD} *vs.* E_{tot} contains a large number of optimal solutions, meaning that there are many possible combinations of the time series for the adaptive insulation materials that could achieve the optimal balance between thermal comfort and energy use. Taking Apr 24 (Day 114) as an example, Figure 6 shows the migration of Pareto Fronts from the first to the last generation. The first notable observation is that the Pareto Front of the initial generation (*Gen*=1) produces t_{PPD} of around 27 hrs and E_{tot} between 0.3-0.312 kWh/m^2, while after 30 generations, one optimal solution reduces t_{PPD} by 41% to as low as 15.9 hrs and another solution reduces E_{tot} by 8%. In comparison, the Pareto Fronts for winter and summer seasons show a much smaller number of optimal solutions (July 20, Figure 7). The hypervolume indicator indicates that in such cases the optimisation converges much earlier, e.g., for July 20, the hypervolume indicator (as well as the Pareto Fronts) for *Gen*=20 are the same as those for *Gen*=30 without any changes in between. This also excludes the possibility of premature stopping of the optimisation process and proves that *Gen*=30 is sufficient for this optimisation problem. The second notable observation is that, for either objective, the performance of the optimally controlled adaptive insulation (represented by the Pareto Front) is always far better than the performance of the static solutions (INS and UN-INS). For example, for July 20 (Figure 7) adaptive insulation provides a saving of around 10% of E_{tot} over static references, and reduces t_{PPD} by 20% and 25% compared to UN-IN and IN, respectively. This indicates that the adaptive insulation solution (if controlled appropriately) could significantly outperform static insulation solutions both in terms of energy use and indoor environmental quality.

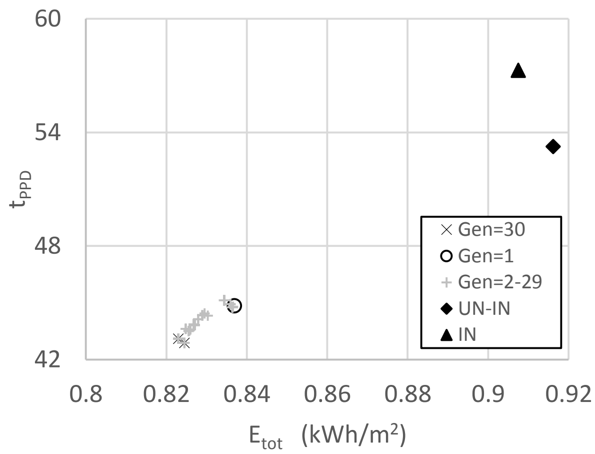

Figure 7 Pareto Fronts of Gen=1, Gen=2~29, and Gen=30 for July 20.

Total Energy Demand and thermal comfort

E_h, E_c, E_l, E_{tot} and t_{PPD} of the office reference room for different seasons are shown in Figure 8, 9 and 10. Table 4 summarises the results, and compares the performance of adaptive insulation solution with the reference static solutions (UN-INS and INS).

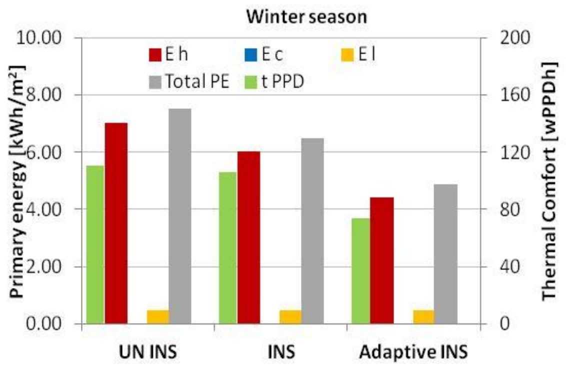

Figure 8 Performance of adaptive insulation compared to static insulations for winter season.

In winter (Figure 8), the adaptive solution reduces the heating energy use by almost 40%, because free solar gains are selectively admitted, stored and/or shifted in the indoor environment depending on the indoor/outdoor insulation level of the panel. This minimises the heat losses through the fabric. Additionally by controlling the insulation level the thermal comfort is improved by 30%, compared to the INS reference case. Similar results can be observed during summer season (Figure 10) in which the adaptive insulation is used in a different way. In fact, the control logic of the insulation level can be used to prevent unwanted solar gains during the day and to maximize nigh time cooling through the fabric. This results in a decreased cooling energy use of nearly 30% and a 50% improvement in comfort compared to the INS reference case. The largest improvements are observed during mid-season (Figure 9), this is because climatic conditions are closer to the human thermal comfort range, therefore the control of the environmental conditions in the office can be almost completely managed by the adaptive insulation, relying less on the HVAC system. Moreover in this season both heating and cooling energy use can be minimized, while thermal comfort is significantly improved (50 to 60%).

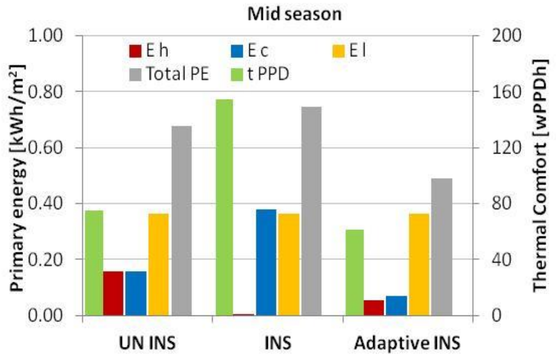

Figure 9 Performance of adaptive insulation compared to static insulations for mid season.

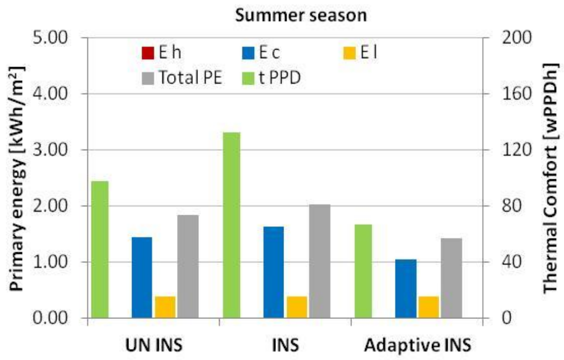

Figure 10 Performance of adaptive insulation compared to static insulations for Summer season.

These figures are explained by interpreting the hourly control sequence of the optimal adaptive insulation solution, which is omitted for brevity. In winter, the adaptive insulation layer is switched to its maximum thermal resistance state during the night, while during the day the thermal resistance is lowered to store free solar heat into the concrete middle layer, which is released to the indoor environment during occupied hours and to reduce the peak heating load on the following day. This behaviour is reversed during summer season in which the insulation level is maintained at its maximum value through the day to prevent solar gains, and reduced during night and unoccupied hours to dissipate heat gains (internal and solar). During mid-season, the RHC optimal sequence does not appear to be directly related to day-night dynamics and further analysis is needed to understand its dynamics.

It is possible to extrapolate the seasonal results in order to forecast a realistic figure for the yearly reduction in energy use and thermal discomfort in the office reference room. Doing so, reveals that an adaptive insulation solution provides a potential energy saving of 25-35%, and a thermal comfort improvement of 40-60%.

CONCLUSIONS

This study investigated the potential performance benefits of adaptive insulation in an office building in a temperate climate. An inverse methodology was implemented by means of a bespoke tool which invokes EnergyPlus for the evaluation of energy use and indoor environmental quality. This tool makes use of multi-objective optimisation to minimise the energy use and thermal discomfort by actively controlling the indoor and outdoor insulation layers of a sandwich panel for the opaque portion of a facade.

The results show that adaptive insulation, if properly controlled, outperforms the static insulation solutions in terms of both energy use and indoor environmental quality. In particular, cooling energy use can be reduced by 40 to 80% (depending on season), while heating energy use can be reduced by 30% to 40%. Thermal comfort can be improved by 30% to 60%. The largest improvement is achieved in the mid-season in which outdoor climatic conditions are closer to human comfort range. The yearly performance can be estimated from these figures, resulting in potential energy saving of 25-35%, and thermal comfort improvements of 40-60%.

Moreover this paper presents a methodology that could be used to evaluate the performance of other adaptive technologies.

NOMENCLATURE

E_h = heating energy use
E_c = cooling energy use
E_l = lighting energy use
f_{NG} = fuel factors for natural gas
f_{El} = fuel factors for electricity
η_h = HVAC efficiency for heating
SEER = HVAC seasonal energy efficiency ratio
t_{PPD} = the time t_{PPD} during which the actual PPD exceeds the comfort boundary
wf = weighting factor for t_{PPD}
PPD_{actual} = actually PPD
$PPD_{boundary}$ = upper boundary of PPD
Pop = size of population in NSGA
Gen = number of generation in NSGA

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Table 4 Performance (Primary energy use and thermal comfort) of adaptive insulation compared to static insulations for the three weekly periods during winter, mid and summer seasons.

Season	**Solution**	**Ep** [kWh/m^2]	**PE heat** [kWh/m^2]	**PE cool** [kWh/m^2]	**PE light** [kWh/m^2]	**wPPDh** [hrs]
Winter	UN INS	7.53	7.05	0.00	0.48	111
	INS	6.51	6.03	0.00	0.48	106
	Adaptive INS	4.89	4.41	0.00	0.48	74
Mid	UN INS	0.68	0.16	0.16	0.36	75
	INS	0.75	0.00	0.38	0.36	155
	Adaptive INS	0.49	0.06	0.07	0.36	61
Summer	UN INS	1.83	0.00	1.45	0.39	98
	INS	2.02	0.00	1.63	0.39	133
	Adaptive INS	1.43	0.00	1.04	0.39	67

REFERENCES

Baetens R., Jelle BP, Gustavsen A. 2011. Aerogel insulation for building applications: a state-of-the-art review, Energy and Buildings 43: 761-9.

Benson D. K., Potter T. F., Tracy C. E., 1994. Design of variable conductance vacuum insulation. Proceedings of SAE 1994, Detroit, US.

Berge A., Hagentoft C., Wahlgren P., Adl-Zarrabi B., 2015. Changing Internal Pressure to achieve variable thermal conductivity in Thermal Insulation. Proceedings of Advanced Building Skins 2015, Graz, Austria.

Brunsell J. 1995. The performance of dynamic insulation in two residential buildings. Air In®ltration Review 16(4):7-11.

Buckley S. 1978. Thermic diode solar panels for space heating. Solar Energy 20:495 – 503.

CIBSE (Chartered Institution of Building Services Engineers). 2006.CIBSE Guide A: Environmental design, 7th ed. Norwich: Page Bros. (Norwich) Ltd.

Corbin, C.D., Henze, G.P. & May-Ostendorp, P.,2013. A model predictive control optimization environment for real-time commercial building application, J Build Perf Sim.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. 2002. A fast and elitist multiobjective genetic algorithm: NSGA II. IEEE Transacions on Evolutionary Computation 6(2): 182-197.

Energy Research Institute of National Development and Reform Commission of China (ERINDRCC), 2008. General principles for calculation of total production energy consumption (GB/T 2589-2008). China.

European Standard EN ISO 7730. 2005. Ergonomics of the thermal environment-analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.

Favoino F., Jin Q., Overend M., 2015. The optimal thermo-optical properties and energy saving potential of adaptive glazing technologies. Applied Energy 156: 1-15.

Favoino F., Overend M., 2015. A simulation framework for the evaluation of next generation Responsive Building Envelope technologies. Proceedings of International Conference of Building Physics 2015, Torino, Italy.

Gan, G. 2000. Numerical evaluation of thermal comfort in rooms with dynamicinsulation. Building and environment 35: 445-453.

Jin Q, Overend M. 2012. Façade renovation for a public building based on a whole-life value approach,Proceedings of Building Simulation and Optimisation Conference, Loughborough, UK, pp 378-385.

Jin Q, Overend M. 2014. A prototype whole-life value optimisation tool for façade design. Journal of Building Performance Simulation 7 (3): 217-232.

Jelle, BP. 2011. Traditional, state-of-the-art and future thermal building insulation materials and solutions- Properties, requirements and possibilities. Energy and Buildings 43, 2549-63.

Kasinalis, C., Loonen, R.C.G.M., Cóstola, D. & Hensen, J.L.M. (2014). Framework for assessing the performance potential of seasonally adaptable facades using multi-objective optimization. Energy and Buildings, 79, 106-113

Kimber, M., Clark, W. W., & Schaefer, L. (2014). Conceptual analysis and design of a partitioned multifunctional smart insulation. Applied Energy, 114, 310-319.

NREL (National Renewable Energy Laboratory). 2011. EnergyPlus8.1, California, USA.

MOHURD (Ministry of Housing and Urban-Rural Development of China). 2005. Design Standard for Energy Efficiency of Public Buildings GB50189-2005.China.

McKinsey & Companies. 2009. Pathways to a Low-Carbon Economy. Version 2 of the Global Greenhouse Gas Abatement Cost Curve, McKinsey & Company.

NREL (National Renewable Energy Laboratory). 2013. Energy plus, Application guide for EMS, Energy Management System User Guide (2013).

Wetter M.2011. GenOpt Generic Optimization program User Manual, Version 3.1.0, Building Technologies Department, LBNL, USA.

MATLAB Release 2013a, The MathWorks, Inc., Natick, Massachusetts, United States.

Varga S, Armando C O, Afonoso C F. 2002. Characterisation of thermal diode panels for use in the cooling season in buildings, Energy and Buildings 34: 227-235.

Xenophou T., 1976. System of using vacuum for controlling heat transfer in building structures, motor vehicles and the like, US Patent No. 3,968,831