A META-MODEL BASED METHOD FOR THERMAL COMFORT AND ENERGY USE BUILDING OPTIMISATION AT A LOCAL RESOLUTION

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ABSTRACT

This paper details a simulation approach to evaluating optimal building thermal comfort and energy use, focussed on the performance at a local level of single spaces. Through the use of dynamically coupled computational fluid dynamics (CFD) and dynamic thermal modelling (DTM) spatial variation of thermal comfort in a room is evaluated. Meta-modelling is used to reduce the total number of simulations required and the two objective functions, thermal comfort and reducing energy use are assessed in terms of a Pareto front. This provides a method of examining the optimum trade-off between the two objectives from which an appropriate solution may be selected.

It is demonstrated that by exploiting the implicit division of the process resulting from meta-modelling, substantial time-saving economies are realised. From a single initial sample of simulations, optimisations can be performed for many different permutations of location and time period, and for any subset of the design variables. Furthermore results are presented from a case study of a single bed hospital room.

INTRODUCTION

To provide thermal comfort is one of the core objectives of buildings. To this end a variety of devices and systems are available to control the internal environment. The devices that drive such systems invariably consume energy. This is the compromise that building optimisation often seeks to clarify; how to achieve acceptable thermal comfort with the minimum possible energy use.

In recent years, a number of researchers have developed models to solve such building optimisation problems. Al-Homoud first presented the ENEROPT model in his PhD thesis (1994), which optimises thermal comfort and energy use in terms of a variety of design and operation variables. Al-Homoud went on to apply the model to various cases (eg. Al-Homoud, 1997 and Al-Homoud, 2005). Chantrelle et al. (2011) developed a model considering these and other objectives. Eisenhower et al. (2012) presented a particularly comprehensive approach, considering over 1000 design variables. The general form of these and the vast majority of other building optimisation models found in the literature is the same; a building simulation program coupled to an optimisation program. The building simulation program provides a means to evaluate the selected metrics of the performance of the building, termed *objective functions*, given values of selected input parameters of the building fabric and its plant systems, termed *design variables*. The optimisation program automates the process of searching for the optimum value(s) of the objective functions in the design space with dimensionality defined by the design variables. This framework has been generalised in a broad sense by the program GenOpt (Wetter, 2001), providing a straightforward optimisation interface compatible with a variety of building simulation programs.

The majority of building optimisation models in the literature are focussed on whole building optimisation. As with all examples of building simulation, this is subject to certain assumptions. One of the most common of these is of well-mixed room air. Whilst this allows a greatly simplified treatment of convection and air flow in building simulation, it limits model resolution on a local level within rooms.

Consider a building optimisation with the size, shape and position of a window as design variables. These parameters may substantially affect thermal comfort in the room by a number of mechanisms. Firstly, the window will generally allow direct solar radiation to impinge on surfaces within the room at some point during the day; the geometry of the window will strongly affect where in the room these solar gains occur and at what time. Secondly, the geometry of the window will have some effect on the radiant field in the room. Sitting next to a large window on a cold day, it is not uncommon for an occupant to feel noticeably colder than elsewhere in the room. Finally, the size and type of the window will determine whether the window can be opened or not, in what directions and to what degree. If the window is opened the air flow could induce draughts in certain parts of the room. All of these effects often

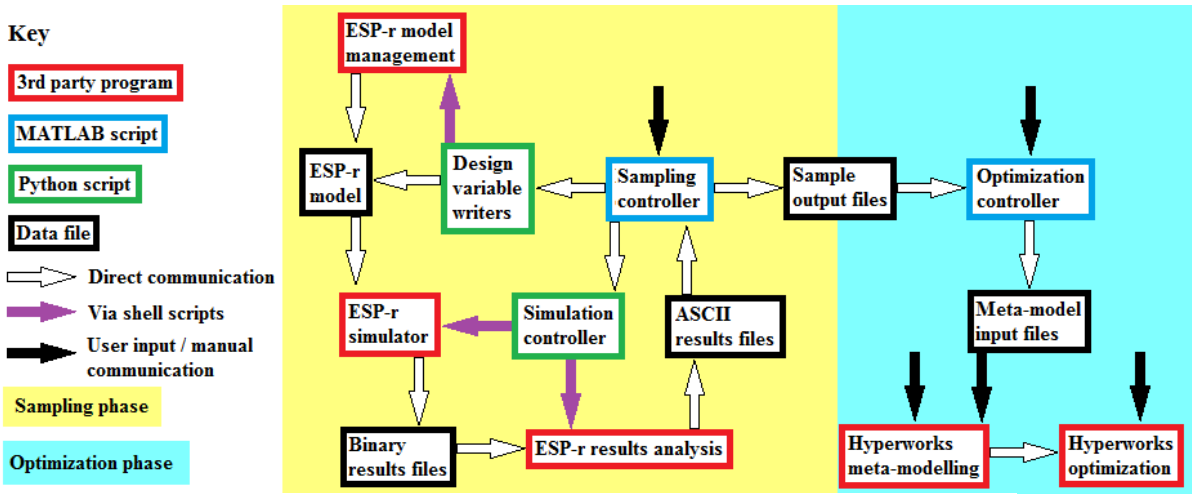

Figure 1 Schematic of the T-BOT building optimisation program.

vary both temporally and spatially, and as such the optimum values of the design variables may vary depending on occupants' positions in the room and the time of day. This variation is often not explored in examples of building optimisation in the literature.

This paper presents a model that considers detailed optimisation of individual spaces, taking into account spatially varying thermal comfort and variable control periods. With increased model resolution comes greater computational load to evaluate it, so meta-modelling is applied to reduce the number of simulations necessary for optimisation. This has been applied in a number of models in the literature, for example Eisenhower et al. (2012), Gengembre et al. (2012), Magnier and Haghighat (2010) and Zemella et al. (2011) have all used meta-modelling in building optimisation processes.

In the present model meta-modelling has the effect of essentially seperating the simulation and optimisation phases of the process. Instead of the optimisation choosing what points in the design space to evaluate with building simulation (direct search), a sample of the design space is simulated initially. Simpler models are fitted to this data, and these are then used to evaluate the objective functions. It is demonstrated that a number of economies in terms of simulation time are realised in comparison to an equivalent direct search technique. Finally, some results are presented from a case study of a single bed hospital room to demonstrate the application of the model, and to highlight the level to which optimum conditions can vary both spatially and temporally.

BUILDING OPTIMISATION MODEL

Overview

The present model was named thermal building optimisation tool (T-BOT). It conforms to the classic building optimisation framework of a building simulation program coupled with an optimisation program. However an intermediate meta-modelling step is employed, a process which effectively splits the simulation and optimisation parts of the process and introduces a number of economies. A schematic of T-BOT is shown in Figure 1.

Building Simulation Program

Building simulation in the present model was accomplished using the open source ESP-r software, which is available free from the ESRU website (www.esru.strath.ac.uk/Programs/ESP-r.htm). The theoretical basis of this program is well documented by Clarke (2001). This program provides functionality for dynamically coupling different simulation domains in an integrated simulation. Three main simulation domains were used in the present model; dynamic thermal modelling (DTM), an air flow network and CFD. These broadly serve to simulate the building fabric, inter-zonal airflow, and intra-zonal airflow respectively. The domains are coupled such that the DTM and the air flow network provide boundary conditions for the CFD domain at each time step. A mechanism known as the adaptive conflation controller (ACC) dynamically controls the handling of buoyancy, turbulence and convection at the domain boundaries (Beausoleil-Morrison, 2000) according to prevailing conditions at each time step.

Objective Functions

An optimisation problem is characterised by objective function(s) which depend on the values of design variables. For the present model, two objective functions were defined; thermal discomfort (since the convention is to minimise objectives) and energy use. The thermal discomfort criterion was time-averaged deviation of operative temperature from a "comfort range" defined by upper and lower limits as shown in Equations 1 and 2.

$$F_1(\boldsymbol{D}) = \frac{\sum_1^n \left(f(\theta_o)\right)_i}{n} \quad (1)$$

Where $\boldsymbol{D}$ is the set of design variable values, $f(\theta_o)$ is given by Equation 2 and n is the number of hours in the optimisation period.

$$f(\theta_o) = \begin{cases} \theta_{o,min} - \theta_o, & (\theta_o < \theta_{o,min}) \\ 0, & (\theta_{o,min} \leq \theta_o \leq \theta_{o,max}) \\ \theta_o - \theta_{o,max}, & (\theta_o > \theta_{o,max}) \end{cases} \quad (2)$$

Where $\theta_{o,min}$ and $\theta_{o,max}$ are the minima and maxima of the comfort range respectively, and θ_o is the operative temperature at the current time step.

Bouchlaghem and Letherman (1990) identified a very similar objective function formulation as being most appropriate for thermal comfort building optimisation from a range of candidates.

Operative temperature is a standard measure of the effective temperature felt by occupants in a building, and is defined in CIBSE guide A (2006) as given in Equation 3.

$$\theta_o = \frac{\theta_a\sqrt{10v} + \theta_r}{1 + \sqrt{10v}} \quad (3)$$

Where θ_a is air temperature (°C), θ_r is mean radiant temperature (MRT) (°C) and v is air velocity (m/s). At air velocities below 0.1 m/s, this is assumed to reduce to Equation 4.

$$\theta_o = \frac{\theta_a + \theta_r}{2} \quad (4)$$

The energy use criterion was taken as the sum of radiant and convective heat flux into the room, as shown in Equation 5.

$$F_2(\boldsymbol{D}) = E_r + E_c \quad (5)$$

Where E_r is the radiant component and E_c is the convective component. An example with specific systems is given in the case study at the end of this paper.

Design Variables

Design variables are highly dependent on the specific problem being studied. T-BOT was thus programmed in a somewhat modular fashion (as is evident from Figure 1), seeking to maintain flexibility to include whatever design variables are necessary. An exhaustive list of all possible design variables in building optimisation is far beyond the scope of the present study; an example with specific design variables is given in the case study at the end of this paper. In terms of T-BOT all that is required is that the user can create scripts to transfer the value of the design variable from the controlling routine to the building model.

All design variables are linearly scaled to a range of 1-11 before optimisation. This maintains axial numerical isotropy in the design space, which is desirable as it can marginally reduce the numerical complexity of the meta-models.

Optimisation Program

The optimisation and meta-modelling processes were automated in the present model using the program Altair HyperStudy. This provided a convenient GUI and smooth functionality for creating meta-models from the sampled data, and using these meta-models to perform optimisation.

A genetic algorithm (GA) was used to conduct the optimisation. This was well suited to the present model for a number of reasons. Firstly the method is population-based and therefore highly appropriate for developing Pareto fronts, used to evaluate optimum trade-offs between multiple objectives. Secondly it is a global search method; it does not hold any data regarding the gradients of the design space and is therefore well suited to optimisation problems with highly non-linear objective functions with unknown derivatives, and less susceptible to falling into local optima. The specific implementation employed in HyperStudy is based upon the de-facto standard GA, the NSGA-II algorithm (Deb, 2002).

Meta-modelling

In direct search building optimisation, each time the optimisation algorithm identifies a point in the design space at which to evaluate the objective functions, a building simulation is run. However, the inclusion of CFD into the building simulation increases the computational requirement of the building simulation by orders of magnitude. It is desirable then to reduce the amount of simulations required if possible. Meta-modelling provides a means to accomplish this.

Table 1 Various sample distribution metrics for nested and non-nested DOEs.

DOE	Sample set	Mean of distance to closest neighbour	Standard deviation of distance to closest neighbour	Standard deviation as percentage of mean
Standard DOE	build	3.15	0.621	20%
	validation	3.86	0.505	13%
	combined	2.81	0.51	18%
Nested DOE	build	3.25	0.637	20%
	validation	4.5	0.468	10%
	combined	2.9	0.559	19%

Instead of direct search, the simulation and optimisation phases are effectively split. First a sample is taken of the design space. In the present model a nested optimal latin hypercube design of experiments (DOE) was used (Bates et al., 2004). This provides a global DOE, which is composed of the combination of two separate “build” and “validation” DOEs. A GA optimises the spread of each of these DOEs simultaneously. Table 1 shows a comparison of sample distribution metrics between synonymous nested and non-nested optimal latin hypercube DOEs of a 5 dimensional design space. It is evident that whilst the nesting only marginally affects the build and combined sets, the validation set is substantially improved. Since it is the validation set that provides the most reliable assessment of meta-model fit, the nested DOE was considered superior.

Each solution corresponding to a sample point in the DOE is simulated to obtain the objective function values. This provides a sample set of input and output data that can be used to fit other functions to the data, providing a means to predict the outputs from any given input values without the need to run a simulation. Thus, provided the sample set is smaller than the total number of function evaluations needed by a direct search optimisation, a net gain is made in terms of time saving. GAs typically require a large number of function evaluations, so this meta-modelling technique is often beneficial when used in conjunction.

In the present model, the method used to "train" the meta-models to represent the objective functions was moving least squares regression (MLSR). This is a variation of traditional least squares regression, whereby the regression functions depend on the point being evaluated as well as the training data, insofar as the training points are weighted by Euclidean distance to the evaluation point. In this way the models tailor themselves to get the best from the training data depending on the point to be evaluated. A moving least squares approximation at point p, given a set of sample points $\{p_i\}_{i=1}^{I}$ and observed data at those sample points $\{d(p_i)\}_{i=1}^{I}$, is obtained by finding an approximation function g that minimises the sum of weighted residuals given in Equation 6.

$$\sum_{i=1}^{I}\big(g(p_i) - d(p_i)\big)^2 \beta(\|p - p_i\|) \qquad (6)$$

Where β is a non-negative weighting function, and $\|p - p_i\|$ is Euclidean distance between points p and p_i. Second order polynomials were used for the approximation functions, and Gaussian weighting functions were used.

Table 2 Quality of fit parameters for MLSR meta-models of a 5 dimensional design space.

Meta-modelled component	Modelling stage	R-Squared	Relative average absolute error	Root mean square error
Cold thermal discomfort	Build	0.994	0.062	0.107
	Validation	0.979	0.110	0.185
	Merged	0.992	0.071	0.121
Warm thermal discomfort	Build	0.997	0.039	0.056
	Validation	0.978	0.114	0.157
	Merged	0.996	0.049	0.067
Radiant energy use	Build	1.000	0.008	0.084
	Validation	0.998	0.065	0.606
	Merged	1.000	0.012	0.118
Convective energy use	Build	0.989	0.070	0.381
	Validation	0.885	0.274	1.299
	Merged	0.984	0.094	0.466

The meta-models are trained in a 3-step process. First the meta-models are fit to the build DOE data. Then they are independently tested using the validation DOE data; this provides a reliable assessment of the quality of the fit. At this stage the validation data is also used to determine the optimum "closeness of fit" (ie. the spread of the weighting function) to best match the data. Finally the build and validation datasets are merged to further refine the meta-models. Table 2 shows quality of fit parameters for various objective components at various stages.

Modelling Economies

Aside from the obvious economy of reducing the overall amount of simulations to be run, the introduction of meta modelling results in a number of additional economies. These revolve around the capacity to perform optimisations for a large number of different scenarios using meta-models derived from the same initial sample.

The meta-modelling technique employed in the present model is similar to that employed by Eisenhower et al. (2010). One of the features of Eisenhower's model is the ability to perform optimisations for any subset of the design variables, and the same principal applies to the present model. Provided sufficient information is gathered in the initial sample, one or more design variables can be given a constant value during optimisation; this effectively removes dimensions from the design space.

Furthermore, the application of this meta-modelling technique to high resolution building optimisation results in additional economies.

Firstly, the assumption that optimum conditions vary spatially provides an opportunity to exploit the domain coupling mechanisms in ESP-r. The vast majority of the simulation time for each time step was taken up by the CFD; subsequent simulations without the CFD included had very low computational requirement by comparison. This means that after the first simulation, many subsequent simulations can be run with a very small increase in computational requirement. The salient point is that the original CFD results remain valid for each subsequent run, provided the building performance remains unaltered. Thermal comfort depends mainly on air temperature and the radiant field; a single CFD simulation will provide spatial variation of air temperatures in the domain, however the radiant field also varies spatially. Evaluating the radiant field involves calculating view factors and the mean radiant temperature (MRT), all of which can be performed in a fraction of the time needed to run a CFD simulation. The upshot of this is that a greater number of locations at which MRT needs to be evaluated (which in ESP-r are specified in the model, not during results recovery) does not appreciably increase simulation time.

Another economy arises from the observation that exactly where the cut-off is made between the simulation and optimisation phases is largely academic. There is a calculation process between getting the outputs from the building simulation and obtaining objective function values. For example in the present model operative temperature is calculated from MRT, air temperature and air velocity according to Equations 3 or 4. Objective function values are then calculated from operative temperature according to Equations 1 and 2. This leaves three distinct options for where to place the cut-off between the simulation and optimisation phases; one could save MRT, air temperature and air velocity, or operative temperatures, or objective function values. Whereas Equations 3 and 4 depend only on the outputs from ESP-r, Equations 1 and 2 further depend on contextual parameters (time period and comfort criteria). These contextual parameters are independent of the design variables, and therein lays the potential to develop an economy. By saving only operative temperature as the sample outputs, the sample becomes independent of the contextual parameters of the objective functions. These contextual parameters are then specified at the beginning of the optimisation phase, and hence the same initial sample can be used to optimise any permutation of time period and comfort criteria.

If a standard direct search algorithm were applied to the building optimisation problem studied presently, none of these economies would apply. Each separate optimisation would require its own simulations, the results of which would likely not be useful for further optimisations. However by applying meta-modelling and dividing the process, optimisations can be performed for any permutation of location, time period, comfort criteria and design variable sub-sets, all from a single sample set, which does not suffer in terms of computation time in order to accommodate such economies.

CASE STUDY

Overview

The performance of T-BOT was evaluated through application to a single bed hospital room. This was based on a real room in the Maternity ward of Bradford Royal Infirmary. Figure 2 shows a diagram of the model. The ceiling of the room was assumed to be a radiant ceiling (labelled “frengC” in Figure 3). Ventilation in the building was mixed-mode, having supply in the central corridor, no mechanical extract and openable windows in the rooms. The zone labelled in Figure 3 as “corridor” represents the central corridor with mechanical air supply, but in terms of the model is a notional boundary zone only, necessary in order to accommodate the air flow network. The geometry, volume and contents of the corridor zone are entirely arbitrary, as no DTM calculations are needed for it; it is present only to provide ESP-r with an entity to represent the other side of air flow through the door. The room model contains a bed and a four-pane double glazed window, the bottom two of which are openable. Only the face with the window on it was considered to be an external wall; all other surfaces were assumed to have internal spaces with similar conditions on the other side.

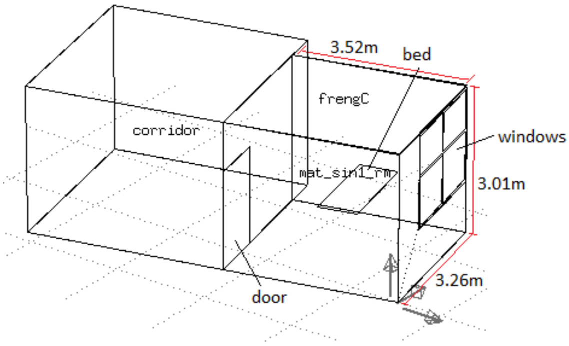

Figure 2 Diagram of the case study model.

The model was calibrated using measured climate and internal temperature data gathered as part of the design and delivery of robust hospital environments in a changing climate (DeDeRHECC) project (Lomas et al., 2012) for November and December 2010. Figure 3 shows a comparison of measured temperature data and simulation results with and without casual gains associated with occupancy, as the periods of occupancy in the room were unknown (Table 3 shows the assumed casual gains of the model). Extremes of the measured data that are not captured in the simulated performance are likely due to circumstances that were not recorded, for example the window being opened, or the use of space heaters.

Table 3 Assumed casual gains in the case study model.

Source	**Sensible (W)**	**Latent (W)**	**Radiant / Convective**
Occupants	75	20	0.5/0.5
Lights	40	0	0.3/0.7
Equipment	50	0	0.5/0.5

In the sample simulations of the case study, summer conditions were represented by 2010 weather data from a CIBSE weather station situated in Bingley, approximately 12 miles from the site. Days were found that were broadly representative of average conditions.

Comfort criteria were taken from CIBSE Guide A, which for a summer case were 23-25 °C, and it was assumed that the windows remained closed for the results presented herein.

Objective Functions and Design Variables

The objective functions used in T-BOT are formulated in a general sense earlier in this paper, in Equations 1-5. In this specific instance, component E_r in Equation 5 was taken as energy delivered to the

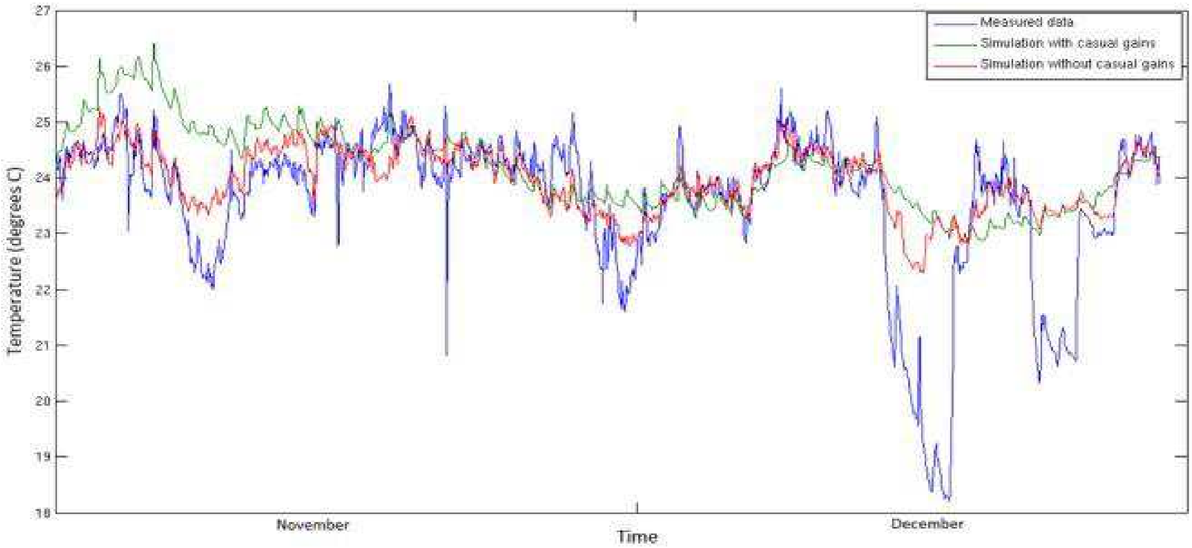

Figure 3 Measured and simulated temperatures in the case study model room.

radiant panel, and component E_c was taken as energy flux as a result of air flowing through the door from the corridor to the room.

There were 3 design variables considered in the optimisations shown herein:

1. Radiant ceiling set point temperature (°C),
2. Corridor temperature (°C),
3. Discharge factor of the room-corridor air flow connection (ie. how far open is the door).

It is noted however that this was a sub-set of a 5 design variable sample; two of the design variables were found to be largely uninformative. Sample sizes of 100 and 50 were used for the build and validation DOEs respectively, resulting in a combined DOE of 150 samples.

Computational Fluid Dynamics

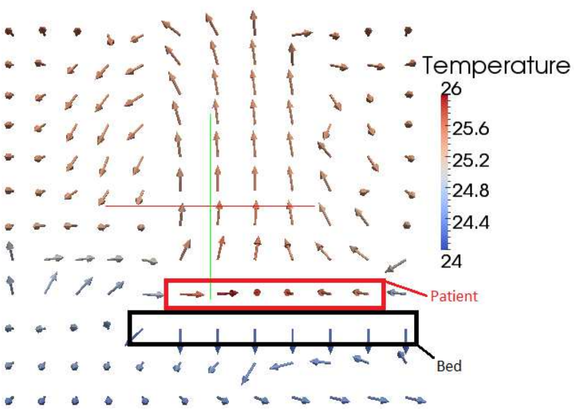

Figure 4 Example results from the CFD domain in the case study model.

As previously detailed, in T-BOT CFD is used to drop the well-mixed room air assumption and facilitate local evaluation of thermal comfort. CFD is notoriously computationally hungry, and even with the substantial economies introduced by the meta-modelling process computation time was still a limiting factor. Coarse grid CFD was found to adequately represent the air flow patterns in the room, minimising the computational requirement. The ACC was used to couple the CFD to other simulation domains; for the sake of conciseness it is left to the literature describing the ACC (Beausoleil-Morrison, 2000) to describe details of the turbulence model, buoyancy, wall functions, etc. However by way of summary, a k-ε turbulence model was used (turbulent Prandtl number 0.9), and buoyancy was conditionally represented by the Boussinesq approximation. Figure 4 shows an example of results from the CFD domain, clearly showing the thermal plume from a patient represented locally.

Results

Figure 5 shows a comparison between Pareto fronts for design variable set 1 optimised at two different positions, in the middle of the room (A) and next to the windows (B). These were optimised for a 24 hour period. Clearly the two are very different; Pareto front A has a clear turning point whereas Pareto front B exhibits more of a smooth curve. The solutions obtaining optimum thermal comfort are also very different; to obtain optimum thermal comfort at the middle of the room entails an energy use of 7.5 kW hrs but the solution near the windows uses only 4.1 kW hrs. This demonstrates that optimum conditions can vary substantially when spatial variation of thermal comfort is taken into consideration.

Table 4 shows energy use at 0 °C time-averaged thermal discomfort for two different sets of optimisation periods. One is optimised in four 6 hour periods, the other is optimised for the whole 24 hour period. The aggregate energy use for solutions of the four 6 hour periods at 0 °C discomfort is approximately 13% lower than for the 24 hour period, suggesting that finer control periods allows for more optimal energy use in this case. This demonstrates that optimum conditions can also very substantially if temporal variation of control periods is taken into account.

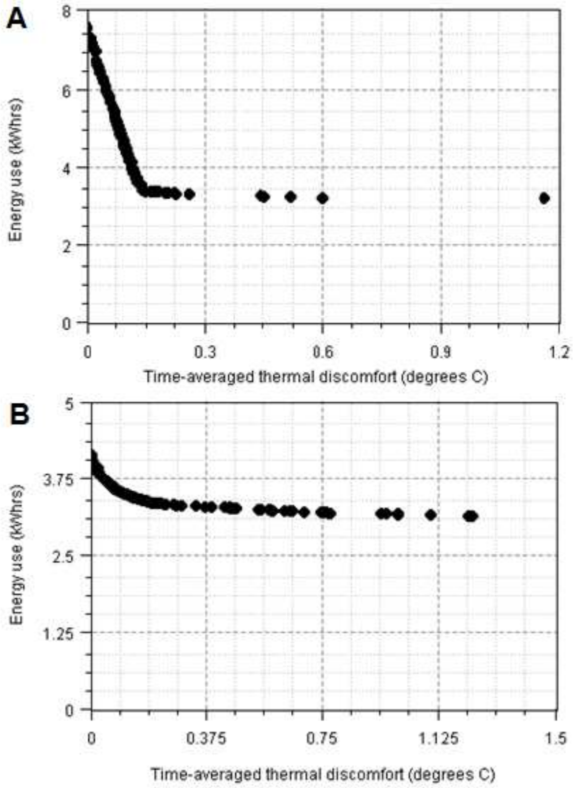

Figure 5 Pareto fronts at two different positions in the room.

Table 4 Energy use values for 6 hour and 24 hour periods.

Period	Energy use (kW hrs)	Aggregate (kW hrs)
1-6	1.087	6.593
7-12	2.404	
13-18	1.688	
19-24	1.414	
1-24	7.539	-

DISCUSSION

Conclusions

This paper has detailed a building optimisation method with the dual objectives of minimising thermal discomfort and energy use in individual spaces. The model seeks to introduce consideration of spatial variation of thermal comfort and temporal variation of control periods into building optimisation, as these tend not to be considered in most building optimisation models in the literature. By applying the model to a case study it has been shown that optimum conditions may vary substantially both spatially and temporally.

It has been demonstrated that the method exploits a number of economies, effectively allowing these variations (among others) to be explored without running additional simulations. Furthermore, the meta-modelling process will typically result in substantially fewer simulations being required than a comparable direct search technique. However, it is noted that due to the inclusion of CFD in the process, the run time of each individual simulation is far greater than most other building optimisation models.

Caveats of Meta-modelling

Whilst meta-modelling introduces many opportunities to develop economies, this does come at a price. By adding an additional layer of modelling between simulation and optimisation, model fidelity can be degraded. If the solutions predicted by the meta-models are not accurate, then the results of the optimisations become moot. In the present method the fit of the meta-models is evaluated by an independent DOE before being further refined, which suggests generally excellent fit to the data as shown in Table 2. However, a number of complicating factors have been identified whilst examining model performance.

Firstly, meta-model fidelity reduces somewhat as solutions approach the boundaries of the design space. It is therefore critical to carefully select design variables and their ranges to minimize the chances of solutions falling at the edges of the design space wherever possible.

Secondly, optimum solutions can be sensitive to very small variations in meta-model predictions. Measures to address this problem are briefly discussed in the next sub-section.

Finally, the size of the initial sample must be proportional to the number of design variables. As the number of design variables increases, the dimensionality of the design space grows, and a sample of the same size implicitly captures less of the variation therein. This results in the meta-model predictions becoming less accurate.

Further Work

Whilst specific formulations of objective functions are given in this paper, the framework of T-BOT is not constrained to these objective functions. Any metric may be used as an objective function provided it is evaluated during the simulation phase, and depends on the design variables. For example instead of operative temperature, predicted mean vote (PMV) or predicted percentage dissatisfied (PPD) (Fanger, 2000) may be used. Metrics of whole-life costing could be included, provided it can be reliably evaluated from the building model.

As detailed above, meta-model fidelity is critical to the method. It is therefore suggested that a useful addition to the method described herein would be to implement an additional iterative self-checking process at the conclusion of each optimisation. This process could take the following form:

1. The user selects their favoured solutions from the Pareto front.
2. The building simulation evaluates these solutions.
3. If the outputs from the meta-model do not match the outputs from the simulation to within a tolerance, the additional simulations are used to refine the meta-models and the optimisation is re-run.
4. The process is repeated until the tolerance is met.

Whilst this would go a long way to ensuring confidence in the results, it would somewhat diminish the time savings introduced by the meta-modelling.

NOMENCLATURE

$F_i(\ldots)$ = objective function
$\boldsymbol{D}$ = set of design variable values
θ_o = operative temperature (°C)
n = number of hours
$\theta_{o,min}$ = lower limit of comfort range (°C)
$\theta_{o,max}$ = upper limit of comfort range (°C)
θ_a = air temperature (°C)
θ_r = mean radiant temperature (MRT) (°C)
v = air velocity (m/s)
E_r = radiant component of energy use (kW hrs)
E_c = convective component of energy use (kW hrs)
$g(\ldots)$ = approximation function
$d(p_i)$ = observed data at point p_i
$\beta(\ldots)$ = non-negative weighting function
p = evaluation point

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