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MULTI-OBJECTIVE OPTIMISATION OF A MODULAR BUILDING FOR DIFFERENT CLIMATE TYPES

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ABSTRACT

A modular hotel unit has been optimised for a range of climate types. The objectives were carbon emissions and construction cost, and the optimisation was performed using a multi-objective genetic algorithm. Variables covered solar and fabric properties as well as heating and cooling systems and renewables. Constraints governed roof area and comfort. Shading provision was determined separately for each orientation. Results are presented for each climate type and the behaviour of variables amongst the optimal solutions examined graphically. PV capacity and system type were the most significant variables, exhibiting clear performance bands; U-values cycled periodically within these bands.

INTRODUCTION

Climate plays a large role in determining the optimal design of a low-carbon building. Usually buildings are bespoke entities, tailored to the climate in which they are sited. However, modular buildings open up the possibility of configuring a single design to function anywhere in the world. Modular construction (e.g. the Verbus system[i]) uses standardised modules and off-site construction methods to keep costs and construction times low. Such designs rely on a high level of uniformity, with units manufactured in a single factory and shipped anywhere in the world. Hotels are a common application of modular construction, as they often require fast construction and uniform specifications.

Modular buildings still require some configuration for the intended climate and use. At present this is done individually for each project. However, there is nothing to prevent a holistic approach, determining the best configuration for any scenario. In this work, a modular hotel unit design has been optimised for different climate types using a multi-objective optimisation process to explore the trade-off between cost and carbon emissions.

Engineering design practice is currently often based largely on informed trial and error (Roy, Hinduja, and Teti 2008), with minimal exploration of the design space. Exhaustive searching of all possible designs is prohibitively computationally expensive. Computational optimisation methods aim to explore a design space in an efficient manner: algorithms aim to navigate quickly to the best solutions. For single objective problems, the aim is to minimise a given function. For optimisation problems with more than one objective, a population of many designs is used, the aim being to find those for which there is no better performing design in all objectives. This is visualised in Figure 1 for a two-objective problem: each axis represents one objective, and the algorithm aims to find the non-dominated points forming the Pareto front. This front can be viewed as a trade-off curve, with each point offering a particular balance between the two objectives. Points not on the curve are sub-optimal, since a point on the curve performs better in both objectives so would be selected in preference. Constraints can also be incorporated into the problem, in which points are excluded from consideration if they fail to meet the given criteria.

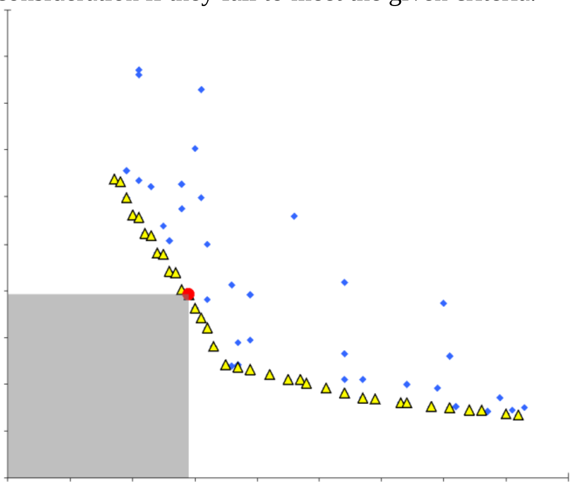

Figure 1
Example of a Pareto front for two objectives. Yellow triangles are non-dominated; blue dots are not. The red circle is non-dominated because there are no solutions in the grey area.

The process of innovisation (Kalyanmoy Deb and Srinivasan 2006) was developed to aid in the understanding of the outputs of multi-objective optimisations problems. It encompasses a broad range of graphical methods of obtaining general rules based on examining the variable values found amongst optimal solutions. This process has been applied to the results obtained here, both in terms of

[i] http://www.verbussystems.com/

the solutions for a given climate and in comparing the solutions across different climate types.

CLIMATE CLASSIFICATION

Climates can be classified into distinct types, based on common characteristics like temperature. The ASHRAE International Climate Zones (American Society of Heating, Refrigerating, and Air-Conditioning Engineers 2007) have been used as the basis for the climate classifications used in this work. Whereas the full list of climate types incorporates humidity and precipitation information, this study is only concerned with the temperature classification. This is based upon heating (H_{DD}) and cooling (C_{DD}) degree-days as shown in (1) and (2): the difference between the current temperature and a base temperature (18C or 10C) is taken every hour, divided by 24 hours and summed.

$$H_{DD} = \sum \frac{|18 - T_{DB}|}{24} \quad (1)$$

$$C_{DD} = \sum \frac{|T_{DB} - 10|}{24} \quad (2)$$

T_{DB} Hourly dry bulb temperature, ^{o}C.

The definitions of the seven climate types considered here (the subarctic type has been dropped) are shown in Table 1. Table 2 gives the specific location chosen to represent each climate type, with the values for heating and cooling degree days.

Table 1
Climate type definitions

Very hot	$5000 < C_{DD}$
Hot	$3500 < C_{DD} < 5000$
Warm	$2500 < C_{DD} < 3500$ *or* $C_{DD} < 2500$ *and* $H_{DD} < 2000$
Mixed	$2000 < H_{DD} < 3000$ *or* $C_{DD} < 2500$ *and* $H_{DD} < 3000$
Cool	$3000 < H_{DD} < 4000$
Cold	$4000 < H_{DD} < 5000$
Very cold	$5000 < H_{DD}$

Table 2
Representative climates selected

	H_{DD}	C_{DD}
Riyadh	391	5943
Macau	290	4640
Marseille	1806	2174
London	2953	926
Aberdeen	3525	492
Helsinki	4757	627
Ulaanbataar	6826	735

Degree days are an imprecise means of estimating the impact of a given climate on a building: whilst they capture both duration and extremity of external temperature fluctuations, they make significant assumptions regarding averaging of internal conditions (CIBSE 2006a). However, they provide a quick means of distinguishing different broad climate categories.

OPTIMISATION

Algorithm

The Non-Dominated Sorting Genetic Algorithm (NSGA-II) developed by Deb (K. Deb et al. 2002) has been used in this work. Genetic algorithms are one of the most common means of conducting multi-objective optimisation. They allow 'black-box' optimisation, i.e. for simulations to provide the objective values with no knowledge of an underlying function. A population of individuals is maintained, with the fittest candidate solutions being selected to progress to subsequent generations. Diversity is maintained in the population by means of crossover (combining features of two individuals) or mutation (random changes to an individual).

The NSGA-II algorithm is one of the most popular multi-objective genetic algorithm implementations. Selection is based firstly on non-domination rank (found by assigning all non-dominated individuals rank 1, then removing them and recalculating to find rank 2 and so on) and secondly on crowding distance (a measure of how closely packed solutions are). The first criteria encourages the population to advance towards the optimum front; the second ensures an even spread along the front

The algorithm used the parameters given in Table 3.

Table 3
NSGA-II parameters

Population size	20
Number of generations	20
Crossover probability	0.9
Mutation probability	0.7

Variables

Variables of the optimisation problem are given in Table 4. They were selected to represent the major areas of importance to building performance: solar properties, fabric properties, HVAC systems and renewable technologies. They are also broad enough to cover configuration of a building for any climate, for example allowing for no heating or cooling system.

The number of variables and the number of options for each variable was kept relatively small to enable each optimisation to be conducted relatively quickly. The focus of this work is on the comparison between different climates rather than the specific optimisation of the design. The process used here could easily be adapted to allow a more detailed optimisation of a modular unit for a specific climate.

Costs

Cost data for each variable choice is also given in Table 4. The high initial costs for systems and renewables include the installation cost, base equipment like storage tanks and inverters, and provision of plant space. It is assumed that there is no cost associated with adding a shading device. Glazing cost is reflected in the price per m^2 given for the window U-value variable; glazing area and wall area were calculated based on the glazing area variable.

Local search

One variable, the presence of a fixed shading device, was determined using ‘local search’ rather than by the genetic algorithm. The inclusion of a local search process within a genetic algorithm (the global search process) is sometimes termed a memetic algorithm (Radcliffe and Surry 1994). In this work, the local search process was simply brute-force: the design was simulated with and without the shade, and the best design selected. Selection was based firstly on the comfort constraint (if one design violated the constraint and the other did not, it was rejected) and secondly on the carbon objective (the design with lower overall emissions was selected). There was no cost associated with the shade, so the cost objective was unaffected; had this not been the case, the multi-objective selection process would have made local search much more complicated.

The use of local search allowed the shade to be selected (or not) for each orientation individually, rather than for all or none. This is clearly important to the performance of the building, allowing solar gain to be reduced only for those facades where is necessary. It is also acceptable within the terms of modular construction: the shade would be added to the building after construction, so can be tailored based on orientation. This is not true of other variables (e.g. glazing area), which must be constant for all modules to allow a single unit to be manufactured on mass.

Local search could have been avoided by using a different shade variable for each orientation. However, this increase in the number of variables (from 8 to 11) would have required more evaluations to locate all optimal solutions, either by increasing the population size or the number of generations. For the local search, two zones (one with the shade and one without) were simulated at the same time. Many calculations were common to both (sun positions, schedule values etc), meaning that while simulation time increased, it did not double, as would have been the case for two separate evaluations. Therefore, the inclusion of local search allowed for a more effective optimisation process.

Objectives

The first objective was annual carbon emissions per module, calculated based on the output of the building simulation. This accounted for carbon emissions due to heating, cooling, lighting (accounting for daylight dimming) and hot water (accounting for solar hot water), as well as carbon credit for PV generation.

The second objective was the capital cost increase per module over the baseline specification (minimum fabric specifications, no heating or cooling provision, no renewable provision). Costs associated with each variable are given in Table 4. Running costs were not accounted for since these are highly dependent on local energy costs.

Constraints

Roof area available for PV and solar thermal panels was limited to 3m^2, reflecting the module roof area of 15m^2 divided by an assumed 5 storeys.

A comfort criteria was applied for the case where heating and/or cooling systems were not present, specifying that no more than 1% of hours may deviate from the desired temperature band. This was defined as <17.9C or >25.1C in order to avoid being triggered by slight errors in maintaining the system set points.

Evaluation

The objective function relating to carbon emissions and the constraint relating to temperatures was evaluated using a dynamic thermal simulation of the module. This was conducted using EnergyPlus (Crawley et al. 2000). Simulation was performed hourly for a full year of weather data for each location. Transient simulation was used to allow for the full range of temporal interactions due to shading,

Table 4
Variables, permitted values and associated costs (in grey).
The shade variable (in black) was locally searched for each orientation.

Variable	*Units*	Values and costs			
Shade		No		Yes	
Glazing area	*m^2*	1	2	3	4
Wall U-value	*W/m^2K*	0.1	0.2	0.3	0.4
	£/m^2	10	6	3	0
Window U-value	*W/m^2K*	0.8	1.0	1.2	1.4
	£/m^2	80	40	30	0
Heating system		None	Gas	ASHP	
	£	0	1000	1500	
Cooling system[i]		None	Electric chiller	ASHP	
	£	0	1200	N/A	
PV	*m^2*	0	1.5	3	3 HE[i]
	£	0	2000	3000	4000
Solar hot water	*m^2*	0	1.5	3	
	£	0	1500	2000	

internal schedules and thermal mass. Whilst it may have been possible to use a simpler means of evaluation, full dynamic simulation allows the system under consideration to be expanded in the future to include more detailed effects.
The model was simulated independently for the four cardinal orientations, applying the local search for the shading variable in each case. The carbon emissions objective was averaged for the four cases, i.e. it was assumed that an equal number of modules face each direction. The comfort constraint was applied across all cases, i.e. if any of the four orientations failed then the constraint was violated. The cost objective and the roof area constraint were unaffected by orientation.
Each EnergyPlus simulation took around 15 seconds on an Intel Core2 Duo 2.8GHz PC. Each evaluation of a solution required four simulations, so around 1 minute. The number of evaluations required for an optimisation run was between 121 and 223; this is less than the maximum of 400 evaluations (20 generations * 20 individuals) because the algorithm did not re-evaluate unchanged or rediscovered solutions. The time taken for an optimisation run was between two and four hours; all seven runs took 21 hours.

MODEL

Geometry

In the modular system under investigation, each unit is the size of one standard ISO shipping container. For the hotel system, each unit contains two rooms and a separating corridor. The module simulated represents one such room (the corridor is disregarded): the zone geometry is given in Figure 2.
The window was centred horizontally, with a width of between 1m or 2m and a height of between 1m or 2m depending on the area variable. The shade (if present) was the width of the zone, 1m deep and located 0.1m above the window. The reference point used for daylight measurements was located at a height of 0.8m and a depth of 2m into the zone.

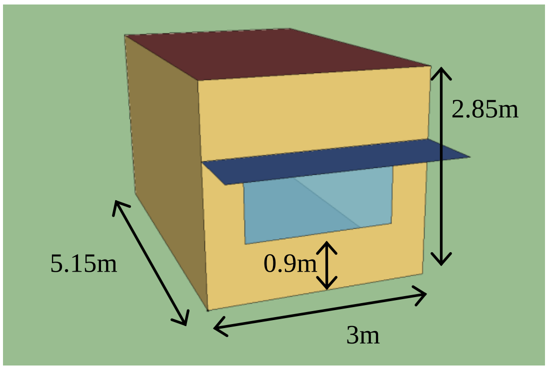

Figure 2
Geometry of the simulated zone

Thermal properties

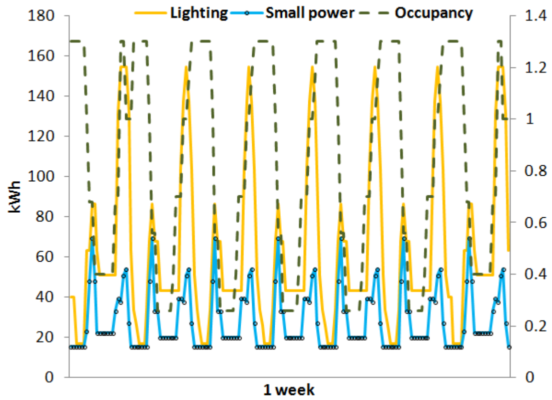

Figure 3
Occupancy, lighting and small power schedules

All surfaces except the front of the zone were modelled adiabatically (i.e. with no heat transfer, as it is assumed that the rest of the building is maintained at a similar temperature). This follows from the assumption that the majority of zones are not ground floor, top floor or end zones.
Schedules for occupancy, lighting and electrical equipment are given in Figure 3. These were taken from the Large Hotel DOE Commercial Reference Building (American Society of Heating, Refrigerating, and Air-Conditioning Engineers 2004). The assumed power densities were 10W/m^2 for lighting and 5W/m^2 for small power. The Daylight available in the zone was modelled to allow dimming of the electric lights, with the target illuminance being 500lux.
The infiltration rate was taken to be 0.6 air changes per hour (CIBSE 2006b). The ventilation rate was taken to be 2 air changes per hour as recommended for hotel bedrooms (CIBSE 2005).

Other calculations

The heating and cooling systems were modelled in the thermal simulation as ideal loads systems. The different system choices were then applied using the efficiencies and carbon factors (The Carbon Trust 2011) given in Table 5. Set points for heating and cooling were 18C and 25C respectively, and were applied at all times.

Table 5
System properties

System	**Efficiency** *%*	**Carbon factor** *kg CO_2 / kWh*
Gas heating	90	0.1836
Electric chiller	300	0.5246
ASHP (heating or cooling)	250	0.5246

Hot water demand was taken as 927kWh/bedroom (60kWh/m^2/year is the good practice benchmark for hotel type 2: business or holiday hotel, (CIBSE 2004)). Energy for hot water was treated in the same way as for space heating.

Energy available from solar hot water and PV systems was modelled based on the available incident solar radiation on an angled surface present in the EnergyPlus model. It was assumed that the panels were optimally orientated (South, since all sites are in the Northern hemisphere) and angled (taken as equal to the latitude of the site).

Energy generated by the PV system is given in (3). Hot water provided by the solar hot water system is given in (4), which was applied daily and the result deducted from the daily hot water demand (this effectively assumes a storage capacity equal to the demand over 1 day).

$$E_{PV} = S_a * kW_p * \gamma \quad (3)$$

$$E_{SHW} = S_d * C * \gamma * \phi * \varphi * L \quad (4)$$

kW_p Installed peak PV capacity (kW);
C Installed solar hot water capacity (m^2);
S_a Annual incident solar radiation (kWh/m^2);
S_d Daily incident solar radiation (kWh/m^2);
γ Overshading factor, 0.8;
ϕ Zero loss collector efficiency, 0.8;
φ Collector efficiency, 0.8;
L Storage loss factor, 0.9.

RESULTS

Overall results

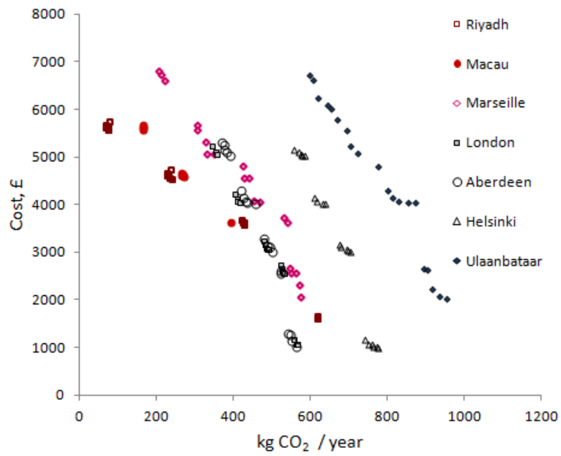

Figure 4
Non-dominated fronts for all optimisations

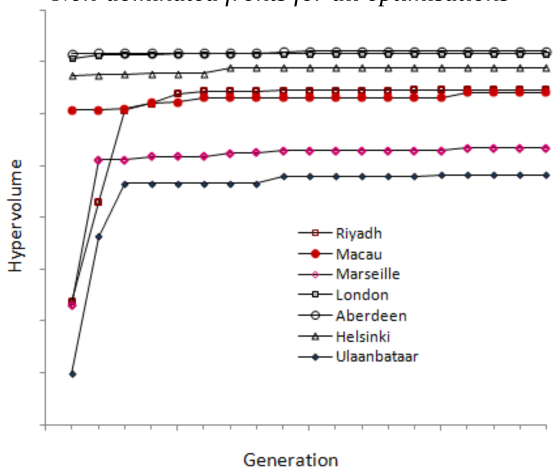

Figure 5
Hypervolume plots for all optimisations

Figure 4 shows the non-dominated fronts for each of the seven optimisations. The location with the highest emissions for any given cost was Ulaanbataar, due to the very high heating load and low PV yield. Helsinki and Marseille followed the same pattern with progressively lower emissions for a given cost. The results for London and Aberdeen were very similar to each other; compared to Marseille they achieved lower emissions at the low cost end but slightly higher emissions at the high cost end, due to the increased benefit of PV in the warmer climate. This increase in slope (i.e. greater return on investment) was continued in the hottest climates (Riyadh and Macau), as this is where the PV brings the most benefit.

For most climates, the algorithm arrived at a population of 20 feasible solutions. However, for Riyadh and Macau the final population consisted of only 17 and 10 feasible solutions respectively. This indicates that the optimal space is smaller in these cases, or that it is harder for the algorithm to fully explore. The former reason makes sense - in an extreme climate, fewer optimal solution modes exist.

For any given climate, these fronts can be used to determine the desired trade-off between carbon emissions and costs. For example, for Ulaanbataar there occurred a significant step in cost for minimal increase in performance; this may discourage increased investment as returns diminish. Conversely, for the hotter climates there was a shallower gradient indicating much better performance improvements with added cost, which may encourage greater investment. Alternatively, if there is a specific target for carbon emissions or for costs, this can be used to determine the required trade-off. For example, if there is a target of 600kg CO_2 per module for Helsinki, the minimum cost for which this can be achieved is £4000.

Another feature of note is the clustering of many solutions: this relates to the PV capacity (see next section). A more detailed optimisation, with smaller increments in PV capacity, would find solutions in between these clusters.

Figure 5 shows the hypervolume[ii] plotted against generation for each of the seven optimisations. This confirms that each optimisation run reached a plateau beyond which further improvement was minimal. This does not guarantee that the algorithm arrived at the best possible set of solutions; this is very hard to prove for global optimisation problems in general, and particularly for multi-objective problems. However, it does give a good indication that further improvements are likely to be small.

[ii] Hypervolume is a measure of the space encompassed by the non-dominated front. In two dimensions, it is equal to the area inside the curve measured from an arbitrary point.

Variable results

Figure 6 gives the variable values for all non-dominated solutions for each climate. Also shown are plots of the associated cost and carbon emissions, which correspond to the axes of Figure 4; the steps in Figure 6 represent clusters or jumps in Figure 4. A given pattern of colours (variable values) defines a certain design. For example, the second design for Riyadh and the first for Macau are the same. They have the same cost (since this does not change with climate) but in Riyadh the design has lower emissions, presumably due to higher PV yield.

The most dominant variable (having the biggest affect on the objectives) was PV capacity - the changes in this variable align with the biggest steps in the objective plots. This is most noticeable for cost (since PV capacity has the greatest influence on cost, up to £4000 per module) and for carbon emissions for Riyadh and Macau (where the benefit is greatest due to high levels of solar radiation). For all climates, PV capacity increased monotonically from the highest emissions design to the lowest, as would be expected; all variable steps were present in all cases. Solar hot water provision was only present in the Marseille, London and Aberdeen climates. In very hot climates there is a greater benefit to installing PV, justifying the higher cost, whereas in very cold climates there is minimal benefit from solar hot water, so it is never optimal. In the three cases where it was present, it was at the low emissions end of the zero PV band; as soon as PV was specified, solar hot water was dropped, despite the roof area constraint allowing for small amounts of both. This is due to the reduced marginal cost of more PV: it is cheaper and more beneficial to double the PV capacity rather than have a small PV array and a small solar hot water array. After the provision of PV and solar hot water, the next obvious banding of solutions is according to HVAC system type. For Riyadh and Macau, no heating system was needed; for London, Aberdeen and Helsinki, no cooling system was needed. This in turn dictated the other half of the system: electric cooling for the former, gas heating for the latter. This is because the ASHP system option is more expensive than either gas heating or electric cooling in isolation; it also does not perform any better, since for cooling an electric chiller is more efficient, whilst for heating the efficiency improvement is outweighed by the increased carbon factor (gas heating emits 0.204 kg CO_2 per delivered kWh; ASHP emits 0.2098). Therefore the only climates where there was a variation in optimal system choice was where both heating and cooling are needed to meet the comfort criteria: Marseille and, surprisingly, Ulaanbataar[iii]. In these cases ASHP was the cheaper, lower performing option (as explained above), with gas heating and electric chillers the more expensive, higher performance option. These options alternated for each band of the PV and solar thermal variables.

Shading options, being independent of cost, were largely unrelated to the bands of renewables provision and system choice discussed above. Often there was a single configuration that was optimal for all solutions - for Riyadh and Macau shades were present on the South, East and West for all solutions. Even where there was variation for a climate, there was always a common configuration: for Marseille the default was as above; for all other climates the default was to have no shading. For Marseille the exceptions (where less shading was provided) corresponded to reduced glazing areas. For the other climates, the exceptions (shading either just on the South, or on all except North) corresponded to increased glazing areas.

Glazing area for Riyadh was the minimum permitted for all solutions, and in Macau for all except two solutions. This is clearly to minimise the need for cooling. For Marseille all glazing areas were present, with no clear pattern – there were good solutions that maximised solar gain or that limited external conduction. In London and Helsinki climates, glazing area was either $1m^2$ or $2m^2$, with shading provided in latter case; it was important to limit both external conduction in winter and solar gain in summer. Conversely in the Aberdeen climate, glazing area was almost always $3m^2$ or $4m^2$; excess solar gain was less of a problem, so beneficial solar gain could be utilised. For Ulaanbataar, glazing area was between $1m^2$ and $3m^2$ with no clear pattern; as with Marseille, there were several possible good solution modes.

U-values for walls and windows were rarely divided into clear bands. Frequently periodic behaviour was apparent, where the variable rapidly cycled in response to changes in other variables – the most obvious example of this is for the window U-value for Riyadh. In all cases but one (Macau) the algorithm found what is presumed to be the lowest emissions solution, that with maximum insulation. In most cases the algorithm did not identify the least insulated option as the minimum cost solution. In cases with either no heating or no cooling system, it may be that a design with minimum insulation breached the comfort constraint - improving the fabric was therefore the cheapest way to achieve a feasible design. In other cases it is likely that the small cost differences due to insulation levels meant that the algorithm failed to locate the very cheapest solution (the greatest deviation from the minimum cost insulation level was £55, whereas the overall cost variation was always greater than £4000).

CONCLUSIONS

A number of broad conclusions may be drawn from the findings detailed above. In general, temperate climates have most distinct solutions modes, due to the complex trade-offs that exist between cooling, heating and lighting demands. This may also be true

[iii] Ulaanbataar in fact has over 700 cooling degree days, in addition to 6800 heating degree days (see Table 2).

in cold climates that have high temperature swings, thus requiring cooling as well as heating. Very hot climates have the simplest solutions, where the objective is simply to minimise solar gain. The increased effectiveness of PV in climates with high solar gain can offset the high cooling loads in those climates. This is not effective in cold climates, where other technologies may have to be investigated.

There is notable banding of the most significant variables (PV capacity), which should be determined first. Other important variables (system types) often have a single optimum for a given climate, making them easy to determine. There is some coupling between certain variables (glazing area and shading provision), so these must be decided in conjunction rather than independently. Finally, there is distinct periodic behaviour amongst the remaining variables (U-values), which should be determined last.

A number of assumptions made in this work could be revisited in future, as more detailed investigation could provide interesting results. Variations within each climate type could be explored, for example cooling requirements in generally cold climates, changes in solar availability, and the influence of humidity on air conditioning requirements. Variations between different locations other than climate could also be investigated, for example in the carbon factor of grid electricity or the absence of gas provision. Running costs could be incorporated into the cost objective, including variation dependent upon location. Modular buildings generally have low thermal mass, however increasing this may have a significant impact on carbon emissions and comfort levels, particularly in temperate climates.

This work has attempted to demonstrated the contributions that optimisation can make to the design process. It can provide a valuable aid to the decision making process in both general and specific terms. Simulation-driven design optimisation and associated field are likely to remain key research areas in the future, as design methods and practices must keep pace with developments in building technology and simulation.

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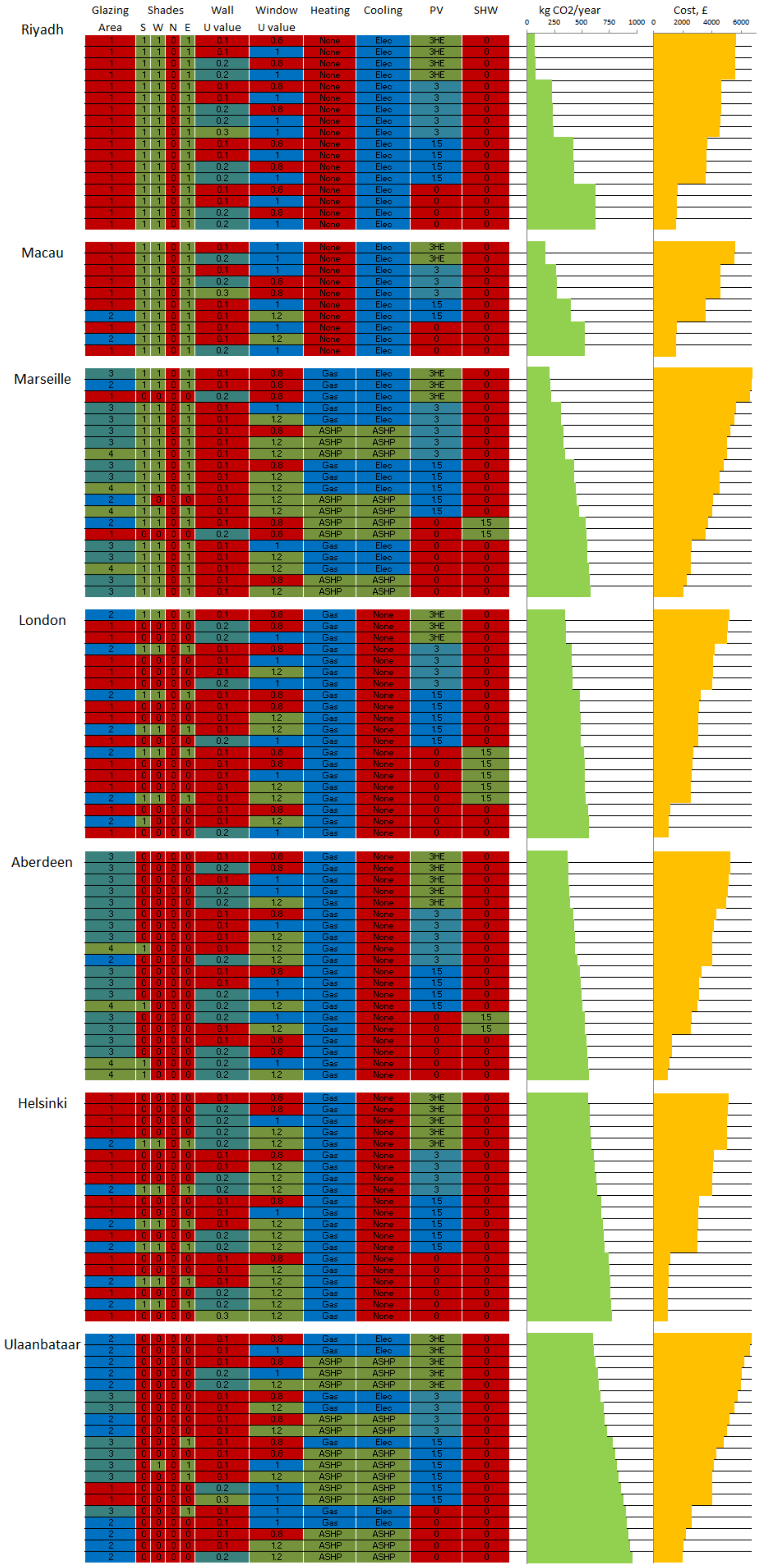

Figure 6
Variable and objective values for all non-dominated solutions for each climate