APPLYING GLOBAL AND LOCAL SA IN IDENTIFICATION OF VARIABLES IMPORTANCE WITH THE USE OF MULTI-OBJECTIVE OPTIMIZATION

Mengchao Wang[1], Jonathan Wright[1], Alexander Brownlee[2], and Richard Buswell[1]
[1]School of Civil and Building Engineering, Loughborough University, Loughborough, Leicestershire, LE11 3TU, UK
Division of Computing Science and Mathematics, University of Stirling, FK9 4LA Scotland, UK
J.A.Wright@lboro.ac.uk

ABSTRACT

Methods for global and local Sensitivity analysis are designed to identify and rank variables importance for each design objective and constraint. This paper investigates the application of local sensitivity analysis to a set of Pareto optimum solutions resulting from the multi-objective minimization of energy use and capital cost, with occupant thermal comfort acting as a constraint. It is concluded that the local sensitivities vary along the trade-off and that these sensitivities are different to the global sensitivities. Different sensitivity behaviour is also observed both along the Pareto trade-off and between variables.

INTRODUCTION

Sensitivity analysis (SA) has been widely applied in the performance design of buildings, to identify and rank variables importance in the design objectives and constraints. For instance, it has been used to evaluate the influence of design variables on the performance of HVAC (heating cooling and air-conditioning) systems (Struck et al., 2008), on the summer overheating risk in the naturally ventilated buildings (De Wit and Augenbroe, 2002; Breesch & Janssens, 2005), and on the mould growth risk in the real-life buildings (Moon and Augenbroe, 2005).

The various sensitivity techniques can be grouped into global and local forms (Saltelli et al., 2000). A global SA is often based on a linear regression model of the sampled solution space whereas a local SA is conducted in a similar way to numerical differencing, where each variable is incremented by a pre-defined amount to evaluate its impact on a given problem uncertainty (Saltelli et al., 2000; Dominguez-Munoz et al., 2010; Breesch and Janssens, 2005).

Building performance design is an inherently multi-objective process, which has led to research into the applications of model-based multi-objective optimization that identifies the Pareto optimum trade-off between two or more conflicting design objectives (e.g. minimized energy demand and capital costs, against maximized thermal comfort) (Brownlee and Wright, 2012).

According to previous research in the field of building performance design (Evins, 2013), very little sensitivity research has been conducted in relation to multi-objectives building. Fesanghary et al. (2008) use the global SA to reduce the number of problem variables for the optimization. Yoshida et al. (2007) use the local SA to explore the future trend of the energy supply systems for hospitals, based on their typical (optimum) condition found from optimization. Wright et al. (2012) state that, to improve computational efficiency, solutions obtained from optimization can be re-used to compute global sensitivities of variables.

This paper extends previous research by investigating:

- The extent to which the local sensitivities vary across a Pareto optimum trade-off between energy use and capital cost.
- The extent to which the local sensitivities differ from the global sensitivities.

SENSITIVITY METHODS

Global sensitivity analysis:

Quantitative measures of variables global sensitivity are usually based on a linear regression model in the stepwise manner (Saltelli et al., 2000). Robustness of the approach is dependent upon the choice of procedure options (e.g. sample size, data form, selection approach and selection criterion). According to Wang et al. (2013), a stepwise regression with the use of bidirectional elimination, rank transformation and Bayesian information criterion (BIC) can be used to rank the most important (sensitive) variables fast and accurately. In particular, the use of rank-transformed data can mitigate against the problems associated with fitting linear models to nonlinear data, e.g. the analysis of solution infeasibility. Thus, the stepwise regression with the use of bidirectional elimination, rank transformation and BIC adopted here to measure the global sensitivities of design objectives and constraints to changes in the variable values; the analysis is performed using the R statistical computing software (V2.15.0; 2012).

The stepwise regression analysis can provide an insight into the relative importance of variables in several ways (Saltelli et al., 2000). The more important the variable is, the earlier the entry into the linear regression model; the larger the absolute value of standardized rank regression coefficient (SRRC); the larger the contribution to model R^2 change (the coefficient of determination). If there is no correlation between variables, the entry-order of variables, the order of variables SRRCs and the order of variables contribution to R^2 changes are identical, indicating the same rank-order of variables importance for a certain output. In this study, both variables SRRCs and entry-orders are used to indicate variables global sensitivities for each of design objectives and constraints.

For a sample size of 100 and above, the difference in the results from different sampling methods becomes slight. For building simulation applications, it is feasible to use a simple random sampling method with approximately 100 samples (Macdonald, 2009; Lomas and Eppel, 1992). Thus, the global SA is performed here using 100 random samples.

Local sensitivity analysis

In this study, the local SA is performed on all solutions from the Pareto optimum trade-off, this indicating the extent to which the sensitivity varies across the optimized solutions. The Pareto optimum solutions form the base-point solutions against which the variable values are incremented by a pre-defined step both positively and negatively from its base-point value. If the base-point value is on the bound of a particular variable, there is only one direction in which to increment the value (away from the bound and towards the defined search space). The total number of 'incremented solutions' used to perform local SA is in the range of $(\mathrm{N_{variables}} \times \mathrm{M_{base\_point}})$ to $(2 \times \mathrm{N_{variables}} \times \mathrm{M_{base\_point}})$, where $\mathrm{N_{variables}}$ is the number of variables; $\mathrm{M_{base\_point}}$ is the number of the base-point solutions along the energy-cost trade-off. Given that the mixed representation and number of increments of the variables, some "categorical" variables providing an index to a construction type (Table 1), the increment used in the local SA is taken to be one incremental value (Table 1) for all variables. The ensures that the local sensitivities represent the smallest possible values for all variables.

The local sensitivity of a design objective (i.e. the energy demand and capital costs) to the change in a variable value ($\mathrm{diff_y}$) is reported here as a percentage change in the objective function value ($\mathrm{y_{increment}}$) in comparison to the base-point objective value ($\mathrm{y_{base\_point}}$):

$$\mathrm{diff_y} = \left(\frac{\mathrm{y_{increment}} - \mathrm{y_{base\_point}}}{\mathrm{y_{base\_point}}}\right) \times 100\% \qquad (1)$$

The local sensitivity ($\mathrm{diff_y}$) can be negative, when the objective function value is reduced with a positive increment in the variable value.

For solution infeasibility (the design constraint), the local sensitivity to the change in a variable value ($\mathrm{diff_{Infeasibility}}$) is given as a percentage change in the solution's infeasibility ($\mathrm{Infeasibility_{increment}} - \mathrm{Infeasibility_{base\_point}}$) against the maximum infeasibility found from the increments across all base point solutions along the trade-off ($\mathrm{max(Infeasibility)}$):

$$\mathrm{diff_{Infeasibility}} = \left(\frac{\mathrm{Infeasibility_{increment}} - \mathrm{Infeasibility_{base\_point}}}{\mathrm{max(Infeasibility)}}\right) \times 100\% \qquad (2)$$

The local sensitivity of a particular variable for solution infeasibility ($\mathrm{diff_{Infeasibility}}$) is normalized against the maximum infeasibility from all variables increments, rather than that of the base point solution, because the infeasibilities of most base point solutions are zero.

The variability of the local sensitivity along the objective trade-off is presented graphically using box-whisker plots, and for some variables, in more detail to illustrate the different kinds of behaviour that can occur for the local sensitivities. The local sensitivities have been compared to the global sensitivities using the mean values of the local sensitivities found across the trade-off.

EXPERIMENTAL APPROACH

Example building and performance model

The example building is based on a mid-floor of a commercial office building with 5 zones located in Birmingham, England (See Figure 1). The size of two end zones and three middle zones are 24m x 8m and 30m x 8m separately, with floor to ceiling height of 2.7m. Each zone has typical design conditions of, 1 occupant per $10m^2$ floor area and equipment loads of 11.5 W/m^2 floor area. Maximum lighting loads are set at 11.5 W/m^2 floor area, with the lighting output controlled to provide an illuminance of 500 lux at two reference points located in each of the perimeter zones. Infiltration is set at 0.1 air change per hour, and ventilation rates at 8 l/s per person. The heating and cooling is modelled by an idealised system that can provide sufficient energy to offset the zone loads and meet the zone temperature setpoints during hours of operation (from 9am to 5pm all year around). The internal zone is treated as a passive unconditioned space. It is simulated through EnergyPlus (V7; 2011a), with the weather data based on the CIBSE reference year (CIBSE, 2002).

Input Variables, Objective Functions and Design Constraints

16 **input variables** associated with perimeter zones are considered in the sensitivity analysis and are optimized (Table 1). The longest facades of the building face North (and South), when the Orientation is set at 0^o. A dead band is used to avoid an overlap of the heating and cooling setpoint. The window-to-wall ratio refers to the window area of 6 equal size windows placed in three groups against the

wall area in each façade (Figure 1), where the names of variables reflect their positions in perimeter zones. The start and stop times are hours of the day. Three construction types are available for external wall and ceiling-floor: heavy weight, medium weight and light weight. Similarly, there are two internal wall types (heavy weight and light weight), and two double-glazed windows types (plain glass and low-E glass). The construction types are index through the use of categorical variables, the heavy weight construction is corresponds to a value of 0, with the construction weight decreasing with increasing variable value. For the categorical variable of window type, the values of 0 and 1 represent the low-E and plain glasses separately.

Table 1
Input variables

INDEX	INPUT VARIABLES	UNITS	LOWER BOUND	UPPER BOUND	INCREMENT
1	Heating setpoint	(°C)	18.0	22.0	0.5
2	Heating set-back	(K)	0.0	8.0	0.5
3	Dead band	(°C)	1.0	5.0	0.5
4	Orientation	(°)	-90.0	90.0	5.0
5	North window-wall ratio	(-)	0.2	0.9	0.1
6	South window-wall ratio	(-)	0.2	0.9	0.1
7	East window-wall ratio	(-)	0.2	0.9	0.1
8	West window-wall ratio	(-)	0.2	0.9	0.1
9	Winter start time	(hrs)	1	8	1
10	Winter stop time	(hrs)	17	23	1
11	Summer start time	(hrs)	1	8	1
12	Summer stop time	(hrs)	17	23	1
13	External wall type	(-)	0	2	1
14	Internal wall type	(-)	0	1	1
15	Ceiling-floor type	(-)	0	2	1
16	Window type	(-)	0	1	1

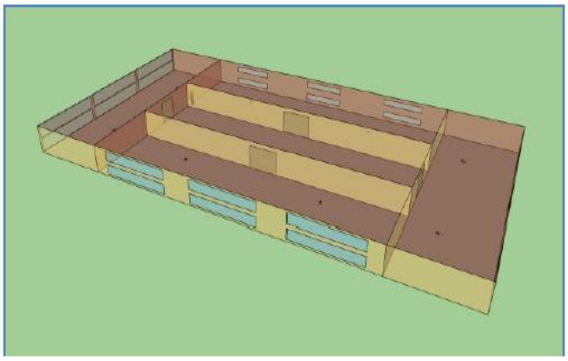

Figure 1 Example building (Wright et al., 2012)

The **design objectives**, to be minimised by the optimization process, are the building annual energy demand (for heating, cooling and artificial lighting), and the capital costs (using a model derived from cost estimating data).

The **design constraints** are that the thermal comfort in each of the perimeter zones should not exceed 20% of predicted percentage dissatisfied (PPD), for no more than 150 working hours per annum. The constraint functions are configured to return the number of hours above 150, or zero if the constraint is feasible. The infeasibility of a solution is the sum of the squares of each constraint violation (i.e. an entirely feasible solution would have an infeasibility of zero).

Optimization algorithm

The Pareto optimum trade-off between the energy use and capital cost has been found using an implementation of the NSGA-II algorithm (Deb et al, 2002), this being used widely to solve bi-objective building optimization problems (Brownlee and Wright, 2012). The specific implementation of NSGA-II is:

- Gray-coded bit-string encoding of the problem variables (163 bits).
- Uniform crossover (100% probability of chromosome crossover with 50% probability of gene crossover).
- Single bit mutation (a probability of 1 bit per chromosome).
- A passive archive of solutions.
- A population size of 20 with the search stopped after 5000 unique simulations.

The search resulted in 169 optimum solutions along the energy-cost trade-off (Figure 2), the 169 being taken from the set of all solutions visited by the algorithm during the optimization, rather than just those in the final population.

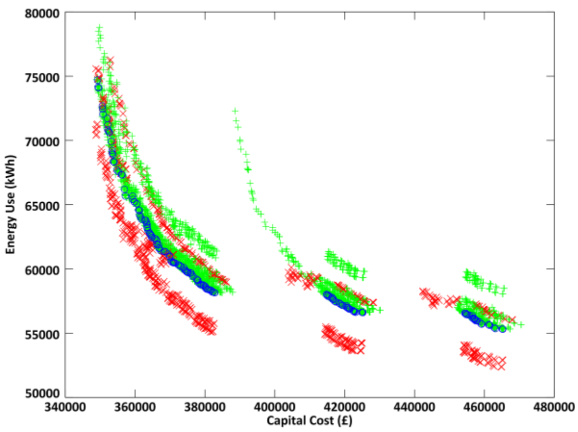

Figure 2 Optimum Trade-off Between Energy Use and Capital Cost and Local Sensitivity resulting from all Variables

RESULTS AND ANALYSIS

The variation in local sensitivity across the trade-off

Figure 2 illustrates the Pareto-optimum solutions and the local sensitivity of the solutions to perturbations in all variables. The blue 'o' solutions show the Pareto optimum solutions, the green '+' solutions perturbations that results in a feasible solution, and the red ‘x’ solutions, variable perturbations that result in infeasible solutions. Since a local sensitivity analysis is equivalent to a local search around the optimum solutions, Figure 2 also illustrates that the Pareto solutions are locally optimal since although some perturbations result in solutions having both a lower energy use and capital cost, all of these solutions are infeasible.

Figures 3 to 5, illustrate the local sensitivity of the objectives and infeasibility to each variable (the variable index being referenced in Table 1). The box-whisker plots show the range of variation of sensitivity across the Pareto optimum set of solutions; the red line is the median value; the box is the inter-quartile range; the whiskers are 1.5 the inter-quartile range; with other symbols representing solutions that lie beyond 1.5 the inter-quartile range.

Figure 3, illustrates the sensitivity of the energy use to the variable values. The most important variables (variable 1 and 3) are the heating setpoint and deadband (the deadband determining the cooling setpoint). The floor and ceiling type (variable15) and the glazing type (variable 16), are the next two most important variables, with glazing type resulting in the widest range of sensitivity.

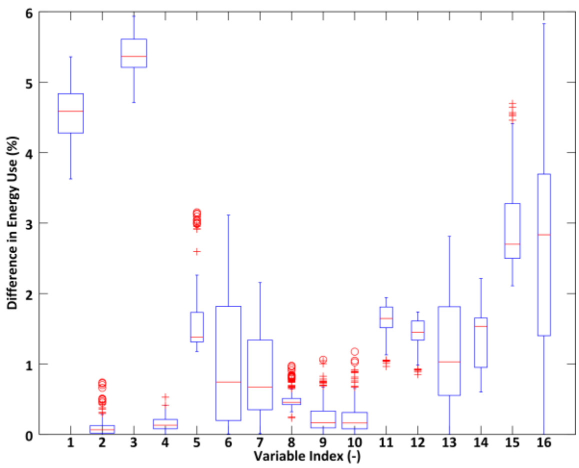

Figure 3 Local Sensitivity of Energy Use across the Trade-off between Energy Use and Capital Cost

Figure 4, illustrates the range of local sensitivity of the capital cost to perturbations in the variable values. The range of sensitivity of the capital cost is in the order of twice that of the energy use (Figure 3), although fewer variables have a significant impact on the cost than for energy use. The capital cost is most sensitive to the type of floor and ceiling construction (variable 15).

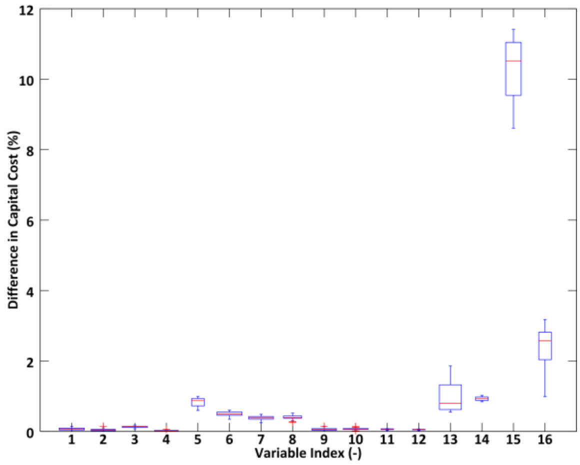

Figure 4 Local Sensitivity of Capital Cost across the Trade-off between Energy Use and Capital Cost

Figure 5, gives the range of sensitivity of the solution infeasibility across the Pareto set, infeasibility being a function of occupant thermal discomfort. Unsurprisingly, the most important variables in determining the feasibility of the solutions are the heating setpoint and deadband (variables 1 and 3). Unexpectedly however, is that the window-wall ratio on one façade (variable 5), and the glazing type (variable 16), are also important in maintaining occupant comfort.

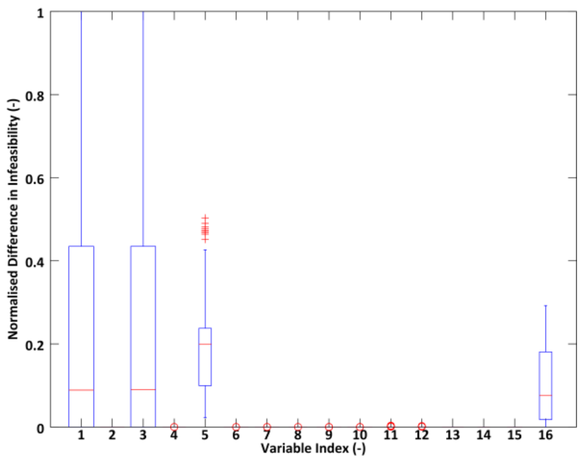

Figure 5 Local Sensitivity of Infeasibility across the Trade-off between Energy Use and Capital Cost

Figure 6 to 9, illustrate the local sensitivity of selected variables along the trade-off between energy use and capital cost. A red line indicates that a change in variable value results in an infeasible solution and a green line a feasible solution.

Figure 6, illustrates the sensitivity due to perturbations in the heating setpoint, this variable having the highest (local) impact on energy use. This “distance variable” (Brownlee and Wright, 2012), causes a shift in position of the trade-off, but all solutions that result in a lower energy use and capital cost are infeasible (red line). The sensitivity is also biased in the direction of energy use.

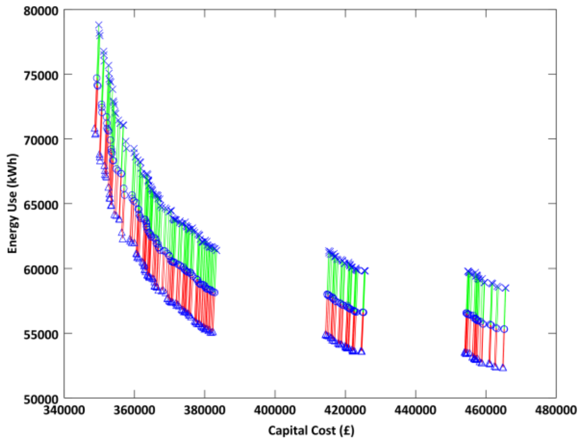

Figure 6 Local Sensitivity due to the Heating Setpoint (Highest Ranked in Energy Use)

The floor-ceiling type is the most important variable in terms of the capital cost. Locally to the Pareto solutions, changing the floor-ceiling type always results in a feasible solution, but significantly increase the capital cost of the building (Figure 7).

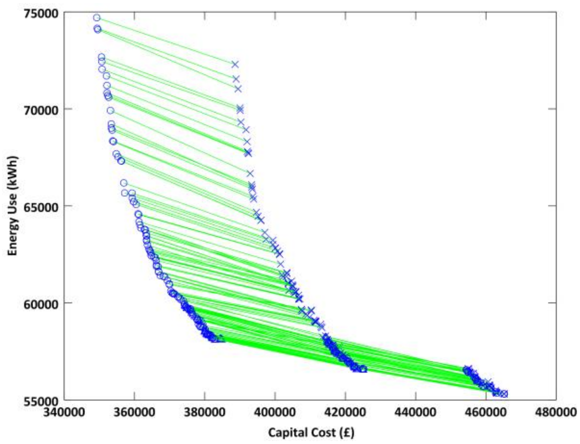

Figure 7 Local Sensitivity due to the Floor-Ceiling Type (Highest Ranked in Capital Cost)

Unexpectedly, the variable having the (marginally) highest impact locally on solution feasibility is the "N" window-wall ratio. Note that the label "N" (North), relates to a default case in which the building is orientated true North-South; the optimization however, resulted in an orientation between 70º and 90º from North, so that the façade tends to face East when optimized. A change in the window-wall ratio always results in an infeasible solution (Figure 8).

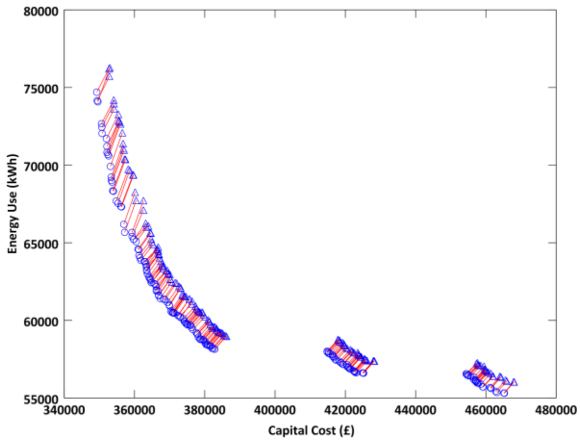

Figure 8 Local Sensitivity due to the "N" Window-wall Ratio (Highest Ranked in Infeasibility)

Figure 9, illustrates the local sensitivity due to a change in the glazing type, this being a variable of mid-importance in both objectives. The extent to which this variable results in an infeasible solution depends on the position along the trade-off.

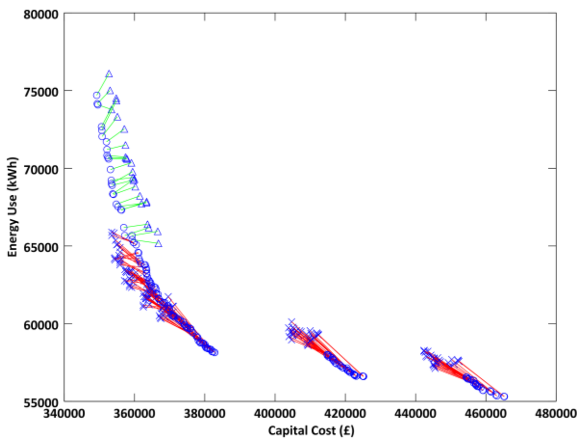

Figure 9 Local Sensitivity due to the Glazing Type

A comparison of local sensitivity and global sensitivity

Tables 2 to 4, compare the global sensitivity to the local sensitivity. In all cases, the global sensitivity is measured using both the relative magnitude of variables SRRCs and the order of entry into the linear regression models. Even though the random samples indicates that there is a small correlation (0.1) between is some pairs of variables, the order of importance for the variable for all objectives and the infeasibility are identical when determined through the SRRC and order of entry into the linear-model. Tables 2 to 4 also give the rank-order of importance of the local sensitivity this being measured by the mean of the sensitivity across the trade-off, with both the mean and rank being given in the tables.

It is apparent, particularly for energy use and capital cost (Tables 2 and 3), that more variables are included in the local sensitivity analysis than the global sensitivity analysis. The number of variables included in the global linear model can be increased by the use of a larger sample size. For instance, for the example problem, a sample size of 1000 solutions increases the number of variables identified for the global sensitivity of the energy use from 10 to 11, for capital cost from 8 to 13, and for the infeasibility, from 5 to 9. However, in all cases, the number of variables identified is less than can be determined through the local sensitivity analysis. Note, that for clarity in comparing the global and local sensitivities, in Tables 2 to 4, the rank-order due to the local sensitivity is reported for the same number of variables identified through the global sensitivity analysis. For instance, in the case of energy use (Table 2), only the first 10 highest ranked solutions are indicate (whereas the mean sensitivity sensitivities associated with all variables is available from the local sensitivity analysis).

Table 2

Global and Local Sensitivity: Energy Use

VARIABLE INDEX	INPUT VARIABLES	GLOBAL SA (SRRC)	LOCAL SA (Mean, %)	GLOBAL SA (Entry Order)	LOCAL SA (Rank Order)
1	Heating setpoint	0.439	4.7	2	2
2	Heating set-back	0.1	0.1	10	
3	Dead band	0.682	5.5	1	1
4	Orientation		0.1		
5	North window-wall ratio		1.6		5
6	South window-wall ratio		1.2		9
7	East window-wall ratio	0.223	1	4	10
8	West window-wall ratio		0.5		
9	Winter start time	0.126	0.2	9	
10	Winter stop time		0.2		
11	Summer start time	0.221	1.6	3	6
12	Summer stop time	0.14	1.4	7	7
13	External wall type		1		
14	Internal wall type	0.091	1.3	8	8
15	Ceiling-floor type	0.195	2.8	5	3
16	Window type	0.19	2.6	6	4
	R^2	0.851		0.851	

Table 2, indicates that the two highest ranked variables for energy use are the same for both the global and local sensitivity, the heating setpoint and the dead-band. However, the order of importance of the mid-ranked variables differs between the local and global analysis. In particular, the importance of the summer system start-time is reduced from the 3rd ranked in the global analysis to 6th ranked in the local analysis. Conversely, the 5th ranked ceiling-floor type in the global analysis is increased to the 3rd ranked in the local analysis. The sensitivity of the East window-wall ratio has also been downgraded from 4th ranked to 10th ranked, whereas the North window-wall ratio has been increased from being unranked in the global sensitivity analysis to 5th ranked in the local sensitivity analysis. However, since the labels, North, South, East and West relate to an orientation that is perfectly aligned North-South, and the solutions along the trade-off are orientated between 70º and 90º from North, the "North" façade faces towards the East in the optimized solutions. Therefore, the rank associated with these most East-facing windows is similar in both the global and local sensitivity analysis.

Table 3

Global and Local Sensitivity: Capital Cost

INPUT VARIABLES	GLOBAL SA (SRRC)	LOCAL SA (Mean, %)	GLOBAL SA (Entry Order)	LOCAL SA (Rank Order)
Heating setpoint		0.1		
Heating set-back		0		
Dead band	0.064	0.1	8	
Orientation		0		
North window-wall ratio	0.2	0.8	2	5
South window-wall ratio	0.1	0.5	5	6
East window-wall ratio	0.09	0.4	6	8
West window-wall ratio	0.128	0.4	4	7
Winter start time		0.1		
Winter stop time		0.1		
Summer start time		0.1		
Summer stop time		0.1		
External wall type	0.094	1.1	7	3
Internal wall type		0.9		4
Ceiling-floor type	0.93	10.1	1	1
Window type	0.187	2.4	3	2
R^2	0.963		0.963	

The type of ceiling-floor construction is the dominant variable that impacts on the capital cost in both the global and local sensitivity analysis (Table 3). While there are some changes to the order of the mid-ranked variables, only the change in rank of the type of internal-wall construction is of note, this being ranked 4th in the local analysis, but unranked in the global analysis.

Table 4

Global and Local Sensitivity: Infeasibility

INPUT VARIABLES	GLOBAL SA (SRRC)	LOCAL SA (Mean, %)	GLOBAL SA (Entry Order)	LOCAL SA (Rank Order)
Heating setpoint	0.662	0.2	1	3
Heating set-back		0		
Dead band	0.534	0.2	2	2
Orientation		0		
North window-wall ratio	0.141	0.2	4	1
South window-wall ratio		0		
East window-wall ratio	0.183	0	3	
West window-wall ratio		0		
Winter start time		0		
Winter stop time		0		
Summer start time	0.11	0	5	
Summer stop time		0		
External wall type		0		
Internal wall type		0		
Ceiling-floor type		0		
Window type		0.1		4
R^2	0.832		0.832	

Since the feasibility of the solutions is a function of occupant thermal comfort, it is unsurprising that the heating setpoint and control deadband are amongst the most important variables resulting from the global and local sensitivity analysis on the solution infeasibility (Table 4). The most noticeable difference between the variable ranks for the global and local analysis is the ranking of glazing (window) type in the local analysis; this reason for this requires further investigation but can be a result of the impact of radiant heat transfer on occupant thermal comfort when the solutions lie on the comfort limit.

CONCLUSIONS

Both global and local sensitivity analysis has been widely applied in the performance design of buildings, to identify and rank variables importance in the design objectives and constraints. This paper extends previous research by investigating the extent to which the local sensitivities vary across a Pareto optimum trade-off between energy use and capital cost and the extent to which the local sensitivities differ from the global sensitivities. The sensitivities are examined in relation to building energy use, capital expenditure, and solution feasibility (feasibility being a function of occupant thermal comfort). The highest ranked variables for energy use and solution infeasibility are the heating setpoint and deadband (which determines the cooling setpoint); the most important variable for capital cost is the type of ceiling-floor construction.

The global sensitivity analysis is based on a stepwise regression analysis with the use of bidirectional elimination, rank transformation, BIC, and 100 random samples. It is concluded that the order of importance of the variables was judged to be the same when variable importance is assessed through the model standardized rank regression coefficient, or order of variable entry into the model, this being the case for the energy use, capital cost, and solution infeasibility.

The local sensitivity analysis is evaluated on all the optimum solutions (base-point solutions) along the energy-cost trade-off, obtained from the constrained multi-objective optimization process. The analysis is conducted by incrementing the value of each variable in a pre-defined step positively and negatively from its base-point values by an amount equal to the minimum increment specified for each variable in the optimization. The ordering of variables local importance (sensitivity) has been examined using box-whisker plots and the mean value of the sensitivity across the trade-off.

It is concluded that the local sensitivities vary across the trade-off between energy use and capital cost for both criteria, and the solution infeasibility. The widest variation in sensitivity for energy use is in the order of 6%, this occurring for the type of window (glazing) construction. Conversely, the widest range of variation of sensitivity of the capital cost across the trade-off is in the order of 2%, although the maximum median sensitivity for capital cost is approximately twice that for energy use (approximately 11% for capital cost and 5.5 % for energy use). A range of different characteristic behaviour is also evident from the local sensitivity analysis, with increments in the value of some variables always resulting in a feasible solution, some always being infeasible, and others resulting in both feasible and infeasible solutions.

It is concluded that differences exist in the variable rankings resulting from the global and local sensitivity analysis, although the top-ranked solutions from each are the same. It is also concluded that the sensitivity to all variables is obtainable from the local sensitivity analysis, but that the global analysis is only likely to identify the most important variables. Further research is required to compare the two approaches for problems having significantly more variables, the comparison including the computational load associated with each approach as well as the difference in global and local sensitivities (the computational load of the local sensitivity analysis being high when all solutions in the trade-off are considered). The use of the sensitivity information in decision-making also requires further research.

REFERENCES

Breesch, H. & Janssens, A., 2005. Building simulation to predict the performances of natural night ventilation: uncertainty and sensitivity analysis, Pro. 9th Int. IBPSA Conf. 2005.

Brownlee, A.E.I. & Wright, J.A., 2012. Solution analysis in multi-objective optimization. Proc. Building Simulation & Optimization 2012, Loughborough University. pp.317-324. © 2012 IBPSA-England.

CIBSE, 2002. Guide J: weather, solar and luminance data CIBSE London. ISBN: 978-1-903287-12-5.

De Wit, S. & Augenbroe, G., 2002. Analysis of uncertainty in building design evaluations and its implications. Energy & Buildings, 34(9), pp.951-958.

Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. on Evol. Comp., 6, pp. 182-197.

Dominguez-Munoz, F., Cejudo-Lopez, J. & Carrillo-Andres, A., 2010. Uncertainty in peak cooling load calculations. Energy & Buildings, 42(7), pp.1010-1018.

EnergyPlus (V7), 2011. Available online: apps1.eere.energy.gov/buildings/energyplus/

Evins, R., 2013. A review of computational optimisation methods applied to sustainable building design. Renewable and Sustainable Energy Reviews, 22, pp. 230-245.

Fesanghary, M., Damangir, E. & Soleimani, I., 2009. Design optimization of shell and tube heat exchangers using global sensitivity analysis and harmony search algorithm. Appl Therm Eng, 29(5), pp.1026-1031.

Lomas, K.J. & Eppel, H., 1992. Sensitivity analysis techniques for building thermal simulation programs. Energy Buildings, 19(1), pp.21-44.

Macdonald, I.A., 2009. Comparison of sampling techniques on the performance of Monte Carlo based sensitivity analysis. Proc. Building Simulation 2009, pp.992-999.

Moon, H.J. & Augenbroe, G., 2005. A mixed simulation approach to analyze mold growth under uncertainty. Proc. Building Simulation 2005.

R statistical software (V2.15.0), 2012. Available online: www.r-project.org/

Saltelli, A., Chan, K. & Scott, E.M., 2000. Sensitivity analysis. UK: Wiley & Sons Ltd.

Struck, C., De Wilde, P., Hopfe, C. & Hensen, J., 2008. An exploration of the option space in student design projects for uncertainty and sensitivity analysis with performance simulation. Intelligent Computing in Engineering (ICE08)– A Joint US-European Workshop, UK.

Wang, M., Wright, J.A., Brownlee, A.E.I. & Buswell, R.A., 2013. A comparison of approaches to stepwise regression forglobal sensitivity analysis used with evolutionary optimization. Pro. 13th Int. IBPSA Conf. 2013. pp. 2551-2558.

Wright, J.A., Wang, M., Brownlee, A.E.I. & Buswell, R.A., 2012. Variable convergence in evolutionary optimization and its relationship to sensitivity analysis, Proc. Building Simulation & Optimization 2012, Loughborough University. pp.317-324. © 2012 IBPSA-England.

Yoshida, S., Ito, K. & Yokoyama, R., 2007. Sensitivity analysis in structure optimization of energy supply systems for a hospital. Energy Conversion and Management, 48(11), pp. 2836-2843.