EMPLOYING A MULTI-OBJECTIVE ROBUST OPTIMISATION METHOD FOR HEALTHY AND LOW-ENERGY DWELLING DESIGN IN DELHI, INDIA

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ABSTRACT

Dwelling design needs to consider multiple objectives and uncertainties to achieve effective and robust performance. A multi-objective robust optimisation method is outlined and then applied with the aim to optimise a one-story archetype in Delhi to achieve a healthy low-energy design. EnergyPlus is used to model a sample of selected design and uncertainty inputs. Sensitivity analysis identifies significant parameters and a meta-model is constructed to replicate input-output relationships. The meta-model is employed in a hybrid multi-objective optimisation algorithm that accounts for uncertainty. Results demonstrate the complexities of achieving a low energy consumption and healthy indoor environmental quality.

INTRODUCTION

Delhi's dwellings must be designed to mitigate hot summers, cool winters and a highly polluted ambient environment in order to provide healthy and low-energy homes. Our research so far suggests that current building performance in Delhi is unsuitable for achieving a healthy indoor environment, risking reliance on energy intensive air conditioning (A/C) use (Nix et al. 2014a). Thus, further research exploring suitable design is necessary for producing guidance to improve current building performance.

Optimising building performance often results in a trade-off between indoor environment quality, energy consumption, and intervention cost (Porritt et al. 2012; Das et al. 2013). A multi-objective assessment was carried out to guide the selection of interventions across a range of archetypes in Delhi, considering cost, health, energy use and settlement type priorities (Nix et al. 2015). More advanced methods to find optimal designs include using genetic algorithm that explore the Pareto-optimal front which results in a set of Pareto efficient design choices. These methods have been used in earlier work and helped identify optimal inventions balancing energy use and health for a government provided top-floor flat in Delhi (Das et al. 2014a).

However, these methods fail to explore design uncertainty arising from fluctuations in environmental conditions, material variability and model assumptions. Uncertainties influence intervention performance and as such, should be understood in the design phase to achieve *robust* solutions. Uncertain optimisation, otherwise known as *robust optimisation*, techniques have been widely applied in other fields of engineering (structural & aerospace) with stringent criteria on system reliability. However, such methods are seldom used in the field of building performance, Nguyen et al. 2014 provides a useful overview of the handful of papers employing such methods, and calls for more investigations to *"determine the significance, necessity, methods and applications"* of robust optimisation in building performance design.

Van Gelder et al. 2014 recently presented a novel methodology using a multi-layered sampling scheme to assess design effectiveness and robustness (Van Gelder et al. 2014b). This method is likely to be slower than employing a genetic algorithm as it uses a space-searching approach. Hopfe et al. 2012 successfully employs multi-objective robust optimisation for a simple example case with limited design parameters (Hopfe et al. 2012). Other studies have limited real-world application, do not consider whole building performance or focus on single design objectives (Huang et al. 2009; Rezvan et al. 2012).

In this paper, we offer a multi-objective robust optimisation method based on widely published tools and techniques, to select interventions that achieve healthy low-energy dwellings in Delhi. We optimise dwelling design for health and energy use simultaneously, (cost and other criteria was deemed outside the study scope for this initial application). Uncertainty was incorporated through hybrid evolutionary multi-objective optimisation algorithm. The work forms part of an ongoing study to provide guidelines for improved dwelling design. Here an overview of methods employed and an application example for a one-story dwelling is presented. The methodology can be applied in similar investigations to provide robust-optimal solutions.

METHODS

In this section, an overview of the methods used to carry out multi-objective robust optimisation is provided. The main four steps taken in the study are illustrated in figure 1.

In the pre-processing stage, a base building simulation model is created. The simulated tool selected should sufficiently predict outputs of interest and should be fully tested and validated. Once a tool has been chosen, the distributions of input parameters to be simulated should be determined. Contributing input parameters will consist of design variables and uncertain variables. Design variables are parameters that can be controlled, such as window size, and through the optimisation scheme these best range for the input variables will be found. Uncertain variables are parameters that cannot be controlled, and can be classed as having either aleatory or epistemic uncertainties. Aleatory uncertainties cannot be reduced as they arise from random variability, such as variability in material properties, however these uncertainties can be described by probabilistic approaches. Epistemic uncertainties arise through lack of knowledge or model simplifications, and have the potential to be reduced. By reviewing various data sources, design and uncertain variables can be described using probability distributions.

The parameters distributions are then sampled in a sampling scheme to represent the variables of interest. Outputs distributions are then found by running the building simulation tool. Details about using a Monte-Carlo approach, various sampling methods efficiencies and sampling convergence for building simulation performance have recently been published elsewhere (Janssen 2013). Furthermore, such methods have been successfully employed in previous research (Paterson et al. 2014; Das et al. 2014b; Bucking et al. 2014)

From this, results are analysed and input-output relationships assessed. Sensitivity analysis can be carried out to identify the key input variables that affect outputs of interest. Such analysis is useful in the construction of a meta-model, as a reduced parameter set with only the most important variables allows for the prediction of outputs in considerably less time. Generally, scatter plots illustrating the input/output relations are first qualitatively analysed, and then the application of statistical tests, such as the *Pearson product-moment correlation coefficient* or *Spearman's rank correlation coefficient*, can quantify sensitivities. Such methods have been utilised elsewhere in assessing drivers of building performance (Lomas and Eppel 1992; Mara and Tarantola 2008; Tian 2013).

The computational resources required to run building simulation models within an optimisation scheme can become computationally expensive. This expense can be reduced through the development of a meta-model. We refer the reader to previous research for further details on meta-modelling (Van Gelder et al. 2014a). These meta-models are then used in the optimisation scheme. Multi-objective optimisation can be determined in two main ways combining the objectives into a single objective or finding the 'Pareto-optimal front'. Pareto-front optimisation is used specifically where objectives are conflicting,

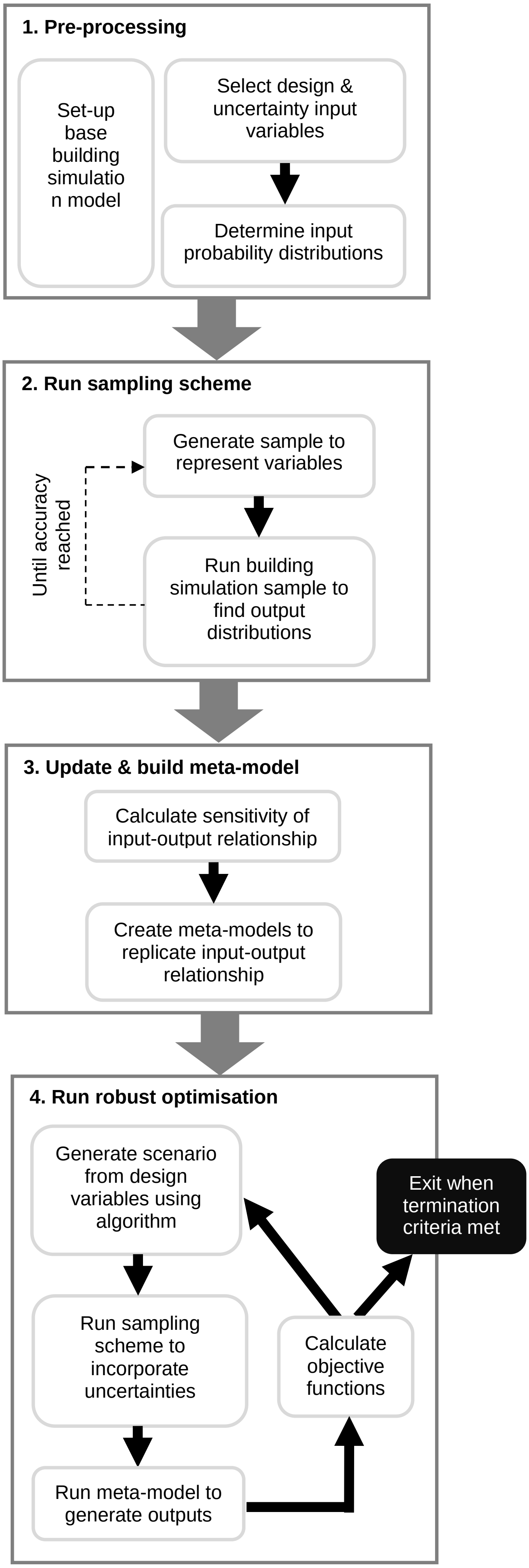

Figure 1: Flow chart of main work components

whereby an improvement in one objective compromises another objective. In this work, the Pareto-optimal front between the conflicting objectives of health and energy are explored by using a multi-objective genetic algorithm. Genetic algorithms evolve populations of chromosomes of potential Pareto-optimal scenarios over generations to find the optimal front. Each generation undergoes uncertainty propagation, through a second sampling scheme that incorporates uncertainty variables. The outputs will have a probabilistic distribution and a deterministic metric is needed to formulate the objective function. As such, we sum the weighted mean and standard deviation for each metric distribution. The results can be analysed by plotting the Pareto optimal front and the range of design variables will be returned.

APPLICATION

Base EnergyPlus model

EnergyPlus 8.2.0, an extensively tested and validated multi-zone building physics tool, was chosen to estimate the impact of parameters on indoor environmental quality and energy consumption (US DOE EERE 2013). EnergyPlus employs heat and mass balance equations, which can estimate heat, moisture, pollutants, and airflow as a function of building parameters, external environment and occupant behaviour. The airflow network was applied to model air movement between internal zones and between the dwelling and external environment. Pollutants were modelled by integrating EnergyPlus' generic contaminant module in the airflow network. Models were simulated for an annual period, outputting hourly indoor air temperature, indoor pollutant concentration and energy consumption variables.

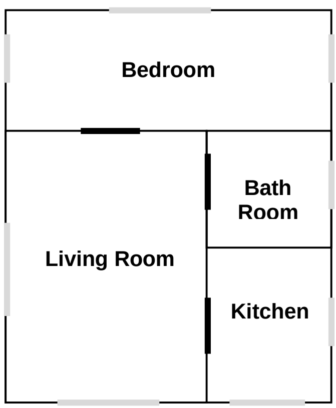

Figure 2: Dwelling layout to undergo uncertain optimisation

For this study, a simple one-story dwelling was used consisting of a living room, bedroom, bathroom and separate kitchen, with the layout as illustrated in figure 2. The dwelling is exposed on all sides, with a constant wall height of 3m. Although, there are multiple possibilities for dwelling layouts (flats etc) that will have an effect on energy consumption and indoor environmental quality, the simple layout selected is likely to be appropriate for a wide range of income groups in Delhi. Field surveys undertaken in Delhi give confidence in the chosen geometry.

The base construction consists of brick walls with internal and external plaster, concrete floor and a reinforced concrete ceiling, as typically found in Delhi housing (Government of National Capital Territory of Delhi 2009). Internal gains include those from occupants and the various appliances. Occupancy schedules and appliance usage was based on various survey data (TERI 2007) and are further detailed in previous work (Nix et al. 2014b). The dwelling is modelled with air-conditioning used during occupied periods in living room and bedroom areas. Windows and door openings were assumed to remain closed.

$PM_{2.5}$ is assumed to be produced by cooking in the kitchen and ingress from the outdoor environment. The cooking generation rate for $PM_{2.5}$ is assumed to be the same as for gas cooking at a rate of 1.6mg/min. The deposition rate for internally- and externally-generated $PM_{2.5}$ throughout the dwelling is assumed to be 0.39/hr (Özkaynak et al. 1996).

Based on previous work (Das et al. 2014a; Nix et al. 2015), outputs for the optimisation included total annual dwelling energy consumption (***E***) and three health metrics. Health metrics were developed as a proxy to indicate 'exposure' to heat ($\boldsymbol{h_{heat}}$), cold ($\boldsymbol{h_{cold}}$) and $PM_{2.5}$ ($\boldsymbol{h_{PM2.5}}$) for an occupant that remains home most of the time. Health metrics are the number of days in which the daily mean exceeds a given threshold. Thresholds for heat and cold were based on previously reviewing external temperature-mortality relationships ((McMichael et al. 2008) and the threshold for $PM_{2.5}$ was based on WHO Guidance (Cohen et al. 2005; Krzyzanowski and Cohen 2008).

These are given by:

$$h_{heat} = \sum_{day=1}^{365} th_{heat}\ (T_{mean}[day]), \quad \text{where } th_{heat}(x) = \begin{cases} 1, & x>29°C \\ 0, & \text{else} \end{cases} \tag{1}$$

$$h_{cold} = \sum_{day=1}^{365} th_{cold}\ (T_{mean}[day]), \quad \text{where } th_{cold}(x) = \begin{cases} 1, & x<29°C \\ 0, & \text{else} \end{cases} \tag{2}$$

$$h_{PM_{2.5}} = \sum_{day=1}^{365} th_{PM_{2.5}}\ (T_{mean}[day]), \quad \text{where } th_{PM_{2.5}}(x) = \begin{cases} 1, & x>75\mu g/m^3 \\ 0, & \text{else} \end{cases} \tag{3}$$

Selection of inputs

Design variables, such as permeability or glazing type, are parameters to be optimised to provide a healthy and low-energy dwelling design. These parameters are based on key determinants affecting building performance in Delhi dwellings derived in previous work (Nix et al. 2014a) and additional parameters considered to affect building performance.

Table 1: Design variables, with symbols, units and input ranges.

DESIGN VARIABLE	UNIT	INPUT RANGE
$\boldsymbol{d_{wallins}}$	m	0.125-3
$\boldsymbol{\lambda_{wallins}}$	W/m.K	0.025-6
$\boldsymbol{\rho_{wallins}}$	kg/m^3	500-2000
$\boldsymbol{d_{roofins}}$	M	0.125-3
$\boldsymbol{\lambda_{roofins}}$	W/m.K	0.025-6
$\boldsymbol{\rho_{roofins}}$	kg/m^3	500-2000
$\boldsymbol{d_{floorins}}$	M	0.125-3
$\boldsymbol{\lambda_{floorins}}$	W/m.K	0.025-6
$\boldsymbol{W_{type}}$	-	Single, Double
$\boldsymbol{S_{overhang}}$	M	0-10
$\boldsymbol{a_{solar}}$	-	0.16-0.98
$\boldsymbol{P}$	m^3/h/m^2@50Pa	3.0-50
$\boldsymbol{W_{area}}$	%	0-50
$\boldsymbol{V_{fan}}$	m^3/s	0-0.2
$\boldsymbol{A_{floor}}$	M	18-250
$\boldsymbol{\Theta}$	°	0-360

Design variables selected for modelling included; a layer of external wall insulation where the thickness ($\boldsymbol{d_{wallins}}$), conductivity ($\boldsymbol{\lambda_{wallins}}$), and density ($\boldsymbol{\rho_{wallins}}$), were varied; thickness ($\boldsymbol{d_{roofins}}$), conductivity ($\boldsymbol{\lambda_{roofins}}$) and density ($\boldsymbol{\rho_{roofins}}$) of the external roof insulation; and a layer of insulation under the floor with varied thickness ($\boldsymbol{d_{floorins}}$), and conductivity ($\boldsymbol{\lambda_{floorins}}$). Ranges for material variables were derived from the WUFI database (Fraunhofer Institute for Building Physics 2013). Windows were modelled with single and double glazing configurations ($\boldsymbol{G_{type}}$). Shading ($\boldsymbol{S_{overhang}}$) was included in the form of an overhang on all facades between 0-3m. The solar absorptance ($\boldsymbol{a_{solar}}$) of the external plaster was selected to vary between 0.16-0.98, which represents applied paint colour. The floor area ($\boldsymbol{A_{floor}}$) was varied from 18m^2-200m^2, which is likely to be representative of the variation in Delhi. Window area ($\boldsymbol{A_{wind}}$) was varied as a percentage of wall area from 0-40%. Dwelling orientation ($\boldsymbol{\theta}$) was varied between 0-360° and dwelling permeability ($\boldsymbol{P}$) varied between 3-50m^3/h/m^2@50Pa, which represents very airtight to a very leaky dwellings. An extract fan, $\boldsymbol{V_{fan}}$, in the kitchen was modelled with a varying volumetric flow rate between 0-0.20m^3/s. Design variables with symbols, units and input ranges are shown in table 1. All design variables were described using uniform distributions.

Uncertain parameters included were occupant number ($\boldsymbol{\#_{occup}}$), set-point temperature to trigger the air-conditioning ($\boldsymbol{T_{AC}}$), set point temperature for triggering window blinds ($\boldsymbol{T_{blinds}}$), and monthly mean levels of external $PM_{2.5}$ were described by a sine wave with varying amplitude ($\boldsymbol{PM_{2.5\_amp}}$) and offset ($\boldsymbol{PM_{2.5\_off}}$). The distribution for occupancy number was given by data from the Delhi Housing Conditions Survey (Government of National Capital Territory of Delhi 2009) and set point temperatures derived from research on thermal comfort by Indraganti (Indraganti 2011). Ranges describing $PM_{2.5}$ levels were derived from $PM_{2.5}$ monitoring data from a central Delhi location (Government of National Capital Territory of Delhi). Uncertain variables are detailed in table 2.

Table 2: Uncertain variable, with symbols, units and input distribution, where G is gamma, N is normal and U is uniform.

UNCERTAIN VARIABLE	UNIT	INPUT DISTRIBUTION
$\boldsymbol{\#_{occup}}$	-	G,3.2,1.4
$\boldsymbol{T_{A/C}}$	°C	N,30,2
$\boldsymbol{T_{blinds}}$	°C	N,28.2
$\boldsymbol{PM_{2.5\_amp}}$	µg/m^3	U,50-100
$\boldsymbol{PM_{2.5\_off}}$	µg/m^3	U,110-160

Sampling scheme

Selected inputs were varied in the base file through a sampling scheme; previous work reviewing sampling efficiency should be referred to for further clarification (Janssen 2013; Das et al. 2014b). In this study, a Latin Hypercube sampling (LHS) was employed; its space-filling scheme provides better efficiency than random sampling. Specially, the LHS maximin scheme is used, which maximises the minimal distance between sampling points.

Both design and uncertain variables were sampled simultaneously. Algorithms provided in MATLAB were employed to generate a hypercube, with uniform distributions between 0 and 1. These distributions were then converted using the inverse cumulative distribution function for each variable. Mini-samples of size 20 were then simulated in EnergyPlus v.8.2.0, with outputs post-processed to find the mean and standard deviations. Further permutations were carried out until sample mean and standard deviations change by less than 1%.

Sensitivity analysis

A sensitivity analysis was carried out in order to analysis the relationship between input parameters and selected output metrics describing indoor environmental quality and energy consumption, which can be useful in developing meta-models.

In this work, scatter plots were initially used to provide visual indication of input-output relationships. The significance of input-output correlations was assessed by testing the hypothesis of no correlation to give *p-values,* a *p-value* smaller than 0.05 was used to indicate significant correlations. Correlations between input- output and their *p-values* generated from *Spearman's rank correlation coefficient* are shown in table 3. A number of parameters were found to be insignificant for the health metrics or energy consumption; as such, a reduced parameter set could be employed in the development of a meta-model.

Table 3: p-values, from Spearman's Rank, indicating significance of input-output correlations, shaded values denote significant relationships below the 0.05 level.

	h_{heat}	h_{cold}	$h_{PM2.5}$	E
$d_{wallins}$	0.816	0.790	0.587	0.331
$\lambda_{wallins}$	0.007	0.263	0.645	0.003
$\rho_{wallins}$	0.558	0.368	0.801	0.539
$d_{roofins}$	0.728	0.864	0.593	0.015
$\lambda_{roofins}$	0.002	0.046	0.096	0.017
$\rho_{roofins}$	0.459	0.187	0.859	0.459
$d_{floorins}$	0.577	0.848	0.524	0.380
$\lambda_{floorins}$	0.842	0.035	0.038	0.102
W_{type}	0.723	0.386	0.447	0.381
$S_{overhang}$	0.060	0.001	0.816	0.248
a_{solar}	0.000	0.000	0.000	0.000
P	0.836	0.173	0.000	0.544
W_{area}	0.822	0.041	0.853	0.330
V_{fan}	0.729	0.960	0.159	0.006
A_{floor}	0.002	0.000	0.000	0.000
Θ	0.738	0.157	0.762	0.518
$\#_{occup}$	0.000	0.000	0.000	0.000
$T_{A/C}$	0.000	0.240	0.392	0.000
T_{blinds}	0.638	0.743	0.937	0.403
$PM_{2.5\_amp}$	0.689	0.754	0.410	0.802
$PM_{2.5\_off}$	0.562	0.694	0.000	0.957

Meta-model development

An artificial neural network (ANN) was used to construct a meta-model. Neural networks can reproduce non-linear and non-monotonic relations between input and output variables through a structure of inter-connected layers of neurons. The first layer contains the inputs, the last layer contains the output, and layers between are hidden layers. The neurons are connected with synapses between layers, weights and biases of the synapses are updated in the fitting process by a training algorithm until the outputs are adequately reproduced. The Neural Network Toolbox provided in `MATLAB` was used in this study. The toolbox provides an array of options including the network type (feed forward, cascade forward), training algorithms (Levenberge Marquardt, Bayesian regularization), number of layers and number of neurons. The simulated sample data is split into a training (70%), validation (15%) and test set (15%). The options are explored to find the best mean error squared for the test group. The minimum mean squared error for the fit to the test set, MSE_{test}, is used to select the best neural network options.

Meta-models were developed using a separate reduced parameter set for each output metric based on the sensitivity analysis. For h_{heat} the preferred ANN construction was a feed forward network with two hidden layers and five neurons per hidden layer, with the Bayesian regularization training algorithm. h_{cold} preferred a construction with a feed forward network with two hidden layers, 20 neurons per layer and Bayesian regularization training. $h_{PM2.5}$ was found to prefer a construction with a feed forward, one hidden layer and 14 neurons per layer with the Levenberge Marquardt algorithm. The best construction for E was a feed forward construction with one hidden layer and 16 neurons and with Bayesian regularization training. Figure 3 shows that a good prediction was achieved, with high correlation between simulated outputs and meta-model outputs. construction R^2 values between simulated and meta-model predictions for h_{heat}, h_{cold} and E are above 0.9, indicating that over 90% of the variance can be accounted by the meta-model.

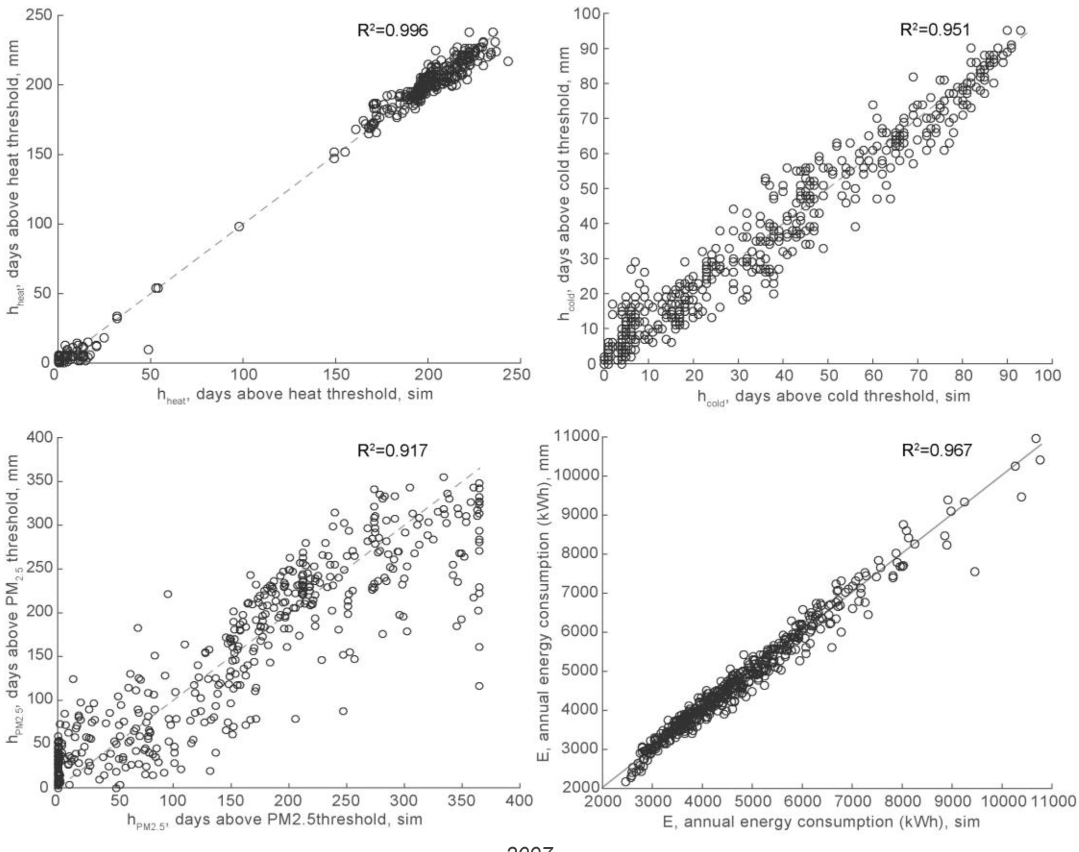

Figure 3: Comparison of simulated (sim) and meta-model (mm) outputs

Multi-objective robust optimisation

The `MATLAB` in-built `gamultiobj` function was used in the next steps, employing the controlled elitist genetic algorithm *NSGA-II*. After an initial random population is ranked in relation to the objective function, the population is continually modified to achieve better rankings. This is then repeated until the criterion is met.

Significant design variables ranges, $\boldsymbol{\lambda_{wallins}}$, $\boldsymbol{d_{roofins}}$, $\boldsymbol{\lambda_{roofins}}$, $\boldsymbol{S_{overhang}}$, $\boldsymbol{a_{solar}}$, $\boldsymbol{P}$, $\boldsymbol{W_{area}}$, $\boldsymbol{V_{fan}}$, $\boldsymbol{A_{floor}}$, were used to bound optimisation problem and generate the inputs for the meta-models. To incorporate uncertainty in optimisation the uncertain variables, $\boldsymbol{\#_{occup}}$, $\boldsymbol{T_{A/C}}$, $\boldsymbol{PM_{2.5\_off}}$, with distributions as previously specified, were sampled in the calculation of the objective functions. Uncertainty in design variables was included by normal distribution with the mean equal to the generated inputs and a standard derivation of 0.1 times the mean. The sampling scheme employed was as described earlier. For each generation, the calculated energy and health metrics have a probabilistic distribution and a deterministic metric is needed to formulate the objective function. This was carried out by summing a weighted mean and standard deviation for each metric distribution. As such, the energy and health objective functions are given by:

$$Obj_E = (1-\alpha)\sigma E + \alpha\mu E \quad (4)$$

$$Obj_h = \sum_{i=1}^{3}\left((1-\alpha)\sigma h_i + \alpha\mu h_i\right), \quad (5)$$
$$Where, 1 = heat, 2 = cold \; and \; 3 = PM2.5$$

For simplicity, in this work, $\boldsymbol{\alpha}$ is kept equal to 0.5 however, this could be altered depending on desired level of robustness needed. Changes in the formulation of objective functions will need to be explored in detail in future work.

Results

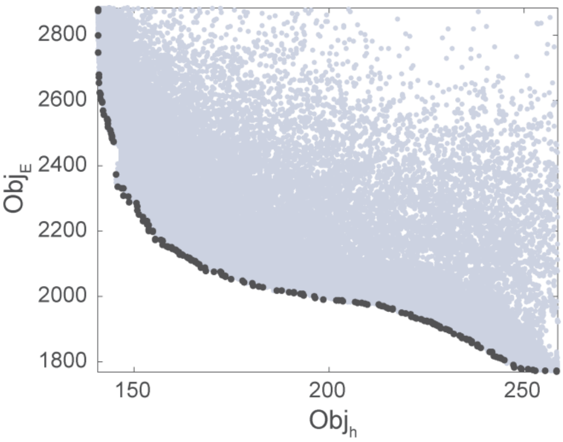

Figure 4: Pareto-optimal front, with the front highlighted in dark grey

The results of the optimisation can be seen in figure 4, with the Pareto-optimal front highlighted in black. $\boldsymbol{Obj_E}$ was found to range between 1770-2880, and $\boldsymbol{Obj_h}$ ranges between 140.8-258.4. It clearly highlights the conflicting objectives with higher energy objective providing lower health objective.

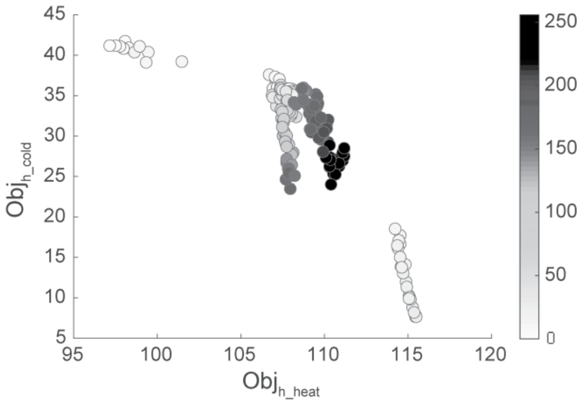

Figure 5: Heat and cold objectives plotted, with $PM_{2.5}$ objective highlighted by colour map

The health objective was broken down into heat, cold and $PM_{2.5}$, and is plotted in figure 5. Similarly, a Pareto-optimal front is shown between heat and cold objectives, suggesting that the any dwelling design will risk some exposure to heat or cold. Interestingly, lower objective values for $PM_{2.5}$ were found to be either a low cold objective or a low heat objective, whereas a balance between heat and cold may risk high $PM_{2.5}$ objective.

Table 4: Pareto-optimal range for each design variable

DESIGN VARIABLE	PARETO-OPTIMAL
$\boldsymbol{\lambda_{wallins}}$	0.52-2.82
$\boldsymbol{d_{roofins}}$	0.21-0.30
$\boldsymbol{\lambda_{roofins}}$	0.03-2.34
$\boldsymbol{\lambda_{floorins}}$	1.69-2.18
$\boldsymbol{S_{overhang}}$	0.04-1.28
$\boldsymbol{a_{solar}}$	0.16-0.76
$\boldsymbol{P}$	8.22-16
$\boldsymbol{W_{area}}$	30.0-34.4
$\boldsymbol{V_{fan}}$	0.001-0.09
$\boldsymbol{A_{floor}}$	33.7-170.4

Pareto-optimal ranges for design variables included in the study are shown in table 4. For the material properties included as design variables, the Pareto-optimal range for $\boldsymbol{\lambda_{wallins}}$ was found to between 0.52-2.82W/m.K, for $\boldsymbol{d_{wallins}}$ between 0.21-0.30m, for $\boldsymbol{\lambda_{roofins}}$ between 0.03-2.34 W/m.K, for $\boldsymbol{\lambda_{floorins}}$ between 1.69-2.18 W/m.K. For other parameters the Pareto-optimal range was found to be 0.04-1.28m for $\boldsymbol{S_{overhang}}$, 0.16-0.76 for $\boldsymbol{a_{solar}}$, 8.22-16 $m^3/s/m^2$@50Pa) for $\boldsymbol{P}$, 30.04-34.42% for $\boldsymbol{W_{area}}$, and 33.7-170.4 for $\boldsymbol{A_{floor}}$. Interestingly, the Pareto-optimal range for many variables is quite large, suggesting that a design trade off between health and energy objectives will be necessary. The complexities in achieving a healthy

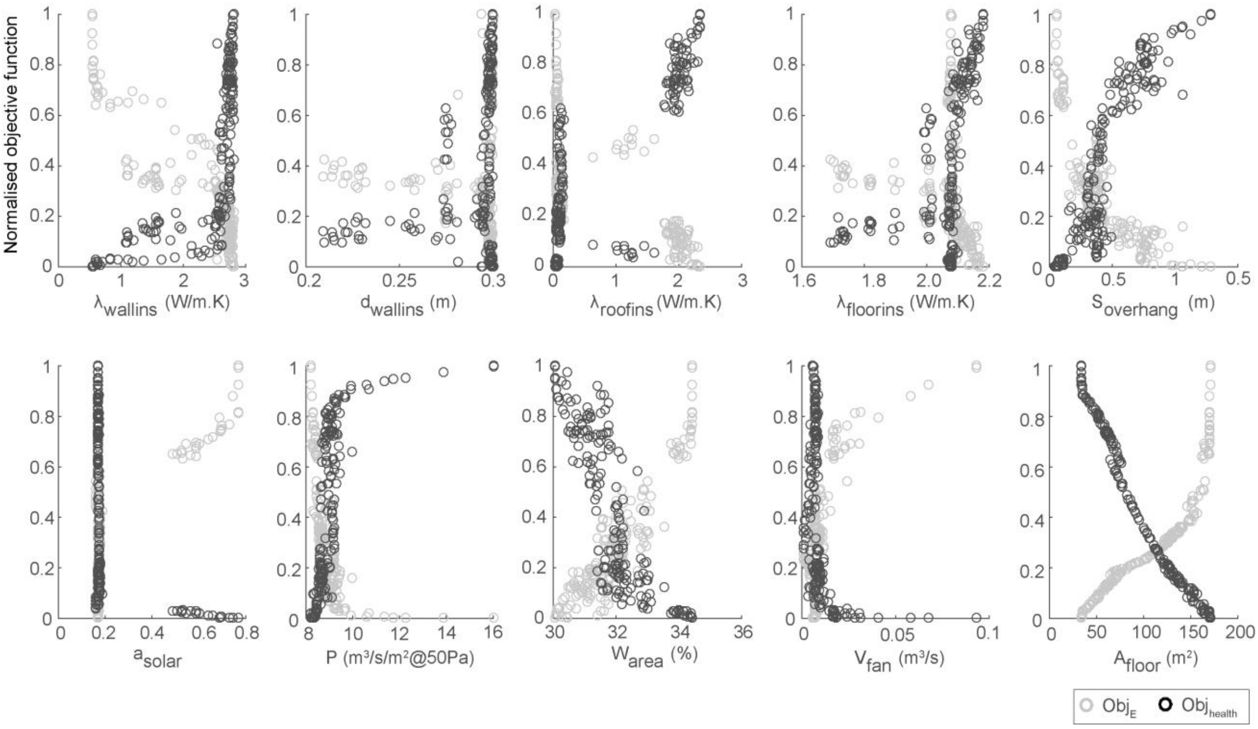

Figure 6: Normalised objective function plotted against Pareto-optimal range for design variable. Black points indicate ***Obj_h*** *and grey points indicate* ***Obj_E***.

low-energy dwelling design are further highlighted by plotting normalised objective functions against Pareto-optimal ranges. Figure 6, shows that each design variable is conflicting, for instance choosing a large floor area benefits the health objective but is detrimental for achieving a low energy objective. This echoes work elsewhere that emphasizes the importance of considering other factors in order to address unintended consequences of decarbonising the built environment (Mavrogianni et al. 2013; Shrubsole et al. 2014).

DISCUSSION & CONCLUSION

The work demonstrates a method for developing guidance for dwelling design when considering multiple objectives and uncertainties. It is clearly shown design parameters are conflicting when considering both indoor environmental quality and energy consumption and as such should be carefully considered. However, it can be concluded that limiting permeability between 8-16 $m^3/h/m^2$@50Pa and a window area between 30-34% will provide improved performance for the one-storey example and other parameters should be selected to balance objective preferences.

Validation of method

Results can be validated initially by assessing if outputs follow expected physical relationships. For instance, by plotting objective functions against Pareto-optimal design variables it can seen that although solar absorptance has a positive impact on the energy objective it has a negative impact on the health objective, presumably due to the increased in cold exposure.

Secondly, we can compare Pareto-optimal outputs directly with EnergyPlus by re-sampling with the Pareto-optimal design variables. The design variables that achieved the lowest health objective were simulated and objective function calculated. An error in the health objective function was found to be 4% and 11% error for the energy objective function. This suggests the method is suitable in predicting the Pareto-optimal front though; some improvements in accuracy are needed.

Limitations and future work

Many other sampling schemes, sensitivity tests and meta-model techniques could be explored to improve efficiency and accuracy of outputs. Although we are confident of the outputs from the methods applied, further work should assess different techniques to assess which are most suited for this study. The formation of the objective function istelf should also be futher analysis and adapted depending on the study and output of interest.

The work should be expanded to additional archetypes (flats, multi-storey dwellings) and parameters, such as number of exposed facades. Further uncertainties could include model errors from set-up of the building simulation tool and errors resulting from the meta-model outputs. Furthermore, the results should be validated by comparing outputs with monitored data.

REFERENCES

Bucking S, Zmeureanu R, Athienitis A (2014) A methodology for identifying the influence of design variations on building energy performance. J Build Perform Simul 7:411–426. doi: 10.1080/19401493.2013.863383

Cohen AJ, Ross Anderson H, Ostro B, et al (2005) The global burden of disease due to outdoor air pollution. J Toxicol Environ Health A 68:1301–7. doi: 10.1080/15287390590936166

Das P, Chalabi Z, Jones B, et al (2013) Multi-objective methods for determining optimal ventilation rates in dwellings. Build Environ 66:72–81. doi: 10.1016/j.buildenv.2013.03.021

Das P, Nix E, Chalabi Z, et al (2014a) Exploring the Health/Energy Pareto-Optimal Front for Adapthing Dwellings in the Delhi Environment. In: Building Simulation and Optimisation Conference. IBSPA, UCL, London,

Das P, Shrubsole C, Jones B, et al (2014b) Using probabilistic sampling-based sensitivity analyses for indoor air quality modelling. Build Environ 78:171–182. doi: 10.1016/j.buildenv.2014.04.017

Fraunhofer Institute for Building Physics (2013) WUFI 1D Pro.

Government of National Capital Territory of Delhi (2009) NSS 65th - Housing Conditions in Delhi.

Government of National Capital Territory of Delhi Central Pollution Control Board. In: http://www.cpcb.gov.in.

Hopfe CJ, Emmerich MTM, Marijt R, Hensen J (2012) ROBUST MULTI-CRITERIA DESIGN OPTIMISATION IN BUILDING DESIGN Cardiff University , UK Leiden University , Netherlands Eindhoven University of Technology , Netherlands. 118–125.

Huang H, Ooka R, Chen H, Kato S (2009) Optimum design for smoke-control system in buildings considering robustness using CFD and Genetic Algorithms. Build Environ 44:2218–2227. doi: 10.1016/j.buildenv.2009.02.002

Indraganti M (2011) Thermal comfort in apartments in India: Adaptive use of environmental controls and hindrances. Renew Energy 36:1182–1189. doi: 10.1016/j.renene.2010.10.002

Janssen H (2013) Monte-Carlo based uncertainty analysis: Sampling efficiency and sampling convergence. Reliab Eng Syst Saf 109:123–132. doi: 10.1016/j.ress.2012.08.003

Krzyzanowski M, Cohen A (2008) Update of WHO air quality guidelines. Air Qual Atmos Heal 1:7–13. doi: 10.1007/s11869-008-0008-9

Lomas KJ, Eppel H (1992) Sensitivity analysis techniques for building thermal simulation programs. Energy Build 19:21–44. doi: 10.1016/0378-7788(92)90033-D

Mara TA, Tarantola S (2008) Application of global sensitivity analysis of model output to building thermal simulations. Build Simul 1:290–302. doi: 10.1007/s12273-008-8129-5

Mavrogianni A, Davies M, Taylor J, et al (2013) The unintended consequences of energy efficient retrofit on indoor air pollution and overheating risk in a typical Edwardian mid-terraced house. In: Future Build.

McMichael AJ, Wilkinson P, Kovats RS, et al (2008) International study of temperature, heat and urban mortality: the “ISOTHURM” project. Int J Epidemiol 37:1121–31. doi: 10.1093/ije/dyn086

Nix E, Das P, Davies M (2014a) Modelling the Disparities in Energy Consumption, Indoor Temperature, and PM2.5 Exposure across Delhi’s Housing Stock. In: Proceedings of the 2014 Building Simulation and Optimization Conference. IBSPA, UCL, London,

Nix E, Das P, Davies M (2014b) MODELLING THE DISPARITIES IN ENERGY CONSUMPTION, INDOOR TEMPERATURE, AND PM2.5 EXPOSURE ACROSS DELHI’S HOUSING STOCK. In: BSO14: Building Simulation and Optimization.

Nix E, Das P, Jain N, Davies M (2015) Strategies for reducing poor indoor air quality and adverse temperature exposure in Delhi’s households: A multi-objective assessment. Build Serv Eng Res Technol 1–17. doi: 10.1177/0143624414566246

Paterson G, Mumovic D, Kimpian J (2014) Using a Monte Carlo Method on Trained Artificial Neural Networks for Identifying Energy Use Determinants of Schools. In: BSO14: Building Simulation and Optimization. IBSPA England, London, pp 1–8

Porritt SM, Cropper PC, Shao L, Goodier CI (2012) Ranking of interventions to reduce dwelling overheating during heat waves. Energy Build 55:16–27. doi: 10.1016/j.enbuild.2012.01.043

Rezvan a. T, Gharneh NS, Gharehpetian GB (2012) Robust optimization of distributed generation investment in buildings. Energy 48:455–463. doi: 10.1016/j.energy.2012.10.011

Shrubsole C, Macmillan a., Davies M, May N (2014) 100 Unintended consequences of policies to improve the energy efficiency of the UK housing stock. Indoor Built Environ 23:340–352. doi: 10.1177/1420326X14524586

TERI (2007) Managing Power Demand, A case study of the residential sector in Delhi.

Tian W (2013) A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 20:411–419. doi: 10.1016/j.rser.2012.12.014

US DOE EERE (2013) EnergyPlus energy simulation software, version 8.0.

Van Gelder L, Das P, Janssen H, Roels S (2014a) Comparative study of metamodelling techniques in building energy simulation: Guidelines for practitioners. Simul Model Pract Theory 49:245–257. doi: 10.1016/j.simpat.2014.10.004

Van Gelder L, Janssen H, Roels S (2014b) Probabilistic design and analysis of building performances: Methodology and application example. Energy Build 79:202–211. doi: 10.1016/j.enbuild.2014.04.042