Development and assessment of representative building performance simulation models for Australian residential dwellings

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Abstract

Purpose / Context - The characterisation of the residential building stock existing in Australia in terms of attributes relevant to energy performance is increasingly an important task for planning and policy purposes. There is a lack of information and documentation on the energy performance characteristics of the existing residential stock in Australia, particularly those constructed prior to the introduction of building efficiency regulations; approximately 85% of the 9 million dwellings in Australia (ABS, 2001,2011). This lack of information creates a significant barrier for studies which have attempted to develop representative energy simulation models for existing buildings.

Methodology / Approach - Statistical review was undertaken on the Australian residential sector, focussed on buildings constructed between 1970 to 2011, for the purpose of developing representative building simulation models to aid in the quantification of the potential for energy efficiency upgrades. Taguchi and ANOVA methods were used to produce a reduced number of models that incorporated significant parameters for the determination of the energy performance. Differential Sensitivity Analysis (DSA) was then undertaken on a single model to quantify the effect of design parameters on the amount of energy needed for maintaining indoor conditions within a comfortable range.

Results – The Taguchi and ANOVA analysis identified floor types, floor area, climate, level of ceiling insulation and wall materials as the most important attributes to be considered in the development of representative simulation models. DSA of design parameters on an example representative model developed in this study showed the parameters with the greatest influence on building energy consumption were airtightness, air conditioning system coefficient of performance, window-to-wall ratio, level of ceiling insulation and glazing SHGC and type.

Key Findings / Implications –This study showed the typical Australian residential stock characteristics and potential energy efficacy upgrade strategies. This work has implications of defining the representative dwelling types for current stock, as well as performance assessment of sample dwelling model with investigation of potential energy retrofitting parameters to address the climate change challenge.

Originality - The paper provides rather informative overview of Australian residential building stock, structured new contribution in order to defining the referenced building and assessing the effectiveness of specific design parameters towards energy demand loads in dwellings.
Keywords Representative dwelling model, Energy Efficiency, Differential sensitivity analysis

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1. Introduction

Numerous previous studies have shown the necessity of making improvements to the energy efficiency of the existing building stock in order to rapidly reduce greenhouse gas emissions (IPCC, 2014; Stern, 2006). However, the selection of the optimal retrofitting strategy for dwellings is a complex task that involves significant knowledge and expertise (Ma et al., 2012). Each dwelling in an existing stock will have a unique combination of form, fabric and operation which will influence the energy performance and optimal upgrade strategies. Individual assessment of a dwellings performance is a time-consuming and costly exercise. Many studies (e.g. Chidiac et al., 2011; Sehar et al., 2012) have employed various stock aggregation techniques to simplify the assessment process. 'Reference' or 'archetypal' buildings have been employed previously as a tool to provide generic energy efficiency assessments of existing building stocks. The purpose of a reference building is to represent the energy performance of a typical building in a segment of the building stock (Theodoridou et al., 2011; Korolija et al., 2013).Whilst there is significant variation in the approaches taken by international studies to define representative residential building models (Filogamo et al., 2014; Famuyibo et al., 2012), some consistent frameworks do exist; for example, the TABULA project in Europe (Droutsa et al., 2014). A discussion of the process and criteria used to segment the building stock into representative typologies for the studies reviewed above, and others, can be found in (Daly et al., 2016).

The aim of the research presented in this paper was to develop a set of representative dwellings for residential buildings constructed between 1970 and 2011 in Australia, for use in building performance simulation. The research further aimed to identify significant parameters which impact heating and cooling energy requirements to aid energy retrofitting decision-making. Significantly less research has been undertaken in characterising the Australian housing stock than in other regions globally. There are several factors that make residential building stock studies in Australia particularly difficult, related to both to the stock characteristics, and the accessibility of data regarding the building stock. Age, which has often been used as a primary segmentation criterion for building stocks in other nations, does not have a strong relationship to building construction techniques and thermal performance in Australia, mostly because the National Construction Code in Australia has only mandated minimum thermal performance since 2003.

2. Methodology

This paper first provides a statistical review on the characteristics of the dwellings under consideration. Simple building simulation models developed on the basis of this review were then analysed using the Taguchi method and an Analysis of Variance (ANOVA) process, in order to identify the key building attributes that influence heating and cooling requirements. The key attributes were then used for defining a reduced number of representative building models for a substantial sub-set of the existing building stock. Finally, one example representative model was analysed using Differential Sensitivity Analysis to quantify the effect of design parameters on the amount of energy needed to maintain indoor comfort conditions within an acceptable range.

2.1 Review of Australian Bureau of Statistics (ABS) Housing Data

In this study, available data from the ABS datasets, in conjunction with other relevant resources, were collected and analysed to determine the most common characteristics of the Australian building stock from 1970 to 2011.Previous studies (Wong, 2013; Ren et al., 2012; Warren-Myers et al., 2012) have used ABS data to understand the relationships between building typology and sustainable renovation outcomes in Australia. A major barrier in the use of ABS data is the inability to access data at the property address level, due to privacy concerns. This prevents the consideration of cross-correlation and clusters of multiple attributes for particular buildings. Therefore, for the purposes of stock level performance modelling based on ABS data, a model which represents each unique set of potential building configurations should be created to represent the full range of construction types. However, this process would result in a large number of building models. By recognizing that certain characteristics will have less significant effects on performance, the total number of representative simulation models can be reduced. In order to reduce the total number of simulation models and to prioritise the attributes for representative models, principles from the Taguchi and ANOVA methods have been used.

The process of converting ABS data into the selected construction types required several assumptions:

- A basic three bedroom, timber frame detached house plan from NSW government housing provider, was assumed for all building configurations (Thomas, 2011).
- The floor plan was adjusted to give a window-to-wall ratio (WWR) of 15%, and then perturbed to create three floor areas (78 m^2, 122 m^2 and 156m^2),
- The generic plan was modified to reflect the full range of characteristics shown in Table 1: Residential building characteristics and assumptions used for baseline representative models and sensitivity analysis. Material thermal properties are from (AIRAH, 2013).

- , and modelled in three climates of New South Wales in Australia (Climate zone 5, 6 & 7).
- The NatHERS indoor comfort conditions, which vary according to climate zone, time of day, and indoor space type, were utilised for this study (NatHERS, 2012). The total heating and cooling demand to keep the internal spaces within the comfortable range for all hours was the output measure considered for this work. This was calculated using the EnergyPlus simulation software.

Table 1: Residential building characteristics and assumptions used for baseline representative models and sensitivity analysis. Material thermal properties are from (AIRAH, 2013).

Model input factor	**Model variable input levels**	**Model constant input levels**	**R-Value (m^2K/W)**
Structure		Detached	-
External wall	Brick veneer	-	0.534
	Double brick	-	0.679
	Fibro	-	0.437
Internal wall		Gypsum board	0.538
Floor	Slab on Ground	-	0.287
	Suspended Timber	-	0.439
Roof	Steel sheet	-	0.206
	Clay Tile	-	0.370
Ceiling	Gypsum board no insulation	-	0.347
	Gypsum board With poor insulation	-	1.34
Floor area	78 m^2-122 m^2-156m^2	-	-
Bedrooms	Two-Three	-	
Airtightness[1]	Poor-Medium	-	
Orientation	North-East-South West	-	
Window to Wall ratio	-	15%	
Glazing	-	Single glazed	
NatHERS Climates	5/6/7		
Thermostat setting	-	Winter 20°C- summer 24.5°C	
COP	-	1	
Occupants	-	1	
Energy supply	-	Electricity	

1: Airtightness is defined by settings correspond to the crack templates as Poor and Medium. In this case every surface in the model has a crack and its size (characterised by flow coefficient and exponent) specified by Designbuilder cracks database (DesignBuilder, 2015).

2.2 Taguchi design of the simulation models

DesignBuilder, a graphical user interface for the EnergyPlus simulation engine, was employed for the simulations in this paper. The Taguchi mix-mode design method was used to reduce the required model runs. This method uses a fractional factorial test design, termed Orthogonal Arrays (OA) (Yang and Tarng, 1998), to reduce the number of simulations required for exploring the influence of building model attributes in the representative models. The selection of a suitable OA depends on the number of attributes and their levels, i.e. the number of building parameters and their possible values. To test the sensitivity of the nine variable design parameters of Table 1, with 3 and 2 levels of possible values, a traditional full factorial design would require 2592 model runs, while with the Taguchi mix-mode design the required numbers of model runs was only 36. The variable attributes and levels considered for this study are given in Table *1*.

Using the Taguchi method allowed factors to be weighted equally and assessed independently of all other factors (Minitab Statistical Software Support, 2016). The Taguchi method applies the signal-to-noise ratio (S/N), a measure of robustness, to minimize the effect of noise and optimize the process performance (Zahraee et al., 2015). In this study the delta S/N ratio; that is the difference between the maximum and minimum average signal-to-noise ratios for the attributes level, was used to determine the relative similarity of the building attribute levels. ANOVA was also performed in order to determine the contribution of each attribute to the total model energy demand. Decision about the significance of attributes or their effect was taken based on the p-value (p-value>0.05) and the variance of effect for parameters of every attributes based on delta S/N ratio (delta S/N<2).

2.3 Differential sensitivity analysis

To understand the influence of different design parameters on dwelling energy load demands, it is also useful to consider the relative influence of these input parameters. In this study differential sensitivity analysis was undertaken, and the non-dimensional influence coefficient was calculated as a comparison index. Previous studies identified non-dimensional influence coefficients as a useful index for building sensitivity studies (Thomas, 2011; Bertagnolio S, 2012; Daly et al., 2014).

The base-case and parametric ranges considered in this analysis are shown in Table 2. The base-case design parameters and the range of variation were determined with reference to: Section J of the Building Code of Australia (ABCB, 2015); the default values included in AIRAH guides (AIRAH, 2013); market products (knauf insulation, 2016); and previously published input values from Australian studies (BRANZ Ltd, 2014; Tony Isaacs Consulting, 2009; Belusko and Timothy, 2011; Department of Industry, 2013). The model was first simulated using the base-case inputs, and then the parameters of interest were varied one at a time, while holding all the other parameters constant, for three climate zones in NSW. The predicted total building energy demand load for each case, and the average influence coefficient across each parameter range were calculated.

T*able 2: Representative model inputs and parametric range for sensitivity analysis*

Parameters of interest	Representative model inputs	Sensitivity analysis ranges
Wall R-value (m^2K/W)	0.5	0.5 - 6.5
Floor R-value (m^2K/W)	0.4	0.4- 4.4
Roof R-value (m^2K/W)	0.4	0.4 - 4.4
Ceiling R-value (m^2K/W)	1.3	0.3 - 6.3
Internal wall R-value (m^2K/W)	0.5	0.5 - 3.5
Glazing types U-value (W/m^2K)	5.8	1.7 – 5.8
Glazing SHGC	0.8	0.2 - 0.8
Window frame U-value (W/m^2K)	3.6	3.5 - 5.9
Airtightness	Poor	Very Poor- Excellent
Occupant number	1	0 - 4
Openable window area (%)	50	25 - 75
South eaves (m)	0.4	0 - 4.5
East-west eaves (m)	0.1	0.1 - 1
Window awning (m)	0.1	0.1 - 1
WWR (%)	15	15 - 75
COP	1	1 - 5

3. Results and Discussion

3.1 Statistical Review of ABS Housing characteristics

Data from the Australian Bureau of Statistics was used to consider the stock characteristics for buildings constructed from 1976 to 2011. In order to leverage the limited data available, the results from numerous ABS surveys and census, which collected different information, were collated and analysed.

Figure presents summary data from a range of ABS surveys undertaken between 1976 and 2011; the table shows the average value where data is taken from more than one survey. Data for dwelling structure, number of bedrooms, and wall materials were taken from the 1976 and 1986 Census of Population and Housing (ABS, 1976,1986), the 1994 and 1999 Australian Housing Survey (ABS, 1999) and the 2011 Environmental Issues: Energy Use and Conservation survey (ABS, 2011). Data for roof materials is gathered from 1994 and 1999 Australian Housing Survey (ABS, 1999), for Insulation from the 1994 ,1999 and 2011 Environmental Issues: Energy Use and Conservation surveys (ABS, 2008; ABS, 2011).

On average, 70% of the housing stock in both Australia and NSW are occupied detached houses or detached bungalows, with two and three bedrooms, as shown in Figure 1. (ABS (2005)) reported that the average floor area of new residential buildings in Australia has increased by 37.4% (from 149.7 m^2 to 205.7 m^2) between 1984-95 and 2002-03.

In Australia, dwellings are made from a variety of materials, brick veneer (22%) and double brick (38%) are the most common wall materials. Tiles (62%) and steel (33%) are the most typical roofing materials. The vast majority of the insulated buildings have the insulation placed in ceiling (98%) and the type of insulation is usually batts or fibreglass (62%). The minimum height of ceilings is 2.4m for habitable areas (ABCB,1996) and single glazed windows are the most common window types (ABS, 2008). Whilst there are significant shortcoming in the available data, the airtightness of Australian homes has been shown to be below the expected standard (Biggs et al., 1986) and may be two to four times as draughty as North American or European Buildings (ZCA, 2013).Whilst the ABS provided no survey data in relation to floor types, (DEHWA, 2008) stated that a significant number of Australian dwellings used concrete slabs and suspended timber for flooring.

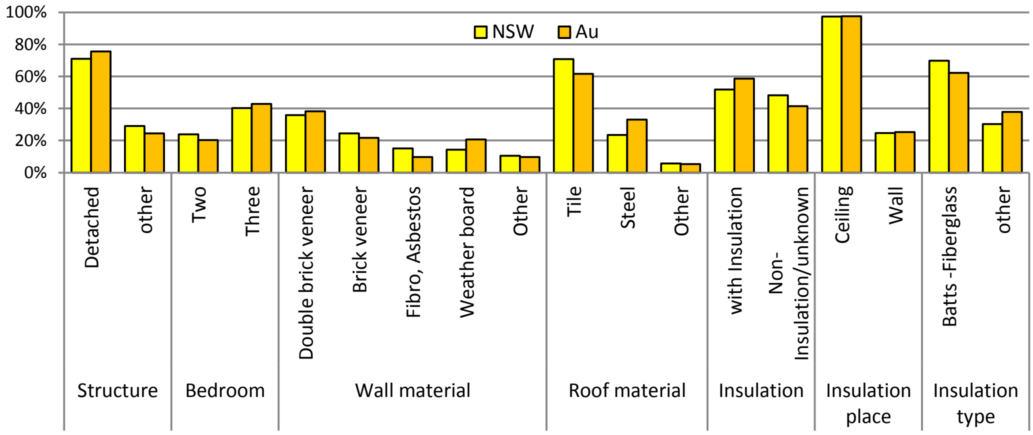

Figure 1: Australian and New South Wales Dwelling characteristics (ABS, 1976,1986; ABS, 1999, ABS, 2008; ABS, 2011).

3.2 Design of Experiment (Taguchi) and ANOVA methods analysis

For the purposes of developing representative simulation models based on the ABS data review, the sets of the most common attribute combinations, as shown in Table *1*, (see variable parameters), are selected to represent the majority of available construction types. To ensure accurate analysis (Sadeghifam et al., 2015), important variables such as size, orientation and climatic data had been considered in design attributes.

In order to reduce the total number of required simulation models and cover at the same time most possible combinations of building stock characteristics, the DOE (Taguchi) method experimental plan was used to prioritise the variable building attributes of Table 1 for representative models. Simulation models were created for the different combinations of the properties that are shown in Table 3. This table displays the summary results of the first iteration of Taguchi mix-mode method with five attributes with 2 levels of variation and four attributes with 3 levels of variation. Each model run had a different combination of design attributes level; the predicted total heating and cooling energy requirements for each configuration in Table 3 is shown in “Total energy” column.

The results of the ANOVA from the Taguchi orders analysis with the delta S/N ratio for the first trial are presented in Table 4. The attributes that most influence the total heating and cooling demand on the modelled dwellings are shown in order of relative contribution. Approximately 90% of the thermal energy demand of the typical building model is directly associated with the floor types, building size, climate, level of ceiling insulation and wall materials attributes. The delta S/N ratio indicates very low variance in the influence of the roof type, number of bedrooms, orientation and airtightness factors levels. This suggests that variables of these attributes have similar effects on response and could potentially be accumulated into a single variable for future works.

To test the effect of ignoring low impact attributes (i.e. when p-value > 0.05) with low variance (delta S/N<2) and rating them as constant for future representative models, four trials for the factors that had the lowest impact (roof types, number of bedrooms, orientation and airtightness) had been simulated with the removal of one of the insignificant factors in each trial. This strategy allowed any errors to be observed. The percentage contribution of attributes remaining after the elimination of insignificant factors showed that the removal of insignificant factors has a small impact on the remaining factors, in all cases less than 2% difference when comparing with the results of Table 4.

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Table 3: Summary table of the Taguchi orders layout and required energy demands data of simulations-1st trial. Full trial require 36 simulations, testing the attribute ranges shown in Table 1.***Error! Reference source not found.***

Table 4: ANOVA with Taguchi delta Signal to Noise Ratio table for the 1st iteration.

Attributes	DF	Seq SS	Contribution percentage %	F-Value	p-Value	Delta S/N Ratio
Floor Types	1	1033893564	36.56%	108.61	0	6.92
Size	2	805091010	28.47%	48.61	0	6.61
Climate	2	471233060	16.66%	24.75	0	4.08
Ceiling Insulation	1	170956279	6.05%	17.96	0	3.13
Wall Types	2	84021898	2.97%	5.12	0.015	2.85
Airtightness	1	24936630	0.88%	2.62	0.12	0.37
Orientation	2	14375700	0.51%	1	0.385	0.37
Number of Bedrooms	1	13306219	0.47%	1.4	0.25	1.12
Roof Types	1	588123	0.02%	0.06	0.806	1.05
Error	22	209432552	7.41%			
Total	35	2827835034	100.00%			

This process effectively reduced the number of attributes requiring further investigation, and allowed the creation of twelve representative simulation models for the retrofit analysis stage which should be modelled by taking into account the building size and the local climate, namely:

Type A. Brick veneer wall with suspended timber floor with and without ceiling insulation.
Type B. Brick veneer wall with slab on ground floor with and without ceiling insulation.
Type C. Double brick wall with suspended timber floor with and without ceiling insulation.
Type D. Double brick wall with slab on ground floor with and without ceiling insulation.
Type E. Lightweight wall with suspended timber floor with and without ceiling insulation.
Type F. Lightweight wall with slab on ground floor with and without ceiling insulation.

3.3 Differential sensitivity analysis of example reference building model

The type A of representative building model with insulation defined in the previous section was then analysed to investigate the relative impact of different energy efficient design parameters on predicted energy consumption. To evaluate the relative influence of each parameter under consideration, the absolute influence coefficient was calculated, as described in 2.3. The calculated influence coefficients are given in Table 5. For all locations, the four most influential parameters were found to be: airtightness, COP of air conditioning system (modelled as an ideal system), WWR and level of ceiling insulation. Airtightness and COP are the two most influential for all locations, but the rank of all other parameters varied depending on location.

When combining the parameters that result to the highest thermal energy needs, we could notice that the thermal energy requirements are more than double of those calculated when combining the parameters that result to the lowest calculated thermal needs (Figure 2). It should be noted the COP was assumed as 1 to have better comparison scale between all scenarios.

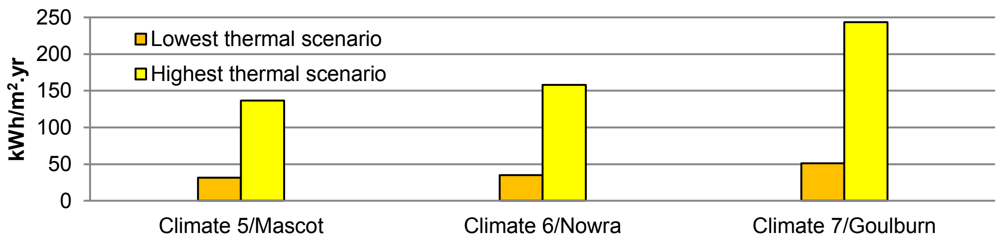

Figure 1: Range of predicted thermal energy use intensity of representative dwellings, type A model, using the simulated range of inputs from Table 2.

Table 5: Influence coefficients of input parameters for type A representative dwelling simulation models

Parameters of interest	Climate 5	Rank	Climate 6	Rank	Climate 7	Rank
Airtightness	0.4006	1	0.3577	1	0.4382	1
COP	0.2667	2	0.2667	2	0.2667	2
WWR	0.1498	3	0.1443	3	0.1095	4
Ceiling insulation	0.116	4	0.1321	4	0.1213	3
Glazing (SHGC)	0.0869	5	0.0634	6	0.0332	7
Glazing types	0.0622	6	0.065	5	0.0619	5
Floor insulation	0.0437	7	0.0472	7	0.0445	6
Openable Window	0.0202	8	0.01	9	0.0044	13
Wall insulation	0.0108	9	0.011	8	0.0149	8
Number of Occupants	0.0074	10	0.0085	10	0.0097	9
Roof insulation	0.007	11	0.0077	11	0.0066	10
Window Frame	0.0055	12	0.0045	12	0.0036	11
East-west Awning	0.0034	13	0.0028	13	0.0019	14
South Eaves	0.0033	14	0.0024	14	0.0047	16
Internal partition	0.0018	15	0.0022	15	0.0024	12
East-west Eaves	0.0004	16	0.0004	16	0.0009	15
North-South Awning	0.0002	17	0.0002	17	0.0001	17

4. Discussion and limitations

The use of statistical data to define dwelling models that can represent a significant proportion of buildings in a stock can be a relatively fast and simple method to quantify the energy savings when upgrading the existing housing stock. However, this approach may not offer precise results or insights into the particular challenges and possibilities for individual buildings. The accuracy of the method depends firstly on the existence of a significant data resource to ensure the defined models are representative of the different construction configurations likely to occur in a stock. In this work, there was important limitation in the data available through the Australian Bureau of Statistics. Therefore, the influence of the main construction characteristics on predicted energy consumption were explored, in order to develop representative models which cover a large proportion of the detached houses within the stock and have substantially different energy performance characteristics. However, the distribution of the representative homes within the considered stock was not able to be determined with the currently available ABS data. Further, the role of occupant behaviour was not considered in this study. Occupancy was represented as a single occupant constantly, and internal gains, for instance the use of domestic equipment, water heating, and lighting were not considered in this study. In actual buildings these patterns can vary, and can often affect whether the benefits from building upgrades are realised fully.

In using Taguchi and ANOVA methods, there is an “Error”, which refers to errors caused by uncontrollable factors (noise) that are not included in the experiment, and the experimental error. Shahavi et al.(2015) advises the value should be less than 50% to be reliable. The errors of all trials in this paper were less than 10%, which suggests that nearly all important and effective factors have been considered, and that errors in developing the Taguchi experiments are not significant. Confirmation test, which is the oprimal combination of process parameters and their levels, also were run in order to verify the result of minimum thermal energy case expectation. Taguchi design was used primarily to study the main effect of building attributes on the value of the annual thermal energy requirements, and possible interactions between attributes were neglected.

The use of non-dimensional influence coefficient from DSA will need to be further investigated in future work. DSA provides information about the sensitivity of a parameter at a single point in the parametric space, and does not provide insight into areas outside the parametric range of a given set of simulations, unless the data can be linearly extrapolated. In this study, a linear relationship between the range of the parameters and the outputs of DSA has been assumed, however the effect of this assumption should also be tested while extending this study in the future. DSA also does not allow the interaction between parameters to be assessed. However, despite the potential for misinterpretation, review of previous literature indicates that influence coefficients is the useful measure available for use in building energy sensitivity analysis comparisons (Daly et al., 2014; Simm et al., 2011).

5. Conclusion

A methodology for developing typical representative dwelling models of the Australian building stock, with a particular focus on the State of NSW was presented. The most prevalent building envelope design parameters for retrofitting were identified after reviewing ABS data. Building simulation, Taguchi and ANOVA methods were applied for evaluating the influence of typical characteristics on dwelling heating and cooling loads, and to filter out those characteristics that have an insignificant effect on the calculated annual thermal energy requirement. This process led to the development of a series of representative simulation models for a large part of the housing stock in NSW. Building simulation was also combined with the DSA method for one of the representative building models in order to demonstrate a method for identifying how sensitive the predictions of thermal loads are on a number of building parameters. The result showed that floor type, building size, climate, level of ceiling insulation and wall materials have a substantial contribution to dwelling performance, and should be explicitly specified in models that represent the stock of existing buildings in Australia. Having fixed the previous parameters for representative models (floor type, building size, etc.) and based on the sensitivity analysis with DSA from the range of values described in Table 2, the most influential parameters on the annual thermal energy requirements were airtightness, COP of the heating/cooling system, WWR, level of ceiling insulation, and SHGC.

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