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Linear regression models for prediction of annual heating and cooling demand in representative Australian residential dwellings

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Abstract

This paper presents the development methodology of linear regression models that were developed for the prediction of annual thermal loads in representative residential buildings across three major climates in New South Wales, Australia, and the assessment of the impact of building envelope upgrades. A differential sensitivity analysis was undertaken for sixteen building envelope parameters, with six parameters being identified as significant. These six parameters were then explored using EnergyPlus simulation, and a number of linear regression models developed from the simulation outputs. Random values for design parameters were generated, and the results of EnergyPlus simulations using these parameters were used to verify the outputs of the regression models. The differences between regression-predicted and EnergyPlus-simulated annual thermal energy requirements were of order 10%-15%. The coefficient of determination (R^2) was over 0.90, indicating a good agreement between simulation and the regression models, and suggesting that the annual heating and cooling energy requirements can be forecasted with an acceptable accuracy using the regression models. It is envisaged that the regression models developed can be used as a quick alternative to building simulation for residential buildings of the area and the climate covered by our study, and can serve to rapidly estimate the likely energy savings/penalty during the retrofitting design stage when different building schemes and design concepts are being considered.

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Keywords: Representative buildings types; Differential sensitivity analysis; Regression model

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1. Introduction

Improving the efficiency of Australia's existing building stock is crucial to reducing emissions in the near future. The existing building stock is replaced by new constructions in the order of 1-3% per year (Ma et al., 2012), meaning that building new low energy constructions will not necessarily have a significant impact on GHG emissions in Australia in the short term. As a result, the upgrading of the existing stock to be of highly energy efficient buildings, and thereby reducing the GHG emissions, is one of the major challenges faced by Australian building sector in the recent years. Several studies have found that refurbishing of existing buildings is the most cost effective method to reduce emissions (IPCC, 2014, McKinsey & Company, 2008), particularly in the residential sector. This sector is one of the fastest growing areas in the building sector, and energy use and associated greenhouse gas emissions are projected to continue to increase in this sector in the future (Morrissey and Horne, 2011).

There is a significant potential for energy efficiency improvements in the residential building stock. Lechtenböhmer and Schüring (2011) found that up to 80% of residential GHG emission production could be avoided using relatively simple measures, e.g. better insulation of the different components of the existing building stock as well as the new buildings. However, selecting the optimal retrofitting strategy for dwellings and estimating their current and future energy demands loads is a complex task that involves significant knowledge and expertise (Ma et al., 2012, Lam and Hui, 1996, Catalina et al., 2013). Sensitivity analysis has been used extensively for assessing the thermal response of buildings and their energy and load characteristics (Athienitis, 1989, Buchberg, 1969, Lomas and Eppel, 1992, Daly et al., 2014, Thomas, 2011), to allow proper selection of design variables and conditions to achieve higher building energy performance.

The present chapter focused on the sensitivity of energy performance improvement parameters in representative building models developed from chapters 4 and 5. The purpose of the analysis is to assess the significance and influence of input design parameters. This chapter also aims to use regression analysis of building simulation results to develop simple energy estimation models, based on the building parameters which most strongly influence the buildings annual thermal energy consumption. The regression analysis was undertaken for fully air-conditioned models in three major climate zones across New South Wales (NSW). This chapter presents information regarding i) the identification of key building design variables using Differential Sensitivity analysis, ii) the development of simple energy estimation models using regression analysis and the Taguchi method, and iii) the evaluation of the developed regression models.

2. Method

Sensitivity analysis was employed in this study, to explore the sensitivity of simulated annual space heating and cooling energy requirements to changes to building envelope attributes in a range of representative buildings that were developed in previous studies (Aghdaei et al., 2016). The amount of energy needed to maintain indoor comfort conditions within recommended comfortable levels (NatHERS, 2012) was the output variable, and simulations were undertaken for three major climate zones across NSW. Parametric energy analysis was the undertaken to explore the design parameters which were found to be influential. Taguchi method and an Analysis of Variance (ANOVA) process were used for to reduce the modelling cost of the parametric analysis. The results of the parametric analysis were then used to develop a simple regression energy estimation models to estimate annual building energy consumption for the three major climate zones in NSW(NatHERS, 2012).

2.1. Representative's dwellings simulation models

The process followed to develop the representative building types for the existing stock, using statistical analysis of Australian Bureau of Statistics data, has been reported previously (Aghdaei et al., 2016). For the current paper, three representative building dwellings were modelled, namely:

Type A. Brick veneer wall with suspended timber floor with ceiling insulation.
Type B. Double brick wall with suspended timber floor with ceiling insulation.
Type C. Lightweight wall with suspended timber floor with ceiling insulation.

The selected representative buildings significantly influence the outcomes of this work, as they form the foundation of all the subsequent analysis. The baseline building simulation models based on the representative dwelling types required the use of a number of assumptions regarding the generic building thermal properties. The key assumptions are outlined and described Aghdaei et al. (2016). DesignBuilder, a graphical user interface for the EnergyPlus simulation engine, was employed for all simulations in this paper.

2.2. Differential sensitivity analysis

To quantitatively assess the sensitivity of the dwelling space heating and cooling demand to different design parameters, it is useful to consider the relative influence of these input parameters. This study has calculated the non-dimensional influence coefficient (IC) for use as comparison indexes in dwelling envelop improvement design parameters effects.

The base-cases , parametric ranges considered in this analysis and further information regarding this section can be found in Aghdaei et al. (2016). The models were first simulated using the base-case inputs. Then, the parameters of interest were varied one-at-a-time while keeping all the other parameters constant for three climate zones in NSW. The predicted total building space heating and cooling demand for each case and the average influence coefficient across each parameter range were calculated.

The three major climate zones in New South Wales as defined by ABCB (2015) were selected as zones 5(warm temperate), 6 (mild temperate) and 7 (cold temperate). This climate classification was appointed to Mascot area (climate 5), Nowra (climate 6) and Goulburn (climate 7) weather data (NatHERS, 2012). 12-month weather profile based on a “Meteorological Year (RMY)” climate files for 2012 from NatHERS have been used to simulate a typical year for every climate zones (NIWA, 2012) .

2.3. Development of regression models

There have been a number of previous studies using simple two-parameter regression analysis techniques for the energy analysis of buildings pre- and post- retrofits (Lam et al., 2004, Lam et al., 2010, Lam et al., 2002). A multiple regression technique was adopted in the present study to develop simple energy estimation models for representative simulation models in three climates.

2.3.1. Taguchi design

The database used for the multiple regression analysis should ideally consist of simulated annual building total space heating and cooling energy requirements covering all possible combinations of the main highly influential parameters (Lam et al., 2010). This process could result to several thousands of simulations and therefore the Taguchi design of experiment 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) and covers a high number of parameter sets. In this study, the Taguchi design order led to a total of 225 simulation runs: five different values for six design input parameters that were the found to be the most influential as a result of the differential sensitivity analysis described in Section 2.2. The resulting six most influential parameters are shown in Table 1 and will be reiterated in the results section of this paper.

Table 1: Summary of base-case values and ranges for the representative simulation models load input parameters

Parameters of interest	Representative model inputs	Range				
		1st-Lower value	2th	3th-Mid value	4th	5th-Higher value
Wall R-value (m^2K/W)-WI	0.5	0	0.5	1	1.5	2
Floor R-value (m^2K/W)-FI	0.4	0	1	1.5	2.5	3
Ceiling R-value (m^2K/W)-CI	1.3	0	2.5	3.5	5	6
Glazing types U-value (W/m^2K)-G	Single (5.8)	Single (5.8)	Single Low E (3.78)	Double (3.16)	Double Low E (2.6)	Double Low E Argon (1.7)
Airtightness -Ar	Poor	Very Poor	Poor	Medium	Good	Excellent
WWR (%)-W	15	10	15	25	35	45

2.3.2. Multiple regression models

In this study, a multiple linear regression model was selected and developed with ANOVA for predicting the total annual heating and cooling energy requirements in the three climates of the study. Compared with nonlinear models, linear regression models are easier and more practical in solving problems (Safa et al., 2014). Multicollinearity between variables has been considered by using the variance inflation factor (VIF), which assesses how much the variance of an estimated regression coefficient increases if parameters are correlated (Martz, 2013). Multicollinearity was not detected as it will be described in section 4. The results are therefore assumed to have a linear dependence with the parameters in the final regression models.

2.4. Model evaluation

An independent set of simulation results was used to verify the predictions of the regression models. Thirty five simulation runs have been undertaken for each model in three climates. A random numerical experiment was carried out by using the random number generator in Microsoft Excel to generate six sets of input design parameters for simulations. The resulting sets of randomly generated input variables, from which the 35 different simulation models were developed, were independent of those used in the development of the regression models and they have been compared with the results of the regression models.

3. Results and Discussion

3.1. Differential sensitivity analysis of representative building models

All types (A, B and C) of the representative building models described in Section 2.1 were simulated at different climates. To evaluate the relative influence of each parameter under consideration, the absolute influence coefficient (IC) was calculated, as described in Section 2.2. Table 2 shows a summary of the IC determined for each design parameter of this study.

Table 2: Influence coefficients of input parameters for type A, B and C representative dwelling simulation models

Parameters of interest	IC for Type A			IC for Type B			IC for Type C		
	Climate 5	Climate 6	Climate 7	Climate 5	Climate 6	Climate 7	Climate 5	Climate 6	Climate 7
Airtightness	0.4006	0.3577	0.4382	0.4610	0.4243	0.5013	0.3278	0.2837	0.3585
WWR	0.1498	0.1443	0.1095	0.1893	0.1870	0.1364	0.0985	0.0911	0.0729
Ceiling insulation	0.1160	0.1321	0.1213	0.1260	0.1443	0.1296	0.0980	0.1102	0.1056
Glazing (SHGC)	0.0869	0.0634	0.0332	0.0819	0.0503	0.0206	0.0873	0.0658	0.0426
Glazing types	0.0622	0.0650	0.0619	0.0476	0.0720	0.0727	0.0489	0.0546	0.0546
Floor insulation	0.0437	0.0472	0.0445	0.0468	0.0548	0.0497	0.0349	0.0367	0.0367
Wall insulation	0.0202	0.0108	0.0149	0.0234	0.0200	0.0162	0.0342	0.0300	0.0300
Openable Window	0.0108	0.0100	0.0044	0.0219	0.0109	0.0044	0.0172	0.0056	0.0030
Number of Occupants	0.0074	0.0085	0.0097	0.0077	0.0101	0.0117	0.0070	0.0069	0.0079
Roof insulation	0.0070	0.0077	0.0066	0.0074	0.0084	0.0071	0.0058	0.0060	0.0054
Window Frame	0.0055	0.0045	0.0036	0.0011	0.0063	0.0022	0.0022	0.0028	0.0033
East-west Awning	0.0034	0.0002	0.0020	0.0029	0.0002	0.0020	0.0028	0.0002	0.0020
South Eaves	0.0033	0.0024	0.0009	0.0050	0.0043	0.0020	0.0014	0.0007	0.0010
Internal partition	0.0018	0.0022	0.0024	0.0022	0.0027	0.0028	0.0013	0.0015	0.0016
East-west Eaves	0.0004	0.0004	0.0004	0.0010	0.0009	0.0004	0.0027	0.0025	0.0004
North-South Awning	0.0002	0.0000	0.0002	0.0000	0.0000	0.0002	0.0000	0.0000	0.0002

A total of six significant design parameters were identified: Airtightness, level of ceiling, floor insulation and wall insulation, window types and window-to-wall ratio (WWR), but their rank varied depending on location. These six design variables have relatively large ICs and should be considered in the retrofitting stage for developing the energy prediction models

3.2. Multiple regression analysis

Simulation models were created for the different combinations of the resulting influential parameters (Table 2) based on Taguchi experiment order design. Table 3 shows an example of simulation designs for building type A and provides a summary of the Taguchi fractional factorial design order plan for six parameters with five levels of variation. In Taguchi design order plan, each model run had a different combination of design parameters variables for creating the dataset.

Total simulated annual building energy consumption data (E) were regressed against the 6 main input parameters (ranges and symbols were described in Table 1, and were derive Aghdaei et al. (2016)) as follows:

$$E\ (total\ heating + cooling\ (kWh)) = A + FI_{(1st\text{-}5th)} + CI_{(1st\text{-}5th)} + WI_{(1st\text{-}5th)} + Ar_{(1st\text{-}5th)} + W_{(1st\text{-}5th)} + G_{(1st\text{-}5th)} \quad (1)$$

Tables 4, 5 and 6 show a summary of the resulting regression coefficients (i.e. A, FI,..and G) for building types A, B and C respectively (see Table 1 for details and corresponding units of the design variables). It can be seen that the coefficient of determination R^2 varies from 0.90 in to 0.97 in all models and locations. In addition, the variance inflation factors (VIF) were in all cases less than 1.6 which indicates an insignificant correlation between the regression model parameters (i.e. because VIF values are less than 5 (Martz, 2013)).

Table 3: Taguchi orders layout for building type A –climate 5 (ranges were shown in Table 3).

Run order	Floor Insulation(FI)	WWR (W)	Ceiling Insulation (CI)	Airtightness (Ar)	Wall Insulation (WI)	Glazing type(G)	Total Heating and Cooling demand (kWh/yr)
1	No insulation	10%	No insulation	Very Poor	No insulation	Single	14005.76
2	R 1	15%	R 2.5	Very Poor	R 1.5	Single Low E	8679.95
…	R 1.5	15%	No insulation	Medium	R 2.5	Double Low E Argon	7568.47
…	R 1.5	35%	R 6	Good	R 1.5	Single	8666.82
24	R 1	45%	R 3.5	Excellent	R 2.5	Single	9901.14
25	R 1.5	10%	R 5	Excellent	R 3	Single Low E	3240.19

Table 4: Multiple regression coefficients for Type A-Brick veneer representative simulation model

Parameter ranges	Climate	Airtightness	Glazing Types	Ceiling Insulation	Wall Insulation	Floor Insulation	WWR	Regression R^2
1st-Lower value	5	2729	506.6	2169	392.6	2255	-2412	
	6	2732	617	2825	503.2	2841	-2535	
	7	5299	868.6	3972	979	4120	-3010	
2th	5	265.7	63.05	-326.2	29.28	-232.4	-1452	
	6	299	136.9	-420.5	24.55	-196.5	-1487	
	7	641.5	214.1	-619.6	-35.83	-257.3	-1720	
3th-Mid value	5	-384.9	87.02	-581.6	-4.34	-517.3	-60.1	0.975
	6	-454.1	53.75	-744.7	-29.3	-668.2	-56.87	0.974
	7	-959.7	36.61	-991	-77.52	-992	-60.46	0.951
4th	5	-1134	-216.6	-627.8	-159.9	-617.1	1195	
	6	-1136	-272	-829.6	-232.9	-789.4	1275	
	7	-2233	-345.7	-1151	-382.1	-1121	1484	
5th-Higher value	5	-1475	-440.1	-633.2	-257.6	-888.6	2729	
	6	-1441	-535.5	-830	-265.5	-1187	2802	
	7	-2647	-773.6	-1211	-483	-1750	3306	
Constant value	5							8247
	6			-				9169
	7							13440

Table 5: Multiple regression coefficients for Type B-Double Brick representative simulation model.

Parameter ranges	Climate	Airtightness	Glazing Types	Ceiling Insulation	Wall Insulation	Floor Insulation	WWR	Regression R^2
1st-Lower value	5	2636	424.8	1753	406.6	2100	-1997	
	6	2699	530.2	2286	516.4	2625	-1997	
	7	5474	886	2877	963.7	3988	-2268	
2th	5	273.4	82.81	-251.7	6.352	-232.5	-1365	
	6	347.2	156.5	-321.4	-1184	-206.4	-1392	
	7	867.5	367.9	-393.9	99.07	-139.3	-2124	
3th-Mid value	5	-378.2	86.15	-411.9	1	-442.1	-151	0.974
	6	-440.9	45.37	-621.5	-12.47	-568.1	-189.3	0. 973
	7	-1464	158.8	-788.6	-185.4	-986	-79.37	0.965
4th	5	-1114	-180.5	-512.6	-160	-624.1	1013	
	6	-1149	-220.8	-663.1	-244	-787.1	1042	
	7	-2072	-146.3	-847.6	-326.6	-1393	1346	
5th-Higher value	5	-1418	-413.3	-577.2	-253.9	-800.9	2500	
	6	-1457	-511.3	-679.8	-248.1	-1063	2536	
	7	-2206	-1266	-947	-550.7	-1469	2824	
Constant value	5				-			6872
	6							7424
	7							11395

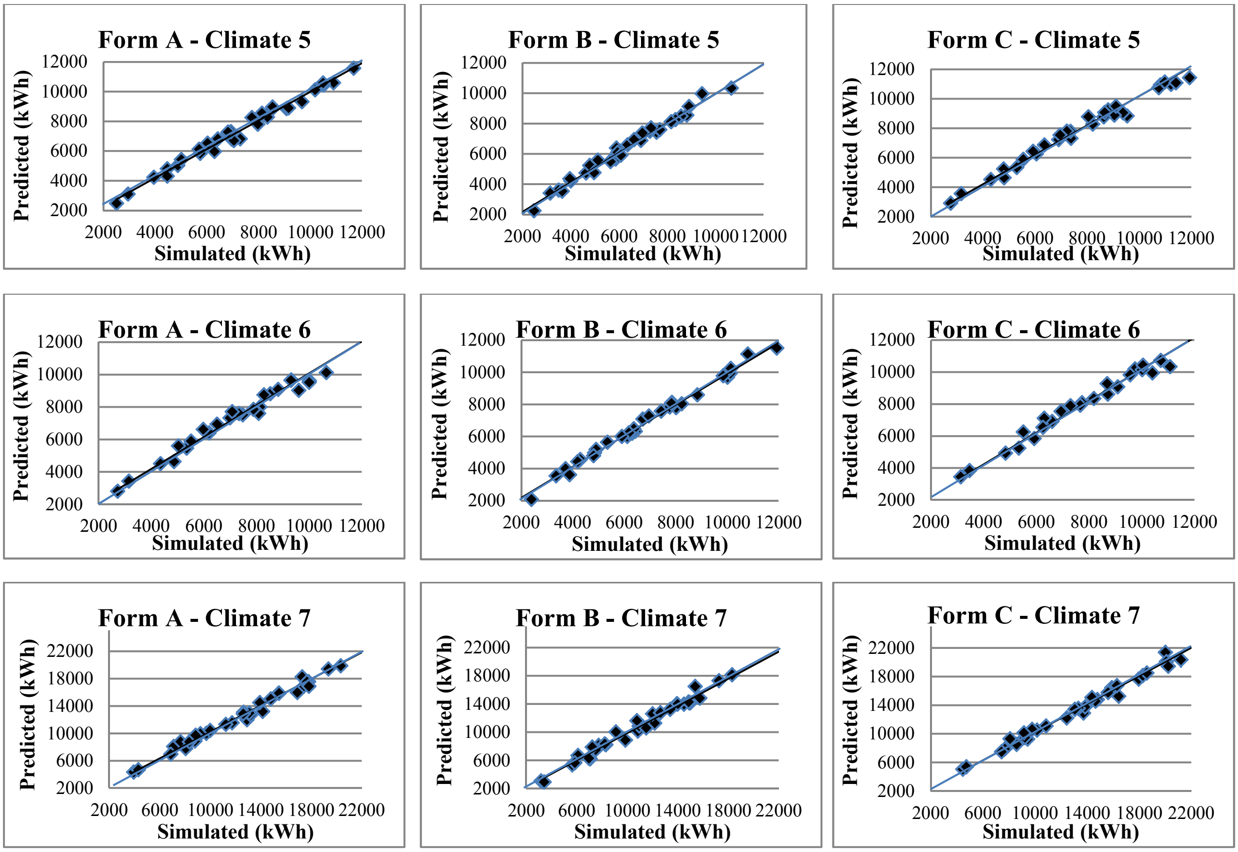
Table 6: Multiple regression coefficients for Type C-Lightweight wall representative simulation model.

Parameter ranges	Climate	Airtightness	Glazing Types	Ceiling Insulation	Wall Insulation	Floor Insulation	WWR	Regression R^2
1st-Lower value	5	2785	535.5	2231	1715	2277	-2345	
	6	2810	663.8	2915	2286	2882	-2440	
	7	5324	899.8	4045	3182	4134	-2941	
2th	5	241.8	57	-364.7	-218.3	-219	-1375	
	6	238.1	126.6	-460.6	-316.7	-184.3	-1404	
	7	556	211.8	-647.2	-443.3	-232.8	-1627	
3th-Mid value	5	-395.9	104.3	-594	-342.8	-580.6	-36.3	0.973
	6	-474.4	67.95	-706.4	-482.1	-742	-23.2	0.967
	7	-964.4	56.58	-950.6	-652.2	-1075	-5	0.942
4th	5	-1144	-264.7	-628.8	-566.7	-589	1157	
	6	-1143	-335.1	-830.6	-679.8	-761.4	1223	
	7	-2212	-420.5	-12159	-899.4	-1088	1446	
5th-Higher value	5	-1459	-432	-643.2	-587.5	-888.4	2599	
	6	-1431	-532.2	-917.2	-807.1	-1194	2644	
	7	-2704	-747.6	-1288	-1187	-1738	3127	
Constant value	5				-			1715
	6							2286
	7							3182

3.3. Model verification: building simulation results vs regression model predictions

In order to verify the reliability of the regression models, sets of independent simulations were run and comparisons were made between the simulated annual total space heating and cooling requirements with the results of the regression models. Figure 1 shows the results of the comparison and it can be seen that in general, the results of the regression models tend to match well with the simulation results. The most significant deviations between the two types of results are of the range of 15%, with the cases of climate 7 (Goulburn) having slightly larger data scattering. It is envisaged that the developed regression models can be used to estimate the likely energy savings/penalty associated with certain design changes during the retrofitting design stage when different building schemes and design concepts are being considered. However, the development of these models is based on the specific building types and climates of this study and their application should not be generalized and should not be considered as an equivalent alternative of dynamic building energy simulation models.

Fig. 1: Comparison between regression-predicted and EnergyPlus-simulated annual total space heating and cooling energy requirements based on the 30 sets of random inputs.



4. Conclusion

In this paper, building energy simulation models aided the development of simple regression models for the prediction of space heating and cooling energy requirements of representative dwelling types in the three major climates in NSW, Australia. The following six key building design parameters were identified as having high influence coefficients through differential sensitivity analysis and were used as inputs in the regression models: airtightness, window-to-wall ratio (WWR), window types and levels of ceiling, wall and floor insulation.

The results presented show that the linear models with simple independent variables can predict the requirements for space heating and cooling of the residential buildings in the specific climates within acceptable errors. A random number generator was also employed to generate random designs in order to verify the accuracy of the regression models outputs. The differences between regression-predicted and EnergyPlus-simulated annual building total heating and cooling demand were within the commonly used published by ASHRAE ranges (ASHRAE Guideline 14, 2002, Lam et al., 2010) and were less than 15%. Decisions for energy retrofits involve a certain degree of complexity and it is difficult for home owners to have an informed opinion for the effectiveness of these retrofits without seeking advice from experts. The advice from experts is often financially prohibitive for home owners and for this purpose this study developed regression models that suit a specific climate and building stock, to enable decisions to be made for envelope retrofits. A similar methodology could be applied for the development of regression models that would suit other climates and building types.

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