Energy and Cost Optimization for Residential Improvement Options

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Abstract: US started to implement building energy codes and energy efficiency regulations from 1980s. However, the existing pre-code buildings are still a significant fraction of the nation's housing stock. Although various retrofit options and technologies are proposed throughout the years, homeowners are still reluctant to renovate due to the high upfront costs. This research focused on pre-code buildings in Atlanta and implemented a retrofit cost optimization analysis on a potential mix of improvements and technologies to investigate the opportunities for cost-effective energy efficiency and renewable energy retrofit options in pre-1980s residential buildings of the region. To this end, a baseline building is selected from previous case studies. The building was originally built in the 1920s, as a one story, single-family detached home with 3,380 square feet of living area located in Atlanta metropolitan. The baseline building was modeled using the Energy Performance Calculator (EPC) energy modeling software. Additionally, multiple improvement options and associated costs were proposed and simulated to investigate the energy efficiency impacts on the baseline model. Finally, an optimization model was solved using the EPC-TechOpt to find the most efficient energy improvement options while keeping the cost at the lowest possible level. The results showed that the best solutions are achievable with approximately 20-40 thousand dollars of investment with the focus on smart lighting management, wall and window insulation and heat pump improvements.

Keywords: Single-Family Detached; Pre-1980s; Energy Modeling; Retrofit Options

1. Introduction

Buildings' share of the total worldwide energy consumption is approximately one third (UNEP, 2009). According to a study in India, in a worldwide scale, 30–40% of all primary energy is used for buildings and they are held responsible for 40–50% of GHG emissions. (Ramesh, Prakash and Shukla, 2010). Additionally, the United Nations Environment Program (UNEP) predicted that 87% of the US population will be living in urban areas by 2030 (United Nations World Water Development Report, 2015). The growing energy use has raised various concerns including heavy environmental impacts.

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Studies estimating operational energy consumption primarily use either top-down or bottom-up models. The top-down models typically estimate local residential energy consumption from regional level estimates using factors, such as gross domestic product (Hirst, 1978; Saha and Stephenson, 1980), technology attributes (Haas and Schipper, 1998), price, total population, and evolution of housing stocks (Nesbakken, 1999; Zhang, 2004). The bottom-up approach consists two genres of models, including the statistical models and the engineering models. The results from statistical models are generally analyzed to interpret the correlations of energy consumption with various individual-level characteristics, such as the size of housing units, socio-economic and demographic features, local heating and cooling degree days (Hirst, Goeltz and White, 1986; Raffio et al., 2007) and behaviors, including financial and cultural motivations in energy use (Douthitt, 1989; Fung, Aydinalp and Ugursal, 1999). The aim of statistical models is to understand the variation in energy use given changes in various occupant characteristics, so that policies can be derived to monitor energy price and provide ethical or financial motivations to regulate or curb energy consumptions (Chen, Wang and Steemers, 2013; Jain et al., 2014). Some recent model efforts use more advanced machine learning models such as neural networks and support vector machine to estimate residential energy consumptions (Aydinalp, Ismet Ugursal and Fung, 2002, 2004; Dong, Cao and Lee, 2005). However, these models are also data intensive and are difficult to be applied to large study areas.

The engineering models compute energy consumptions based on the energy ratings of various appliances, building materials, applied energy saving technology on-site and thermodynamic theorems (Zhao and Magoulès, 2012). Specifically, this approach first estimates energy consumption for a series of typical prototypes or archetypes of housing stocks in the region, using a small sample of buildings. The occupant behaviors are not captured but simplified to various assumptions. Different from the statistical models, the objective of engineering models is to extrapolate the results to the entire region so that the total residential energy consumption or the changes in consumption under various technology penetration scenarios can be obtained. The extrapolation is usually made by assigning weights, estimated based on regional housing inventory, to the sampled buildings. several software and calculation standards are developed to estimate building energy consumption using this modeling approach (Crawley et al., 2008).

In this paper, the authors used an engineering method to model a residential building, located in the Atlanta metropolitan area. Additionally, multiple improvement options and associated costs were proposed and simulated accordingly to investigate the energy efficiency impacts on the baseline model. The paper finally conducted an optimization methodology to find the most efficient energy improvement options while keeping the cost at the lowest possible level.

2. Baseline case study

The Case study of this project is a one story, single-family detached house located in Atlanta Metropolitan area. The house was originally built in 1920s, with 3380 square feet living area (314 square meters) and 11 feet (3.35 meter) height. The initial information and characteristics of the building were extracted from the Oak Ridge National Lab (ORNL) report (Jackson, E. Kim, et al., 2012). Based on the extracted information, a family of two adults and one child has rented this home for more than three years. Figure 1 represents the house.

The house has a traditional vented attic and a vented crawlspace. Regarding the energy conservation measure, the residents set the thermostat to 58°F (around 15°C) at night and a typical range of 62-68°F (around 17-20°C) in the day. The envelope is bounded by an insulated framed floor above the vented crawlspace and an insulated ceiling plane above the first floor (Attic ceiling = R-11). The R-13 batts (rock wool) is the most common material of the attic knee walls. In addition to the knee walls, there were also attic bypasses into interior wall cavities. No exterior wall insulation was observed for the house. In the ceiling of the crawlspace (i.e. subfloor), there were R-13 fiberglass batts that were recently installed. The windows in this home are all single pane windows with wood frames. The total air leakage rate was 9,840 CFM50. With a conditioned volume of 39,853 cubic feet, the air exchange rate for the house was approximately 14.8 ACH50.

Figure 1. The one story, single-family detached house of the case study

2.1. Case study energy simulation

After extracting the initial characteristics of the case study from the ORNL report, required information were gathered for modeling the building into a building energy simulation tool. Based on the residents' feedback on the usual thermostat sets, the setpoints were identified as shown in Table 1 and used to model the building. Additionally, several assumptions were made as listed as listed in Table 2 for the unknown variables based on the characteristics of a generic building in the region.

Table 1. Temperature setpoints on weekends and weekdays

Day/Time	12-8 am	8 am – 6 pm	6 pm - midnight
Weekday (Heating)	15 °C	20 °C	16 °C
Weekend (Heating)	15 °C	18 °C	16 °C
Weekday (Cooling)	27 °C	25.6 °C	27 °C
Weekend (Cooling)	27 °C	27 °C	27 °C

Table 2. Additional assumptions made to cover the unknown variables for modeling

Assumption Number	Assumption Description
1	The house is facing South
2	It is a 37.5 * 90 sqft (27.432 * 11.43 m^2) rectangular house
3	0.4 window/wall ratio in south side
4	0.2 window/wall ratio in other 3 sides
5	All windows with white curtain inside with 0.8 Shading Reduction Factor (SRF)

The case study was then modeled using a building energy simulator called Energy Performance Calculator (EPC) developed by the High Performance Building Lab at Georgia Tech (Quan et al., 2015). The monthly heating and cooling results are shown in Figure 2 and the total delivered heating and cooling energy is presented in Figure 3.

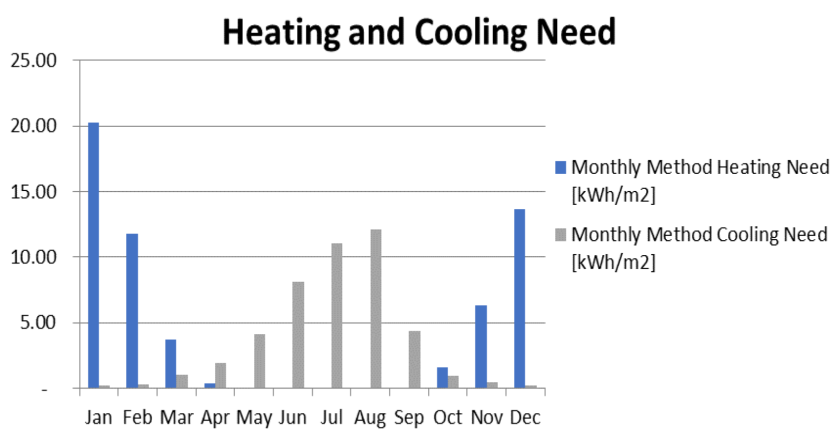

Figure 2. Heating and cooling per month through the year for the baseline building

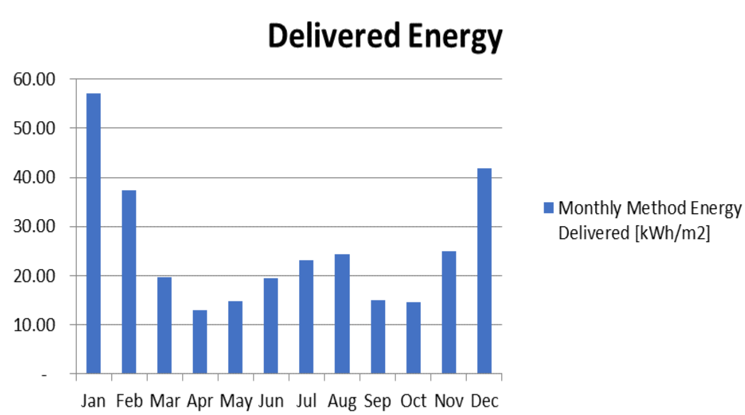

Figure 3. Total delivered energy (heating & cooling) of baseline building per month through the year

Based on the EPC models, the building used 13 kWh/m^2/year more heating in comparison to cooling which is acceptable based on the location of the building in south east of the US. Moreover, the total heating and cooling load of the building is calculated as 102 kWh/m^2/year which is close enough to reference number of the energy consumption of a house in that area.

3. Improvement options

Improvement technology options of the region and the associated costs were extracted from both the ORNL case study and the actual options which were used to retrofit the residential buildings in the study (Jackson, E.-J. Kim, et al., 2012) as well as the US National Renewable Energy Laboratory (NREL) repository of retrofit audits and cost estimations (Eisenberg, Shapiro and Fleischer, 2012). These numbers then were adjusted for the baseline case study of section 2.

Based on the identified improvement options, the options were then categorized into static or continuous variables. Hence, the input variables were added to the model to be accounted for the optimization problem. The advanced version of EPC-TechOpt were used for adding the retrofit options and the cost constraints into the originally developed simulation model of the building. The final selected static retrofit options, their characteristic and the associated costs were discussed clearly in Tables 3, 4, 5 and 6.

Table 3. Identified improvement options for roof and opaque insulation of the building.

	Improvement Options	U-value	Emissivity	Absorption Coefficient	Cost (USD)	Cost Reference
Roof Insulation	2	0.276 (W/(m^2 K))	0.6	0.7	3,400	ORNL Report
	3	0.162 (W/(m^2 K))	0.5	0.6	7,330	ORNL Report
Opaque Insulation	2	0.34 (W/(m^2 K))	0.7	0.6	3,500	ORNL Report
	3	0.29 (W/(m^2 K))	0.8	0.6	6,800	ORNL Report

Table 4. Identified improvement options for the Heating and Cooling Plants Efficiencies (COP).

	Improvement Options	Heating COP	Cooling COP	Cost (USD)	Cost Reference
Heating and Cooling Plants Efficiencies (COP)	2	0.91	3.9	7,000	ORNL Report
	3	0.95	4.32	9,000	ORNL Report
	4	0.95	4.86	12,000	ORNL Report

Table 5. Identified improvement options for window insulation of the building.

	Improvement Options	U-value	SHGC	Emissivity	Cost (USD)	Cost Reference
Window	2	2.46 W/(m^2)	0.35	0.7	6,145	NREL
	3	1.25 W/(m^2)	0.475	0.24	14,410	NREL
	4	1.16 W/(m^2)	0.53	0.25	25,786	NREL

Table 6. Other identified improvement options for the building.

	Improvement Options		Cost	Cost Reference
Appliances	Energy star	1.68 watt/m^2	3,337	ORNL Report
Lighting	2	4.1 watt/m^2	825	ORNL Report
Lighting Occupancy Factor	Fully automated	-	250	NREL
DHW Generation System	Heat pump (1.4)	-	2,760	ORNL+NREL

On the other hand, the only technology option identified as the continuous variable was the building leakage level. To correctly implement this variable into the model, the following regression analysis conducted as shown in Figure 4 and the extracted continuous equation was used instead for this variable in the model.

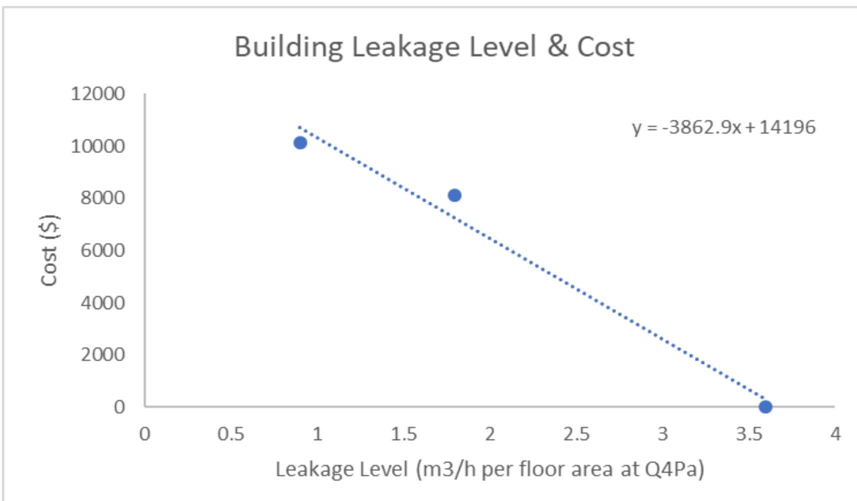

Figure 4. Regression analysis conducted to find the continuous equation for this variable.

4. Optimization results analysis

The objectives of the optimization in this research was to minimize total delivered energy while restricting improvement cost to a certain amount. As mentioned previously, EPC-TechOpt tool was used to conduct the optimization process throughout the building energy modeling. Tech-Opt is an added feature to the original EPC calculator which is also developed by the High-Performance Building Lab at Georgia Tech. It actually brings a template in the EPC 'input' spreadsheet to be populated with data related to the optimization problem (Simmons et al., 2015).

Table 7. The result of economic estimation with NPC method

Improvement Options	Technology Cost Restriction	Minimized Delivered Energy (kwh/m^2/year)	Energy Improvement Percentage	NPC (USD)	Total Saving (USD)
Baseline	-	305	-	142,525.85	-
Solution 1	70k	99.09	67.5	116,095.10	26,431
Solution 2	60k	99.85	67.26	105,076.55	37,449
Solution 3	50k	105.32	65.47	99,010.63	43,515
Solution 4	40k	119.76	60.7	95,939.15	46,587
Solution 5	30k	136.86	55.1	93,919.91	48,606
Solution 6	20k	164.30	46.1	96,736.87	45,789
Solution 7	10k	228.16	25.2	116,578.88	25,947

The results of the optimization analysis are shown in Table 7, considering various cost restrictions. As we can see from the results, by decreasing the retrofit cost restrictions, the minimized delivered energy increased. From the authors' point of view, the solutions number 4, 5 and 6 are the best options which save the highest amount over years and also still decrease the energy consumption by 55-65%. Details about some of the aforementioned solutions are provided in the following paragraphs.

4.1. Nominated Solution #4

The objective of the optimization in this scenario was to minimize total delivered energy while keeping the retrofit cost lower than 40k. The final solution for this optimization problem is listed in Table 8.

Table 8. Cost details in case of solution #4

Variable	Technology Result	Cost (USD)
Roof Insulation	2	3400
Heating and Cooling Plants Efficiencies (COP)	2	7000
Window	3	14,409
Appliances	Baseline	0
Lighting	Baseline	0
Lighting Occupancy Factor	Fully automated	250
Opaque Insulation	2	3500
DHW Generation System	Heat pump (1.4)	2760
Building Air Leakage Level	1.43	8680.21

In this solution, the delivered energy will reduce to 119.75 (kwh/m^2/year) from the original number of 305 (kwh/m^2/year) for the base case scenario. On the other hand, by saving around 60% on the operational energy consumption over the next 20 years of the operation of the building, this solution will save the total amount of $46,586.3 (considering 3% interest rate) for the building.

4.2. Nominated Solution #5

The objective of the optimization in this scenario was to minimize total delivered energy while keeping the retrofit cost lower than 30k. The final solution for this optimization problem is listed in Table 9.

Table 9. Cost details in case of solution #5

Variable	Technology Result	Cost (USD)
Roof Insulation	Baseline	0
Heating and Cooling Plants Efficiencies (COP)	3	9000
Window	2	6145
Appliances	Baseline	0
Lighting	Baseline	0
Lighting Occupancy Factor	Fully automated	250
Opaque Insulation	2	3500
DHW Generation System	Heat pump (1.4)	2760
Building Air Leakage Level	1.51	8344.93

In this solution, the delivered energy will reduce to 136.83 (kwh/m^2/year) from the original number of 305 (kwh/m^2/year) for the base case scenario. On the other hand, by saving around 55% on the operational energy consumption over the next 20 years of the operation of the building, this solution will save the total amount of $48,605.46 (considering 3% interest rate) for the building.

4.3. Nominated Solution #6

The objective of the optimization in this scenario was to minimize total delivered energy while keeping the retrofit cost lower than 20k. The final solution for this optimization problem is listed in Table 10.

Table 10. Cost details in case of solution #6

Variable	Technology Result	Cost (USD)
Roof Insulation	Baseline	0
Heating and Cooling Plants Efficiencies (COP)	Baseline	0
Window	2	6145
Appliances	Baseline	0
Lighting	Baseline	0
Lighting Occupancy Factor	Fully automated	250
Opaque Insulation	2	3500
DHW Generation System	Heat pump (1.4)	2760
Building Air Leakage Level	1.78	7328.11

In this solution, the delivered energy will reduce to 164.30 (kwh/m^2/year) from the original number of 305 (kwh/m^2/year) for the base case scenario. On the other hand, by saving around 46% on the operational energy consumption over the next 20 years of the operation of the building, this solution will save the total amount of $45,788.98 (considering 3% interest rate) for the building.

5. Conclusion

In this paper, a 1920s one story, single-family detached home located in Atlanta Metropolitan area was modeled and analyzed using a reduced order building energy simulation model created in the EPC which originated from the ISO 2008 energy performance of buildings and was later adapted for specific research use (Lee, Zhao and Augenbroe, 2013). The optimal improvement option is tested with different existing technologies. The ultimate optimization goal is to minimize the energy consumption rate over an investment time horizon of 20 years.

The results of the optimization analysis showed that the best solutions are achievable with approximately 20-40 thousand dollars of investment with the focus on smart lighting management, wall and window insulation and heat pump improvements. The results were also compared with the real retrofit solutions used in the ORNL report to retrofit the same building (Jackson, E. Kim, et al., 2012). In this case, the report showed the attic and knee wall insulation as well as heating and cooling system improvements among the retrofit solutions used for the building. The actual retrofit solutions resulted in an approximation of 27% energy saving over a year of building operation.

References

Aydinalp, M., Ismet Ugursal, V. and Fung, A. S. (2002) 'Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks', Applied Energy. Elsevier, 71(2), pp. 87–110. doi: 10.1016/S0306-2619(01)00049-6.

Aydinalp, M., Ismet Ugursal, V. and Fung, A. S. (2004) 'Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks', Applied Energy. Elsevier, 79(2), pp. 159–178. doi: 10.1016/J.APENERGY.2003.12.006.

Chen, J., Wang, X. and Steemers, K. (2013) 'A statistical analysis of a residential energy consumption survey study in Hangzhou, China', Energy and Buildings. Elsevier, 66, pp. 193–202. doi: 10.1016/J.ENBUILD.2013.07.045.

Crawley, D. B. et al. (2008) 'Contrasting the capabilities of building energy performance simulation programs', Building and Environment. Pergamon, 43(4), pp. 661–673. doi: 10.1016/J.BUILDENV.2006.10.027.

Dong, B., Cao, C. and Lee, S. E. (2005) 'Applying support vector machines to predict building energy consumption in tropical region', Energy and Buildings. Elsevier, 37(5), pp. 545–553. doi: 10.1016/J.ENBUILD.2004.09.009.

Douthitt, R. A. (1989) 'An economic analysis of the demand for residential space heating fuel in Canada', Energy. Pergamon, 14(4), pp. 187–197. doi: 10.1016/0360-5442(89)90062-5.

Eisenberg, L., Shapiro, C. and Fleischer, W. (2012) Retrofit Audits and Cost Estimates: A Look at Quality and Consistency. Golden, CO (United States). doi: 10.2172/1055375.

Fung, A., Aydinalp, M. and Ugursal, V. (1999) 'Econometric models for major residential energy end-uses'. Available at: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C11&q=Econometric+models+for+major+residential+energy+end-uses&btnG= (Accessed: 21 April 2018).

Haas, R. and Schipper, L. (1998) 'Residential energy demand in OECD-countries and the role of irreversible efficiency improvements', Energy Economics. North-Holland, 20(4), pp. 421–442. doi: 10.1016/S0140-9883(98)00003-6.

Hirst, E. (1978) 'A model of residential energy use', SIMULATION. Sage PublicationsSage CA: Thousand Oaks, CA, 30(3), pp. 69–74. doi: 10.1177/003754977803000301.

Hirst, E., Goeltz, R. and White, D. (1986) 'Determination of household energy using "fingerprints" from energy billing data', International Journal of Energy Research. Wiley-Blackwell, 10(4), pp. 393–405. doi: 10.1002/er.4440100410.

Jackson, R. K., Kim, E., et al. (2012) Advancing Residential Retrofits in Atlanta. Oak Ridge National Laboratory.

Jackson, R. K., Kim, E.-J., et al. (2012) Advancing Residential Retrofits in Atlanta. Available at: http://www.ntis.gov/support/ordernowabout.htm (Accessed: 27 August 2017).

Jain, R. K. et al. (2014) 'Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy', Applied Energy. Elsevier, 123, pp. 168–178. doi: 10.1016/J.APENERGY.2014.02.057.

Lee, S. H., Zhao, F. and Augenbroe, G. (2013) 'The use of normative energy calculation beyond building performance rating', Journal of Building Performance Simulation, 6(4), pp. 282–292. doi: 10.1080/19401493.2012.720712.

Nesbakken, R. (1999) 'Price sensitivity of residential energy consumption in Norway', Energy Economics. North-Holland, 21(6), pp. 493–515. doi: 10.1016/S0140-9883(99)00022-5.

Quan, S. J. et al. (2015) 'Urban data and building energy modeling: A GIS-based urban building energy modeling system using the urban-EPC engine', in Lecture Notes in Geoinformation and Cartography. Kluwer Academic Publishers, pp. 447–469. doi: 10.1007/978-3-319-18368-8_24.

Raffio, G. et al. (2007) 'Targeting Residential Energy Assistance', in ASME 2007 Energy Sustainability Conference. ASME, pp. 489–495. doi: 10.1115/ES2007-36080.

Ramesh, T., Prakash, R. and Shukla, K. K. (2010) 'Life cycle energy analysis of buildings: An overview', Energy and Buildings, 42(10), pp. 1592–1600. doi: 10.1016/j.enbuild.2010.05.007.

Saha, G. P. and Stephenson, J. (1980) 'A model of residential energy use in New Zealand', Energy. Pergamon, 5(2), pp. 167–175. doi: 10.1016/0360-5442(80)90005-5.

Simmons, B. et al. (2015) 'Determining the cost optimum among a discrete set of building technologies to satisfy stringent energy targets', in Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM. Cambridge University Press, pp. 417–427. doi: 10.1017/S0890060415000414.

UNEP (2009) 'Buildings and Climate Change'.

United Nations World Water Development Report (2015). Available at: http://www.unwater.org/publications/publications-detail/en/c/281166/.

Zhang, Q. (2004) 'Residential energy consumption in China and its comparison with Japan, Canada, and USA', Energy and Buildings. Elsevier, 36(12), pp. 1217–1225. doi: 10.1016/J.ENBUILD.2003.08.002.

Zhao, H. and Magoulès, F. (2012) 'A review on the prediction of building energy consumption', Renewable and Sustainable Energy Reviews. Pergamon, 16(6), pp. 3586–3592. doi: 10.1016/J.RSER.2012.02.049.