

4-22-2021

## Automated Residential Energy Audits Using a Smart WiFi Thermostat Enabled Data Mining Approach

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### Recommended Citation

Alanezi, Abdulrahman, "Automated Residential Energy Audits Using a Smart WiFi Thermostat Enabled Data Mining Approach" (2021). *Graduate Student Showcase*. 9.  
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### ABSTRACT

Smart WiFi thermostats, when they first reached the market, were touted as a means for achieving substantial heating and cooling energy cost savings. These savings did not materialize until additional features, such as geofencing, were added. Today, average savings from these thermostats of 10–12% in heating and 15% in cooling for a single-family residence have been reported. This research aims to demonstrate additional potential benefit of these thermostats; namely as a potential instrument for conducting virtual energy audits on residences. In this study, archived smart WiFi thermostat measured temperature data in the form of a power spectrum, corresponding historical weather and energy consumption data, building geometry characteristics, and occupancy data are integrated in order to train a machine learning model to predict attic and wall R-Values, furnace efficiency, and air conditioning seasonal energy efficiency ratio (SEER), all of which were known for all residences in this study. The developed model was validated on residences not used for model development. Validation R-squared values of respectively 0.9408, 0.9421, 0.9536, and 0.9053 for predicting attic and wall R-Values, furnace efficiency, and AC SEER were realized. This research demonstrates promise for low cost, data-based energy auditing of residences reliant upon smart WiFi thermostats.

### OBJECTIVE

Develop a unique automated residential energy audit technology capable of identifying priority energy saving opportunities in residences at regional and/or national scales.

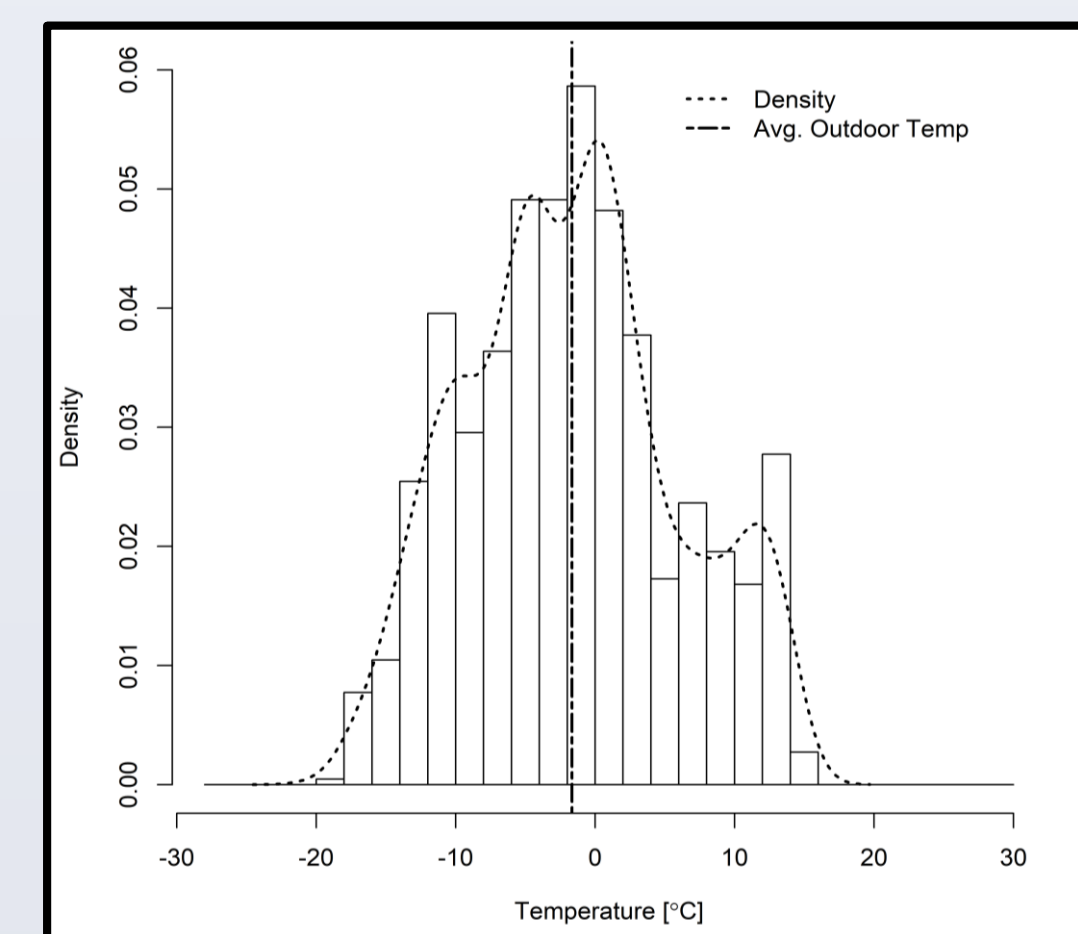
### DATA

- **Residence Geometry and Occupancy** (~150 homes)
  - ✓ Acquired through detailed energy audits made by another research in 2015 and 2020.
- **Monthly Metered Energy Consumption for Each Residence**
  - ✓ Collecting for each residence from January 2016 to the present, obtained from the university owner of the residences.
- **Smart WiFi Thermostat Data**
  - ✓ Raw thermostat data, referred to as “delta data”.
  - ✓ For each residence, collected and archived from 6/1/2018 to the present.
- **Historical Weather Data**
  - ✓ Only the dry bulb temperature was used, obtained from the U.S. NOAA National Climatic Data Center.
- **Residence Energy Characteristics** (only to ‘calibrate’ model)
  - ✓ Wall and attic insulation amount, heating, cooling, and water heater efficiencies

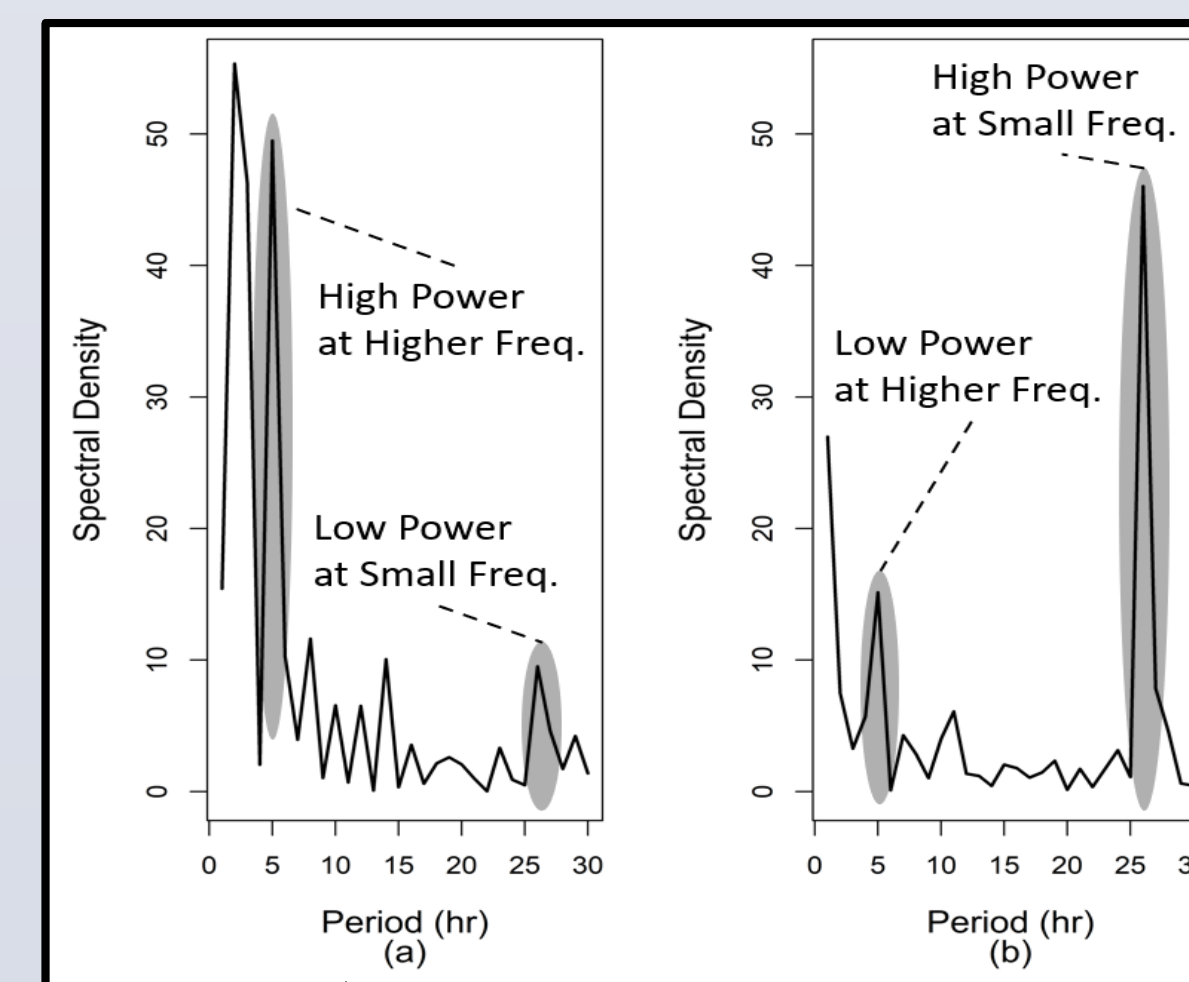
### UNIQUE METHODS

#### 1) Developed New Weather Features Characterizing Outdoor Temperature Variation During Each Meter Period

- ‘Bin’ the outdoor temperature data within a meter period into discrete temperature bands
- Calculate the probability density distributions for the outdoor temperature being in each of the discrete bands over each energy consumption meter period
- These discrete were averaged in separate 2 degrees Celsius bins.



#### 2) Developed Power Spectral Densities of Measured Smart WiFi Thermostat Temperatures for Each Residence to Characterize the Different Dynamics Associated with the Different Systems



High efficiency house:  
Highest energy at low periods (response faster to heating and cooling)

Low efficiency house:  
High “energy” at diurnal Period.

#### 3) Data Merging and Preparation

- All Data were synched and merged with the monthly energy consumption data by common address.
- Eliminate very similar houses by measure distances between the houses, in order to mitigate observation bias
- Remove missing observations

#### 4) Developed Data-Based Machine Learning Model to Predict Energy Characteristics

Input Features	Targets			
	Attic R-Value	Wall R-Value	Furnace Efficiency	AC SEER
Floor area (m <sup>2</sup> )	X	X	X	X
Basement area (m <sup>2</sup> )	X	X	X	X
Attic area (m <sup>2</sup> )	X	X	X	X
Window area (m <sup>2</sup> )	X	X	X	X
Wall area (m <sup>2</sup> )	X	X	X	X
Attic thermal insulation (m <sup>2</sup> K W <sup>-1</sup> )		X	X	X
Walls thermal insulation (m <sup>2</sup> K W <sup>-1</sup> )			X	X
Furnace efficiency (%)				
A/C SEER (Btu/W-hr)				
Water heater efficiency (-)	X	X	X	
Refrigerator efficiency (EF)	X	X	X	X
Refrigerator size (L)	X	X	X	X
Is there a wash and dryer machine (yer/no)	X	X	X	X
Is there a dishwasher machine (yer/no)	X	X	X	X
Number of occupants	X	X	X	X
PDD bins for outdoor temperature (34 bins)	X	X	X	X
Power spectral densities for smart WiFi thermostats	X	X	X	X
Monthly electric usage (kWh month <sup>-1</sup> )				X
Monthly gas usage (MJ month <sup>-1</sup> )	X	X	X	

### RESULTS

#### Identifying the Best Thermostat-Derived Feature Set

Model Training Metrics

Target	Best ML Algorithm	PSD Frequency Number	R <sup>2</sup>	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	16 and 24	0.94	0.34	0.12	0.27	0.06
Walls R-Value	GBM	13	0.94	0.14	0.02	0.10	0.07
Furnace Efficiency	GBM	46	0.95	0.01	2E-4	0.01	7E-3
AC SEER	GBM	6 and 23	0.90	0.44	0.20	0.42	0.03

Validation Metrics

Target	Best ML Algorithm	R <sup>2</sup>	RMSE	MSE	MAE	RMSLE
Attic R-Value	GBM	1	7E-4	5E-7	6E-5	1E-4
Walls R-Value	GBM	1	4E-4	1E-7	7E-5	2E-4
Furnace Efficiency	GBM	1	1E-5	1E-10	1E-6	5E-6
AC SEER	GBM	0.99	0.08	6E-3	0.02	6E-3

### CONCLUSIONS

- It demonstrated the value of smart WiFi thermostat data when combined with other residential data.
- It showed potential for conducting virtual energy audits (never having set foot in a house) extensively at-scale across any region if the trained model includes all types of possible residences data within that region/area.

### POTENTIAL IMPACT

- A regional program could utilize smart WiFi thermostats and metered energy consumption data to audit residences with collaboration between Thermostat manufacturers and utility companies.
- Potential savings from upgrades of every energy characteristic in each residence could be estimated.
- This technology could be used to identify priorities for deep energy reduction needed for climate caction.

### REVIEWER RESPONSE

- “This is a very interesting article, with innovative research and information and thus it is worth to be published after minor revision.”
- “Well structured original study”
- “This is an interesting research area.”

### CONTACT

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