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Identifying Inefficient Single-Family Homes With Utility Bill Analysis

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IDENTIFYING INEFFICIENT SINGLE-FAMILY HOMES WITH UTILITY BILL ANALYSIS

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ABSTRACT
Differentiating between energy-efficient and inefficient single-family homes on a community scale helps identify and prioritize candidates for energy-efficiency upgrades. Prescreening diagnostic procedures can further retrofit efforts by providing efficiency information before a site-visit is conducted. We applied the prescreening diagnostic to a simulated community of homes in Boulder, Colorado and analyzed energy consumption data to identify energy-inefficient homes.

A home is defined as efficient if it is compliant with the prescriptive measures of the 2009 International Energy Conservation Code (IECC-2009) for Boulder, Colorado. Previous research indicates a correlation between building operational efficiency and the Heating Slope (HS) regression parameter resulting from the variable-base degree day method.

We compared the HS values across a community of houses and those of an IECC-2009-compliant home to identify energy-inefficient homes on a community-scale. To simulate community-wide HS identification, we used DOE-2 energy simulation software for defined home archetypes and corresponding occupant behavior to artificially generate 567 sets of monthly natural gas consumption data Home archetypes were either compliant or non compliant at three conditioned areas; occupant effects were also simulated. Each simulation produced twelve months of natural gas use data. We used monthly energy consumption datasets to estimate the HS values with regression analysis and sorted the homes based on HS values.

INTRODUCTION
The U.S. residential sector consumed 11.3 quads (11.9 EJ) in 2008, 11% of national annual consumption. This figure is projected to increase 5% by 2030 [1]. Improvements in construction practices and building codes will increase the energy-efficiency of new buildings, but energy retrofits can effectively reduce energy consumption and carbon dioxide emissions. As more attention is paid to building energy-efficiency, community-scale conservation programs must identify energy-inefficient homes and retrofit opportunities. Comprehensive energy audits traditionally fill these roles, but readily available information such as energy consumption data, conditioned building area, and local daily weather data can be used in a pre-screening diagnostic tool to identify energy-inefficient homes before a site visit is conducted. Further, the prescreening information obtained can aid the analyst infer design and operational characteristics. The crux of the analysis consists of inversely modeling utility data and inferring efficiency characteristics of the homes from the model parameters.

Previous work has addressed the physical significance of model parameters resulting from inverse modeling [2-4]. Further, the variable base degree-day (VBDD) is a suitable prescreening tool to help identify retrofit candidates in commercial buildings [5]. Raffio et al. has shown that the proactive use of inverse modeling methods can identify retrofit candidates when compared across multiple buildings [6]. Our process is similar, but uses the VBDD method instead of a change point model, compares VBDD parameters to building simulation inputs, distinguishes homes that are compliant with 2009 International Energy Conservation Code (IECC-2009) from those that are noncompliant, and identifies specific design and operational characteristics.

PRESCREENING PROCESS DEVELOPMENT

The prescreening methodology is based on heating slope (HS) ranking of homes and uses a four-step process to test whether energy-inefficient homes can be differentiated from energy-efficient homes:

1. Collect electricity and natural gas consumption data for the analysis community. DOE-2, a detailed whole building simulation tool, was used to simulate the community's consumption data [7].
2. Create VBDD models for each home.
3. Calculate the HS metrics and rank the area-normalized model parameters for each home.
4. Compare the HS ranking to the simulation inputs by checking for IECC-2009 compliance.

Step 1 –Monthly Consumption

In the absence of real utility data, the goal is to simulate 567 "synthetic" utility bills in DOE-2. Each consists of 12 months of natural gas consumption. To simulate each home's annual energy consumption, we defined the construction characteristics including thermal, operational, and mechanical information, as well as occupant effects, to define thermostat behavior and miscellaneous loads. Homes were classified into three possible size archetypes:

- A 1058-ft^2 (95-m^2) one-story ranch with crawlspace
- A 2116-ft^2 (190-m^2) one-story ranch with conditioned basement
- A 3174-ft^2 (285-m^2) two-story home with conditioned basement.

For each archetype, three possible construction conditions were defined [8]:

- Compliant with IECC-2009 for residential buildings in Climate Zone 5b (Boulder, Colorado)
- Moderately below code
- Substantially below code.

For each home, three occupant behavior schedules were defined:

- High user
- Medium user
- Low user.

Figure 1 presents a schematic of the combinatorial process that produces 567 DOE-2 simulation input files. Each file was simulated using TMY3 weather data for Boulder, Colorado, and resulted in an annual simulation of hourly energy use. Post-processing summed hourly energy use to form monthly totals

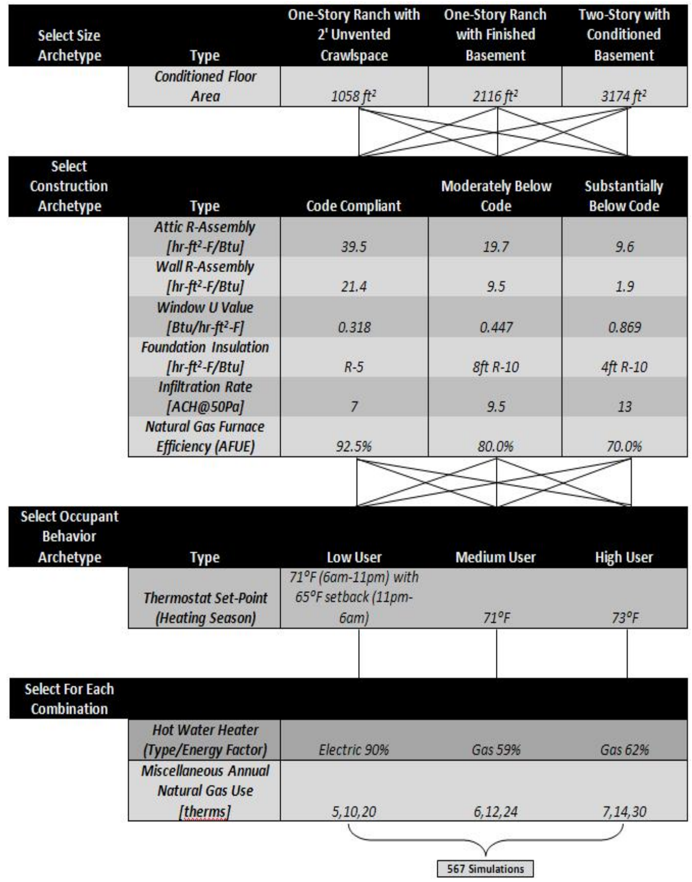

Figure 1: Diagram of energy simulation process

that represent a typical monthly utility bill. The hourly temperatures for the TMY3 weather file were averaged to form 365 daily average ambient temperatures. The synthetic utility bills and the daily average ambient temperatures are used in Step 2.

Step 2 – Variable Base Degree-Day Modeling

Single-family homes can be treated as single-zone buildings, where space heating energy use maintains the thermostat set-point temperature. The heat balance is:

$$\dot{Q} = \dot{BLC} \cdot \left(T_{sp} - T_a\right) - \dot{Q}_{int,sol}, \tag{1}$$

where:

$\dot{Q}$	=	Space-conditioning heating Rate, Btu/h (W)
$\dot{BLC}$	=	Sum of building UA and infiltration, Btu/h-°F (W/°C)
T_{sp}	=	Set-point temperature, °F (°C)
T_a	=	Ambient temperature, °F (°C)
$\dot{Q}_{int,sol}$	=	Rate of internal and solar heat gains, Btu/h (W).

The $\dot{BLC}$ is the sum of building enclosure properties, which include all $\dot{U}A$ products and infiltration loads (seen in Eq. 2):

$$\dot{BLC} = \dot{U}A_{attic} + \dot{U}A_{walls} + \dot{U}A_{windows} + \dot{U}A_{foundation} + \dot{m}c_p, \tag{2}$$

where U is the thermal transmittance per unit area in units of Btu/h-°F-ft^2 (W/°C-m^2), A is the heat transfer area in units of ft^2 (m^2), and $\dot{m}c_p$ is the product of the air infiltration rate and specific heat of air.

It is useful to define an additional temperature, where no additional heat is required to maintain the temperature set-point. This is known as the balance-point temperature, T_b, and is:

$$T_b = T_{sp} - \dot{Q}_{int,sol}/B\dot{L}C. \quad (3)$$

The result is a range of ambient temperatures, below the thermostat set-point temperature, where no space-conditioning energy is required. Instead, internal and solar gains provide the heat necessary to maintain the thermostat set-point temperature. Previous work has shown that the thermostat set-point and enclosure insulation properties determine the balance-point temperature [9]. Thus, the balance-point temperature is a combination of specific operational (such as thermostat) and specific design (such as insulation) properties.

As the ambient temperature decreases, the building's heating system provides the necessary make-up energy to balance system losses. To model this energy use behavior, the VBDD method was developed, featuring an algorithm that calculates a best fit balance-point temperature based on regression coefficients between energy use and degree-days. Specifically, the linear proportionality between monthly heating energy use and monthly heating degree-days (HDDs) is suitable for residential buildings where the heating load never exceeds the capacity of the heating system and consumption data are widely available in monthly intervals (see Eq. 4).

$$Y = \alpha + \beta \cdot HDD(T_b) \quad (4)$$

where α is the monthly base-load energy use, β is the HS, and $HDD(T_b)$ quantifies the heating degree-days calculated to the balance-point temperature. In an analysis period of *n* days, heating degree-days are the sum of the positive temperature differences for this period:

$$HDD(T_b) = \sum_{i=1}^{n} (T_b - T_a)^+ \quad (5)$$

where T_a is the average daily ambient temperature. For example, to calculate the degree-days for December, one would sum the positive temperature differences for each days. Generally, winter months have lower daily average temperatures than summer months and thus, have more HDDs.

Conventionally, degree-days are calculated to a balance-point temperature of 65°F (18°C), but in VBDD modeling, an iterative process is used to calculate a best-fit balance-point temperature. To find the best fit, the VBDD method uses the following steps:

1. Choose an initial balance-point temperature of 40°F (4°C).
2. Calculate the degree-days for each of the 12 months.
3. Regress the monthly energy use with the monthly degree-days at the balance-point temperature.
4. Record the regression R^2.
5. Repeat the process with the next balance-point temperature.

The upper balance-point boundary is set at 70°F (21°C). After completing all regressions, the algorithm will:

1. Select the optimal balance-point temperature with the highest R^2.
2. Report the regression parameters.
3. Continue the analysis on the next 12-month data set.

We performed VBDD regressions on all datasets; the results are used in Step 3. Figure 2 shows analysis results from three example VBDD regressions. Each is performed on 12 months of simulated natural gas consumption versus monthly HDDs to the individual best-fit balance-point temperature. The listed balance-point temperatures illustrate differing values from home to home. The regressions show the amount of heating energy needed per month to maintain the thermostat set-point and those with smaller slopes use less heating energy and indicate efficient homes. Favorable R^2 values were found for all 567 regressions: 97% were at least to 0.98.

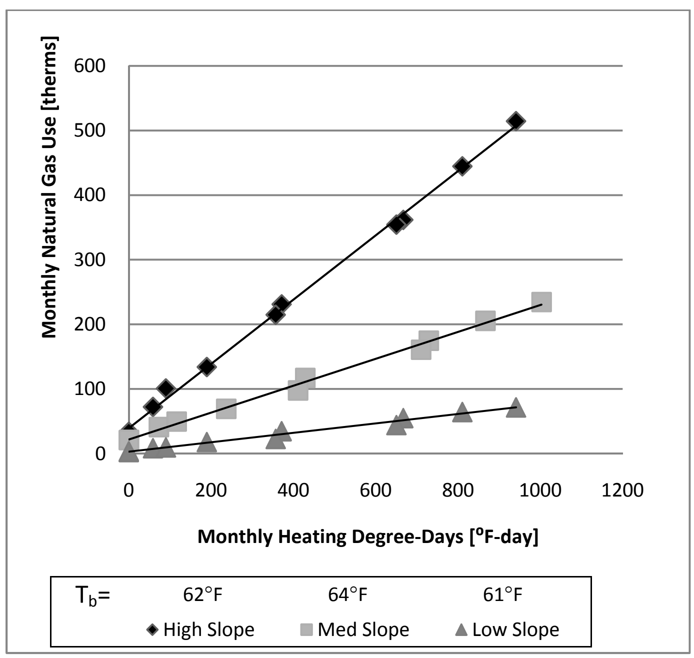

Figure 2: VBDD linear regressions of natural gas consumption and heating degree-days for three simulations with different best-fit balance-point temperatures

Step 3 – Heating Slope Metric

The regression parameter β from the VBDD models in Step 2 was used as the HS metric. To test accuracies of different ranking metrics, we calculated two additional comparative metrics for each simulation. The first, fuel use (FU), is the annual sum of natural gas use. The second, fuel use per heating degree-days (FU/HDD65°F), is the FU metric divided by the number of HDDs based on TMY3 weather data, which are calculated for a balance-point temperature of 65°F, (5781°F-day/3194°C-day for Boulder, Colorado) [10]. This is a conventional weather-normalized metric for comparing energy use between homes. FU/HDD65°F is:

$$\mathrm{FU/HDD\ 65°F} = \frac{\mathrm{FU}}{\sum_{i=1}^{n}(65°\mathrm{F}-\mathrm{T_a})^{+}}. \quad (5)$$

Step 4 – Test: Identifying IECC 2009-Compliant Homes

The final step shows the accuracy of the HS ranking in identifying energy-efficient homes in a Boulder, CO community. Before ranking the homes, we separated them into the three archetypes and identified them as either compliant or incompliant with IECC-2009, based on simulation inputs. For each archetype, a HS threshold was defined that serves as a cut-off score for code compliance: any score above the threshold is labeled incompliant and vice-versa. The HS threshold for each archetype was defined as the highest HS value for a compliant home and any simulation with a HS equal or less than the threshold is assumed to be compliant. The experiment was conducted over three home archetypes, so each has a unique HS threshold (see Table 1).

Table 1: Summary of HS threshold for all archetypes

Archetype	HS [Btu/h-°F]	HS [W/°C]
1-story with Crawlspace	365	186
1-story with Basement	480	245
2-story with Basement	1002	512

For instance, if a one-story ranch with crawlspace archetype simulation resulted in an HS of 450 Btu/h-°F (230 W/°C), according to Table 1, this exceeds the HS threshold and the house would be classified as incompliant. The primary assumption is that a home's energy efficiency is related to its enclosure and mechanical energy efficiencies, which are directly related to the amount of space-conditioning energy consumption per household. The goal for HS ranking is to give a relative indication of the home's energy efficiency. The metrics FU and FU/HDD65°F, along with threshold values, were calculated for each simulation along with threshold values. The results for ranking by each metric are applied to all 567 simulations. Figure 3 shows those for the one-story ranch with crawlspace archetype. The black bars represent incompliant, inefficient homes and the gray bars represent compliant, efficient homes. The x-axis shows the 189 archetype simulations, the y-axis shows the ranking metric, and

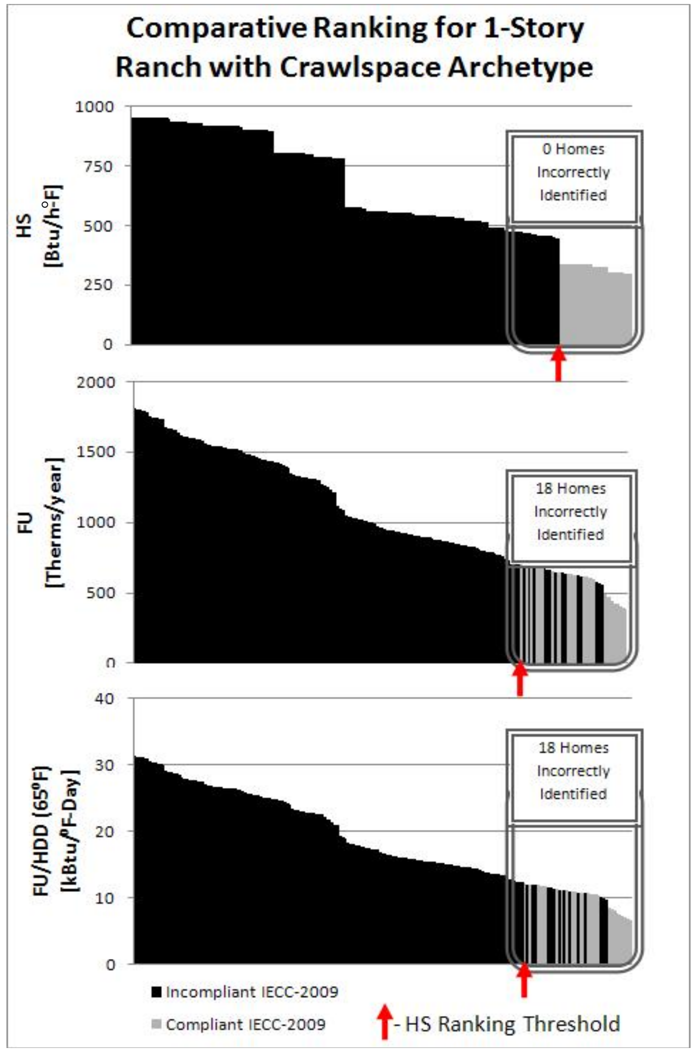

Figure 3: Comparative results of HS, FU, and FU/HDD (65°F) ranking for 1-story ranch with crawlspace archetype

the threshold for each metric is indicated as a red arrow. Table 2 lists the threshold values for each ranking metric.

Table 2: Summary of ranking threshold values for 1-story ranch with crawlspace archetype

Metric Type	Threshold Value
HS	365 [Btu/h-°F]
FU	704 [Therms/year]
FU/HDD(65°F)	12 [kBtu/°F-day]

As seen in the one-story ranch with crawlspace archetype, both the FU and FU/HDD65°F rankings classify several code-compliant homes as incompliant. The same homes, however, were correctly identified by the HS ranking. Both had high base-load and miscellaneous gas use, which were disaggregated by the VBDD method, but not by the FU and FU/HDD65°F rankings. This highlights the strength of the VBDD method: it disaggregates of weather-independent energy use from space-conditioning energy use.

Discussion

The HS ranking identifies inefficient homes more accurately than do the FU and FU/HDD 65°F rankings. Table 3 shows a 10% difference between ranking accuracies and the success rate of HS ranking in identifying IECC-2009compliant homes is favorable. One explanation for more favorable results using the HS ranking is that the VBDD modeling parameters contribute more information to the identification process. The VBDD method separates base loads from weather-dependent energy uses, which the other rankings cannot disaggregate. In practice, weather normalizing total FU to ambient temperatures helps correct for colder and warmer conditions compared across years, but does not add disaggregation to the analysis. An advantage to the VBDD method is that energy use can be attributed to different end uses, such as space-conditioning and base load. This enables heating performance to be characterized individually and compared across the community. An important issue is the assignment of a threshold value, as it is the primary identification criterion. In simulated communities, threshold values can be calculated from the known simulation inputs. In a "real world" application, the characteristics of the home are not well known, unless an extensive technical audit has been performed.

Table 3: Summary of all ranking metric results

Ranking Metric	Number of Homes Identified	Number of Homes Missed	Overall Identification Accuracy
HS Ranking	567	0	100%
FU Ranking	513	54	90%
FU/HDD 65°F Ranking	511	56	90%

Inferring Design Properties

The HS of a VBDD regression is related to the BLC and the furnace efficiency:

$$HS = BLC/\eta_{furnace}. \tag{6}$$

The BLC consists of the building enclosure properties including all building UA (attic, walls, windows, and foundation) and infiltration loads, $\dot{m}c_p$. The furnace efficiency, $\eta_{furnace}$, is the Annual Fuel Utilization Efficiency. Figure 4 shows a linear proportionality of the average HS metric from the VBDD regressions for each given simulation BLC. Each property is a simulation variable defined in Step 1 of the HS ranking process (See Figure 1).

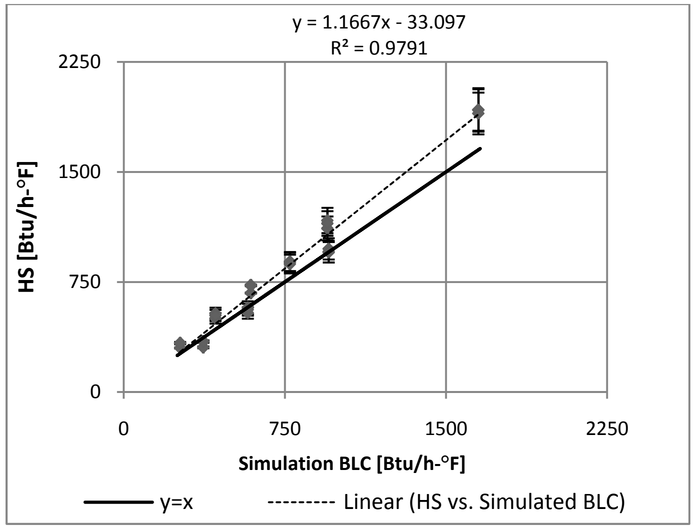

Figure 4: Comparison of HS and calculated simulation BLC

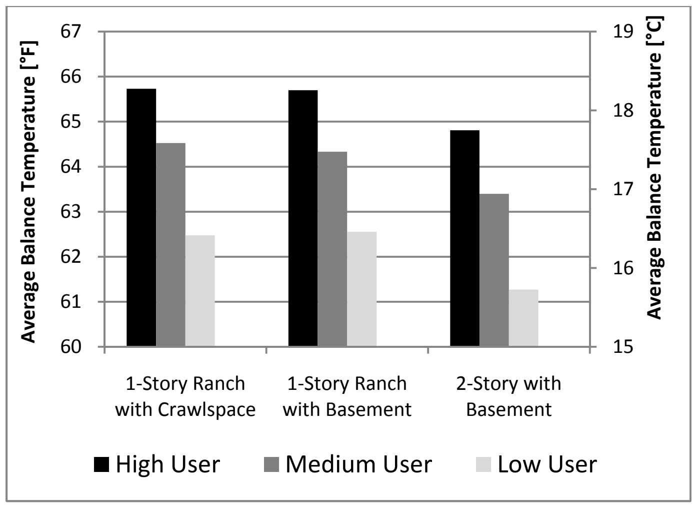

Figure 5: Average balance-point temperatures compared to occupant archetypes

Inferring Operational Properties

We inferred building characteristics from the VBDD models. Figure 5 shows that the balance-point temperature correlates with occupant behavior. On average, the higher heating thermostat set-points result in higher balance-point values for all home archetypes. This shows one example of an operational characteristic that can be inferred from the VBDD regression parameters, namely, high thermostat set-points. As mentioned by Raffio et al. [6], regressions with high balance-point temperatures are candidates for programmable thermostats. The monthly base load, which is the VBDD parameter α, can also be inferred. High monthly base loads indicate hot tubs, energy-inefficient hot water heaters, and other large energy-consuming appliances. Figure 6 compares the different monthly base-load gas uses across the simulations and shows that homes with high base-load energy uses can be identified.

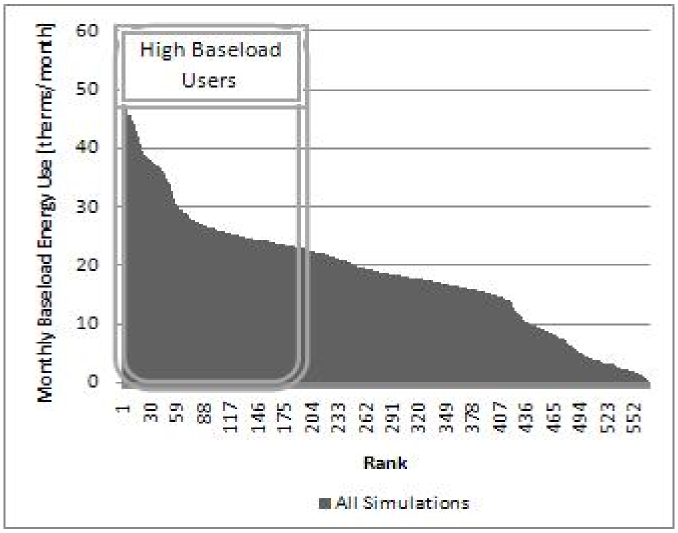

Figure 6: Ranking of α parameter values for VBDD models

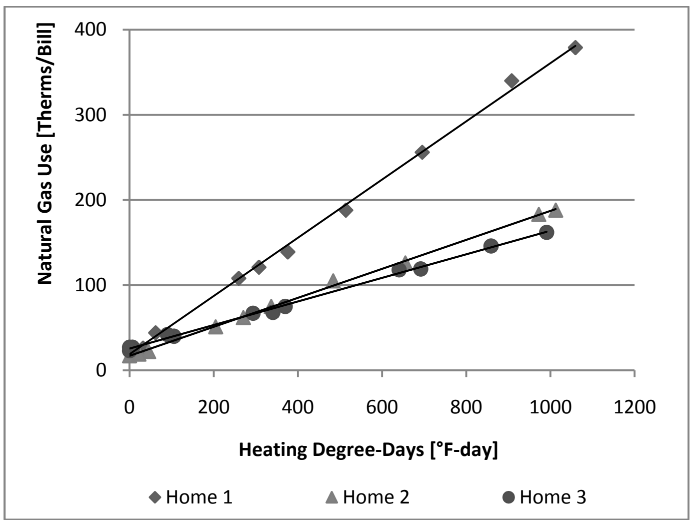

Figure 7: VBDD regression results for three example single-family homes from Boulder, CO dataset

Utility Bill Applications
The VBDD method can be applied to empirical utility data and shows similar results. It was applied to a collection of actual electricity and natural gas utility bills for several single-family homes in Boulder, Colorado, using local daily weather data and monthly natural gas consumption. Figure 7 shows VBDD regressions for three example homes and the results illustrate the VBDD method's applicability to actual utility data.

SUMMARY, CONCLUSIONS AND FUTURE WORK

Summary
This study demonstrates a four-step prescreening diagnostic process in which a Heating Slope (HS) ranking is applied to a simulated community of homes. A whole-building detailed energy simulation tool was used to simulate 12 months of natural gas use for 567 homes for various home and occupant archetypes. Each simulation was labeled as compliant or incompliant with IECC-2009, given the home archetype and energy simulation inputs. VBDD models were estimated using TMY3 weather data and the simulated natural gas consumption. HS values were calculated from the VBDD modeling, along with comparative ranking metrics. Finally, the HS rankings were compared with the pre-ranking IECC-2009 compliance label to test the accuracy of using HS values to identify incompliant, energy inefficient homes. Additional characteristics were investigated including base-load energy use and thermostat set-points.

Conclusions
This study concluded that:

- The HS ranking identified 100% of the inefficient homes, compared to 90% for FU and FU/HDD 65°F rankings.
- High base-load natural gas users were identified.
- Homes with high thermostat set-points were identified.
- The HS ranking is an effective identification procedure for inefficient homes, as well as other design and operational characteristics.

Further Studies
Further investigations are needed to demonstrate the HS ranking of empirical utility data and to evaluate the effectiveness of identifying inefficient homes when energy-efficiencies and operational characteristics are uncertain or unknown. Two difficulties are commonly encountered when analyzing empirical utility data:

- While the occupant behavior is known in this study, it is often highly uncertain with empirical data.
- Incomplete, missing, or erroneous monthly data may impact the ranking results. While this has a large effect on the annual FU, the HS ranking can still be applied with missing data because it relies on regressions, rather than sums.

Future studies will include analysis on the effects of missing months and statistical outliers of consumption data. The HS ranking has been demonstrated on a heating-dominated climate and only on natural gas consumption. Further studies should be conducted in different weather conditions, including cooling-dominated climates.

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REFERENCES

[1] Energy Information Administration, 2009. *Annual Energy Outlook 2010 Early Release with Projections to 2035,* DOE/EIA-0383.

[2] Fels, M., 1986. "PRISM: An Introduction", Energy and Buildings, Vol. 9, pp. 5-18.

[3] Kissock, K. Haberl J. and Claridge, D, 2003. "Inverse Modeling Toolkit (1050RP): Numerical Algorithms", *ASHRAE Transactions*, Vol. 109. Part 2.

[4] Reddy T.A., Deng S. and Claridge D.E., 1999. Development of An Inverse Method to Estimate Overall Building and Ventilation Parameters of Large Commercial Buildings, *ASME Journal of Solar Energy Engineering,* 121(1):40-46.

[5] Reynolds C., Komor P. and Fels M.F., 1990. "Using Monthly Billing Data to Find Energy Efficiency Opportunities in Small Commercial Buildings", *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington D.C., Volume 10, pp. 10.221—10.232.

[6] Raffio, R., Isambert, O., Mertz, G., Schreier, C., Kissock, K., 2007. "Targeting Residential Energy Assistance", Proceedings of the ASME 2007 Conference on Energy Sustainability, ES2007-36080.

[7] Winkelmann, F.C.,B.E. Birdsall, W.F. Buhl, K.L. Ellington, A.E. Erdem, J.J. Hirsch, and S. Gates., 1993. "DOE-2 Supplement Version 2.1E", LBL-34947, November 1993, Lawrence Berkeley National Laboratory. Springfield, Virginia, National Technical Information Service.

[8] International Code Council, 2009. "International Energy Conservation Code – 2009 Edition".

[9] Huang, J., Ritschard, R.L., Bull, J.C., Chang, L., 1987. "Climatic indicators for estimating residential heating and cooling loads". ASHRAE 93, 72–111.

[10] Wilcox, S. and W. Marion, 2008. *User's Manual for TMY3 Data Sets*, NREL/TP-581-43156. April 2008. Golden, Colorado: National Renewable Energy Laboratory.

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