Simulating Expected Residential Building Cooling Performance Under Extreme Temperature Conditions[1]

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Despite a policy orientation toward energy-efficient buildings, California has failed to improve its residential HVAC system performance. Research has shown that ceteris paribus one impairment to increased efficiency is the installation of oversized residential HVAC systems. This market failure can be expressed in terms of risk-aversion on the part of homeowners and contractors who worry that a rightly-sized HVAC system will fail to maintain the building's desired indoor temperature during heat waves. In this study, we compare modeled and actual building cooling performance using a novel KPI, cyclical cooling load, which can be quantified in terms of HVAC system runtimes. Simulating from an extreme value distribution, we show that buildings equipped with rightly-sized air conditioners do not run for excessive periods of time during heat waves. Intuiting a building's expected cyclical cooling load can assist builders and homeowners in assessing the risk associated with installing an energy-efficient climate control system.

Keywords: energy modeling, energy efficiency, HVAC, heat waves, climate change

[1] Replication files are available on the author's Github account (http://github.com/blakeshurtz). Current version: R-3.6.3)

Introduction

What is good for the economy can also be good for the environment. As Goldstein (2007) and others have shown, energy efficiency standards provide an economic free lunch by incentivizing emergent, innovative technologies and best practices that bolster economic growth while reducing energy usage and related negative environmental externalities. While manufacturers have discovered that it is in their self-interest to comply with energy efficiency standards, Hoeschele (2017) has provided ample evidence for potential improvement in residential HVAC energy efficiency. The larger point is that energy efficiency policies that intervene in direct market transactions face additional barriers to adoption.[2]

In this study, we examine the residential air conditioning market in dry-climate California, where Blasnik (1996) has shown that air conditioners are over-sized by a half ton or more. The evidence shows that in confronting the trade-off between building energy-efficiency and HVAC system over-sizing, homeowners and contractors continue to opt for "bigger is better." Why do homeowners and contractors coordinate to install over-sized, inefficient HVAC systems despite direct incentives from their utility in the form of rebates PGE (2021)? While ACCA (2013) provides much technical discussion around correct air conditioner sizing and selection, we focus on an economic calculation: the assessment of the risk that the rightly-sized air conditioning equipment will fail to cool the building under extreme climate conditions, ie. heat waves. Understandably, consumers fear for their own comfort and safety over having lower energy bills. Meanwhile, contractors are afraid of the costs (loss in reputation, low-profit parts replacements) associated with mistakenly installing an under-sized air conditioner. Cooling load calculations, a subcategory of building energy models, are recommended to determine air conditioner system size by modeling a building's cooling needs at the top 1% outdoor dry-bulb temperature (typically around 100°F in CA). At temperatures exceeding this threshold, how much trust would you put in a model? The purpose of this analysis is to validate modeled cooling load calculations against actual building performance data in order to understand the risk associated with operating a rightly-sized HVAC system under extreme temperature conditions.

Materials and Methods

During the summers of 2016 and 2017, data loggers were installed on n = 22 different new residential air conditioner installs in Yolo and Solano County, CA. The data loggers measured the condensers' amperage draw every minute over an average study duration of 60 days. Each system went

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[2] Current Title 24 energy regulations do not have any requirement around HVAC system sizing (Weisenmiller (2018)). In lieu of this, Proctor (1996) recommends that homeowners provide their contractor with a "Recommendations for Contractors" checklist and firing contractors who do not observe Manual J HVAC sizing protocols.

through at least one heat wave where outdoor air temperatures exceeded 100°F. Based on these amperage draws, we constructed a key performance indicator called the cyclical cooling load (CCL).

Here's how it works: Air conditioner cooling capacity (measured in BTUh) in inferred from the amperage measurements based on the Lennox (2020) equipment engineering tables and installation settings for each air conditioner. For variable capacity air conditioners, staging is inferred from amperage using a k-means clustering algorithm and verified independently for each system. This data allows us to measure the actual cooling load (as apposed to the modeled cooling load) for each system cycle based on the identity that the heat energy removed by an air conditioner is equivalent to the cooling needs of the building.

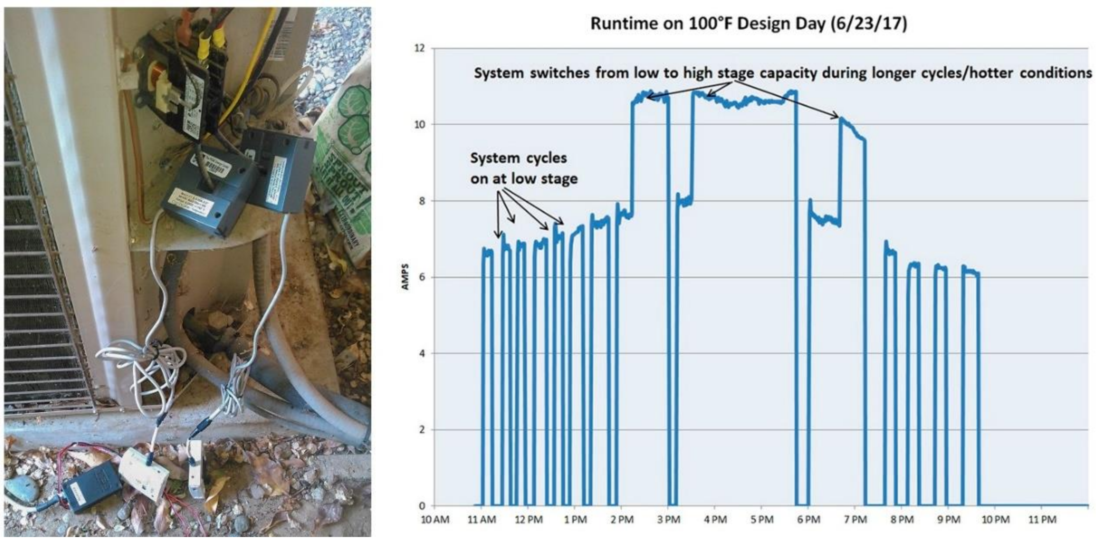

Figure 1: Left: Dataloggers installed on air conditioner. Right: Two stage air conditioner cycling

Then, for each air conditioning system cycle, the minute-by-minute cooling capacity is aggregated and divided by the building's modeled cooling load.[3] This allows us to standardize the CCL across the disparate buildings in the study. For example, a 36 kBTUh air conditioner that runs for 15 minutes would provide 8 kBTUh of cooling for that particular cycle. The 8 kBTUh of cooling provided during this cycle is divided by the building's 32 kBTUh modeled cooling load to produce a CCL of 0.25.

[3] Cooling loads were modeled by experienced energy auditors following ACCA's Manual J load calculation practice and working in ACCA Certified software, Right-Suite Universal. While there is some room for subjectivity, any variance between modeled and actual (unknown) cooling loads is factored into the statistical model.

The formula for the cyclical cooling load is below:

$$x_{jk} = CCL_{jk} = \frac{\sum_{i=1}^{n} y_{ijk}}{z_k}$$

Figure 2: Cyclical Cooling Load

Where *y* is the minute-by-minute measurement of the condenser's capacity, which is aggregated over all measurements *i* for each system cycle *j* and system *k*, which is then divided by the modeled cooling load *z* of building *k*. Over the duration of the study, each climate control system had over 1000 measurements of the CCL with over 22,000 observations for all buildings.

For each cycle, the cyclical cooling load has the following interpretation:

- CCL < 1 indicates that the building's cooling needs are less than the modeled cooling load. This is typical for most cycles on most days.
- CCL = 1 indicates that the building's cooling needs exactly match its modeled cooling load. Should the installed system capacity match the modeled cooling load, then the system will run for exactly one hour.
- CCL > 1 indicates that the building's cooling load exceeds its modeled cooling load on a per-hour basis and that a rightly sized air conditioner will run for the number of hours equal to the CCL.[4]

The research question of interest, re-framed in terms of the CCL, asks "What size CCL can we expect under extreme conditions?" We can use a probability model to pivot our question and ask, "What is the most extreme CCL of a rightly-sized air conditioning system?"

In order to answer this question, we fit a Generalized Extreme Value distribution (GEV) to the data. The history of the GEV distribution extends back to the Fisher-Tippett-Gnedenko theorem (credited to Fréchet (1927)) demonstrating that regardless of the underlying probability distribution of the random variable X, the probability distribution for the last order statistic converges to the GEV distribution. In other words, we are estimating the maximum CCL for each system.

More recently, a class of threshold models (introduced in Coles (2004)) have emerged that model the tail distribution (ie. extreme values) of a given phenomena (which, as Taleb (2020) and others have noted, often exhibit non-normal behavior). Threshold models provide a continuous probability distribution of extreme values by removing a large sample of the data and focusing on the distribution of

[4] CCL > 1 does not imply that the home is over-heating, nor is a CCL of 2 double the CCL of 1- the only implication is that system ran for a longer period of time.

the exceedances (CCLs on the tail-end of the distribution) only. The method used for establishing the exceedance threshold, which is used for both GEV distributions as well and threshold models, is to examine CCL density plots and mean residual life plots to determine when excessive variance in tail observations begins to occur. The exceedances are determined independently for each building in the dataset and comprise approximately the top 10% of all observations, ranging between 0.2 and 1 CCL.

The behavior of the exceedances is modeled using the Generalized Pareto distribution, a threshold model that has the same qualities as the GEV (such as the ability to fit either concave or convex curves to the data) but assigns probability levels based on a continuous distribution rather than using order statistics.

$$f(X|\mu, k, \sigma) = \frac{1}{\sigma}(1 + k\frac{x-\mu}{\sigma})^{-(1/k+1)}, x > 0$$

Figure 3: Pareto Distribution

The model finds the optimal values for the location parameter k and the scale parameter σ, while the threshold parameter μ represents the exceedance threshold value. The generalized extreme distribution is coded in the probability programming language Stan. Stan creates generative Bayesian statistical models that allow us to simulate new systems and in particular, the behavior of the average system.

Along with modeling the CCL for each building (the individual effects model), we also built a random effects model that allows us to infer the expected CCL across all possible buildings. By simulating draws from the random effects model, we are able to measure the expected extreme CCL and variance at various probabilities and levels of confidence.

Results

The two models (individual effects and random effects) are plotted on a complementary cumulative distribution function (CCDF), $P(X > x)$, a curve that shows the declining percentage of observations exceeding some threshold (in this case, the top x% of CCL).

First, the individual effects model is fit to the data in order to estimate how well the model performs. The model fits the data as expected and is flexible enough in its parameters to provide concave or convex CCDFs as needed. This indicates the flexibility of the generalized Pareto distribution over more traditional forms of extreme value analysis (which requires 3 separate probability distribution functions depending on the nature of the data).

Many of the buildings have a top 1% CCL of 3 or less, implying that a rightly-sized system would run for a maximum of 3 hours under extreme conditions. Other buildings have 1% modeled thresholds that are off the charts but are missing any actual observations at the 1% threshold (ex. building_15 and building 16). Generally, we are seeing the variation in energy performance that traditional cooling load calculations fail to capture[5].

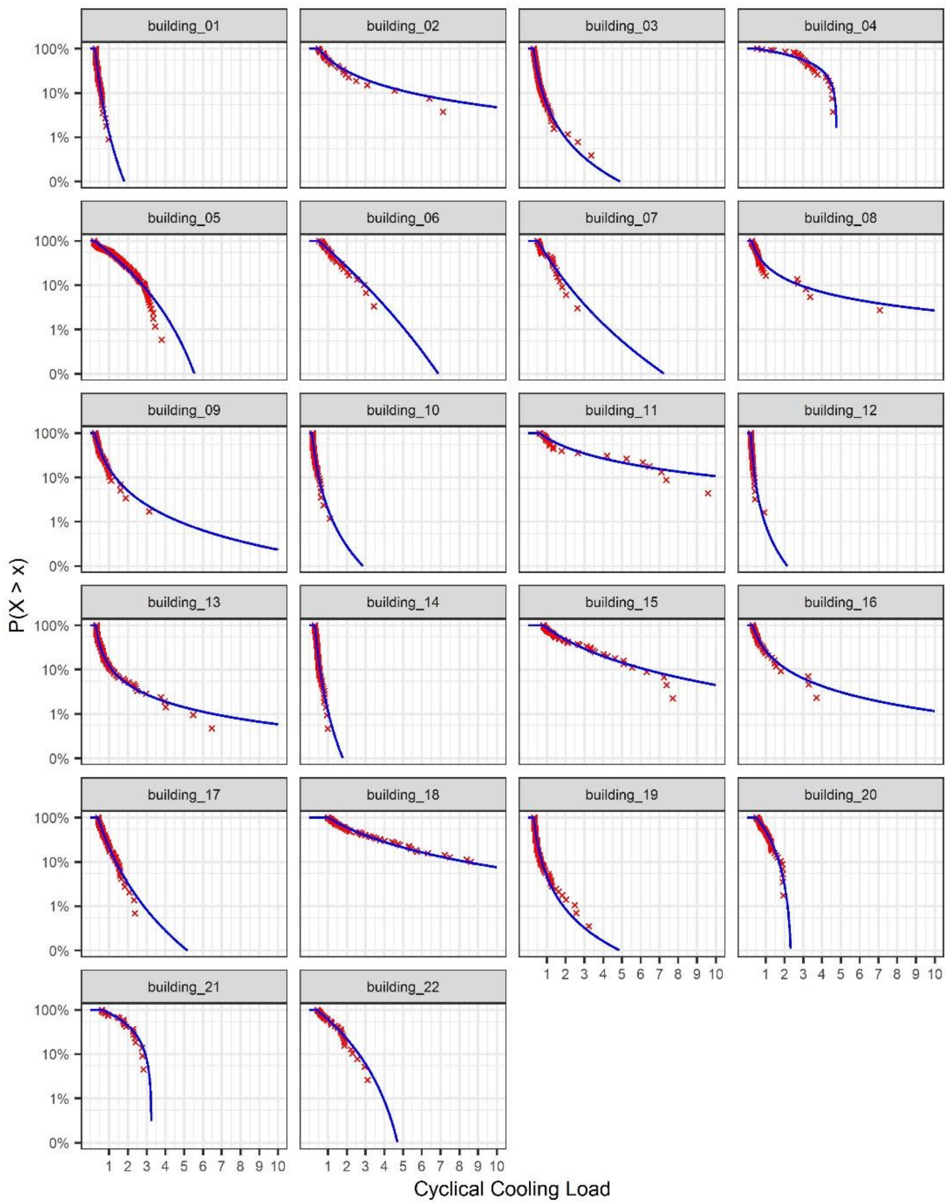

Figure 4: Individual Effects model overlaying exceedances for each building

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[5] One real-world factor that affects performance is homeowner operation of the system. While the recommendation for high-efficiency systems is to set the thermostat to the desired temperature and leave it alone ("set it and forget it"), some homeowners in the study left their system off until 5 PM. Others would leave the system at 78°F but turn it down to 75°F during the hotter hours of the day. Both contribute to larger CCL values and longer runtimes.

The random effects model is used to infer the expected CCL for all buildings (including those not in the study). Overlaid with the data below, the random effects model plots the expected (mean) CCL along with a 50% probability interval (which is akin to a confidence interval but with a Bayesian interpretation).

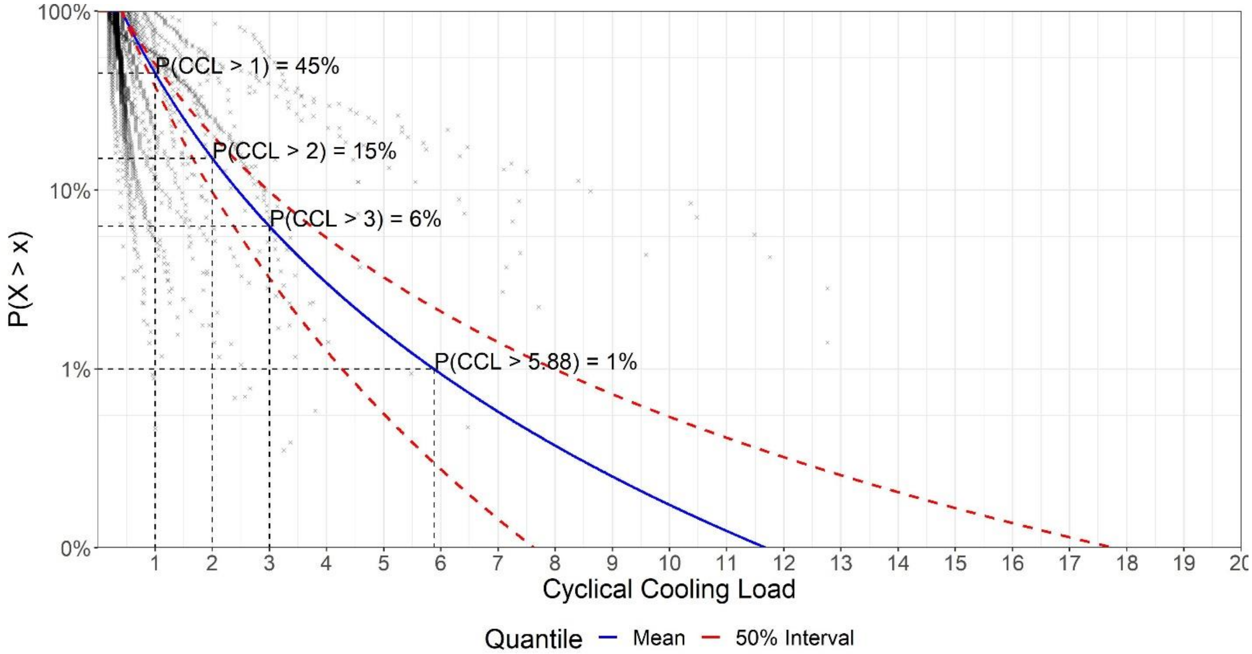

Figure 5: Random effects probability model of expected CCL exceedances overlaying data

A full probability model allows us to infer CCL's at various probabilities. Of primary interest is the 1% probability CCL of 5.88. In other words, under the most extreme conditions, a rightly-sized air conditioner is expected to run for 5.88 hours with a 50% probability interval of (4.28, 7.98). Extreme values at the various quantiles of the distribution are shown below (with 50% probability intervals):

Quantile	Mean	25%	75%
Median	0.92	0.82	1.01
95%	3.3	2.58	4.15
99%	5.88	4.28	7.98

Figure 6: Cyclical cooling loads at various quantiles (with 50% probability interval)

The median CCL of 0.92 (0.82, 1.01) affirms that a rightly sized system will run for less than an hour during most heat waves. The top 5% threshold of CCL is 3.3, indicating a 3 hour and 20 minute runtime for a rightly-sized system

We can also infer probabilities at various CCLs. For example, the probability of having a CCL > 1 is 45%, indicating that the majority of CCLs during heat waves are less than the building's cooling load and less than one hour in duration.

Discussion

Contractors and homeowners can be confident in their expectations for how a rightly-sized system will perform under extreme temperature conditions given our results.

The 1% threshold CCL of 5.88 is akin to an air conditioner running from 12 PM to 6 PM continuously on the hottest day of the year. Given that the system shuts off after this time, it follows that the building has reached the desired set-point temperature after 6 hours. A 6 hour run-time is not considered excessive at the extreme (any indoor temperature rise during the 6 hour window would also fal in that time) and indeed contributes to homeowner comfort by continuously circulating 55°F air throughout the home.

Our vision is for a contractor to say, "If I properly size your system, it will have an expected maximum run time of about 6 hours during the most extreme heat wave. So on the hottest day of the year, if your air conditioner starts running at 12 PM, it may get a degree or so warmer in that time, but your home will return your desired setpoint by 6 PM."

However, if a homeowner is uncomfortable with that fact, or prefers to leave their system off all day and then wants it to cool the building quickly, they may opt for a less efficient system that cools the building faster. Alternatively, a homeowner can opt for more expensive, multi-stage equipment that runs at a lower capacity the majority of the time.

While we are hopeful that this information persuades homeowners to opt for more energy-efficient, rightly-sized cooling equipment, regardless of the outcome this information can help homeowners make the right choice for themselves in HVAC equipment selection.

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Declaration of Interest

The author declares no competing interests.

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