Fault Detection and Diagnosis for Residential HVAC Systems using Transient Cloud-based Thermostat Data

Fangzhou Guo
Texas A&M University

Bryan P. Rasmussen
Texas A&M University, brasmussen@tamu.edu

Fault Detection and Diagnosis for Residential HVAC Systems Using Transient Cloud-based Thermostat Data

Fangzhou GUO, Bryan P. RASMUSSEN

Texas A&M University, Mechanical Engineering,
College Station, Texas, U.S.
Email: {fzguo, brasmussen}@tamu.edu

ABSTRACT

Fault detection and diagnosis (FDD) using aggregated smart thermostat data is a relatively new research field, but one with immediate practical application to residential indoor climate control. This paper analyzes a cloud-based dataset which contains thermostat history records of nearly 370,000 distinct residential HVAC systems in the U.S. The large, diverse, and growing dataset enables novel methods for detecting and diagnosing faults on systems with limited sensor data. This paper proposes a statistics-based FDD method for non-variable speed heat pump and air conditioning units, and demonstrates the effectiveness with several case studies. The proposed method identifies systems within a similar climate region, and then segments and classifies the time series data based on operational mode and behavior. Various data features are then extracted from the time series segments to identify systems that exhibit poor transient behavior. Additional features are used to refine and classify the problem severity. Statistical methods are then used to compare system performance to the entire population and identify outlier behavior due to operational faults that affect system efficiency and occupancy comfort. The resulting algorithm demonstrates the potential of big data fault detection for air conditioning systems using limited cloud-based sensor information.

1. INTRODUCTION

Space heating and air conditioning accounts for a large amount of residential households' energy expenditures. From the Residential Energy Consumption Survey (EIA, 2015), the average annual energy expenditure for a household is $1,856, among which $543 (29.3%) spent on space heating and $265 (14.3%) spent on air conditioning. In order to reduce residential households' energy consumption on space heating and air conditioning, researchers have been working on improving system efficiency, employing better control strategies, and improving preventive maintenance using fault detection and diagnosis (FDD). By detecting operational faults caused by system aging or improper commissioning early, failures can be prevented and system inefficiencies avoided.

HVAC system faults have a considerable impact on system efficiency and occupant comfort. Studies report that the average performance of residential HVAC systems is at least 17% below their design performance (Proctor and Downey, 1999). Correcting only refrigerant charge and air flow problems has an estimated 17% demand savings potential and 7% peak demand savings potential (Neme *et al*., 1999). Incorporating FDD into the preventive maintenance routines has the potential for increasing occupant comfort and reducing energy expenditures. Additionally, manufacturers could improve brand loyalty by ensuring high-performance and reliable systems; service companies would be able to provide better maintenance to their customers. With regard to FDD performed on building systems, Kim and Katipamula (2018) pointed out that only 16% studies are associated with small commercial and residential buildings, such as rooftop packaged units and split systems, while the majority of research focus is on variable air volume air handling units (VAV-AHUs), chillers, cooling towers, and overall building diagnosis. Thus traditional FDD methods are usually designed for one large system and require installing additional sensors (Rogers *et al*., 2019). But residential split systems are produced in large quantities, with limited sensors, and with a variety of system types and custom installation. For many systems, the addition of the sensors required for traditional FDD techniques is prohibitively expensive.

Cloud-based data from smart thermostats provides an opportunity for alternative FDD methods that do not require additional sensors, but utilize historical records of basic system operation. The popularity of smart thermostats that upload data to a remote server is increasing, allowing for computationally intensive fault detection on distributed platforms. Many manufacturers are establishing a cloud database, remotely monitoring thousands of installed residential systems. Typically, this cloud-based thermostat data includes indoor temperature and relative humidity measured by built-in sensors, system mode status, cooling and heating temperature setpoints, and outdoor temperature acquired from a third party. The resulting big data creates an opportunity for novel FDD approaches.

FDD methods for residential HVAC systems with smart thermostat data is still a relatively new research field, and few published studies are currently available. Ham *et al*. (2016) proved the capability of thermostat data to evaluate the thermal characteristics of a house, such as insulation levels, thermal capacity, and thermal time constants. With these indicators, houses showing inferior thermal response characteristics, known as construction-level faults, could be detected. Turner *et al*. (2017) developed a recursive least-squares model to detect faults on cooling, heating and ventilation equipment. However, the method was only validated by simulated indoor and outdoor temperature data, and focused mainly on total equipment failures. Jain *et al*. (2019) trained a linear model to learn the normal behavior, and then applied the model to monitor capacity degradation faults such as refrigerant leakage. Although the model was originally developed for cold rooms in retail outlets, the author mentioned that its application could be extended to residential buildings. Besides, combining smart thermostat data with building assessor's data and energy data, Do and Cetin (2019) showed the potential to predict the electricity demand of residential HVAC systems, and then perform fault detection by comparing the predicted demand with the actual demand. In short, these studies all focused on a small group of systems, training models and performing fault detection for individual systems. In contrast, this paper seeks to leverage large-scale cloud-based thermostat data of thousands of systems to determine hard and soft faults. Service companies are generally more interested in finding soft faults, such as capacity degradation and control problems, rather than hard faults or total failures, since soft faults are generally difficult to detect and may not be recognized by occupants for an extended period of time (Rogers *et al*., 2019).

We propose a statistics-based FDD method that finds anomalous operation behavior and preliminarily categorizes fault types by comparing fault indicators (known as *features*) among multiple systems. In this way, systems having soft faults would be identified as outliers exhibiting anomalous operational behavior. The general analytical process is described as follows. First, the method identifies systems within a similar climate region by relating the system location information to the U.S. climate zones, according to the International Energy Conversion Code climate regions and moisture regimes shown in Figure 1 (International Code Council *et al*., 2012). Second, from a particular climate region, thermostat time-series data of a group of systems is queried from the database and preprocessed. From the resulting data, raw system cycling mode data (i.e., cooling on, heating on, system off) are transformed to more specific categories of operating modes, namely regulating, tracking and free response modes. The time-series data is segmented and classified with these new mode labels (Rogers *et al*., 2020). Based on the type of abnormal behavior to be identified, multiple features will be selected and extracted from the segmented data. Generally, the features characterize system performance, indicate faults, and problem severity, or describe the overall condition of a house and its ambient environment. Third, statistics methods are applied to compare the features among all systems in the selected group to identify outliers. Finally, labeled systems with operational faults affecting system efficiency and occupancy comfort are outputted.

Using this general approach, the performance of a system can be deeply inspected, including both the pseudo steady-state and transient behavior in cooling and heating modes. This paper focuses on the time periods that exhibit poor *transient* behavior, known as poor tracking periods. Both cooling mode and heating mode can exhibit this type of behavior, but this study only focuses on the cooling mode. A poor tracking period is defined as a single cooling on-cycle that usually occurs during high cooling load, and during which the indoor temperature can increase a few degrees above the cooling setpoint, unable to be controlled although the system is operating continuously. Note that the term 'high cooling load' is regarded as relative to the system capacity. If the capacity of a system is far below its rated capacity, even normal loads may well be incapable for it to deal with and thus will be considered as high loads. Therefore, this situation is unlikely to happen for a properly sized fault-free system, and is often related to the capacity degradation fault.

In this paper, Section 2.1 and 2.2 discuss two necessary and innovative data preprocessing steps: data cleansing and mode labeling, which are applied prior to every statistics-based FDD algorithm we proposed. After this, the algorithm will analyze the poor tracking periods specifically. Section 2.3 will introduce a list of features which help to find this poor transient behavior and are able to indicate its severity. Section 2.4 will discuss an unsupervised machine learning method, hierarchical clustering, to identify the poor tracking period using some of the extracted features. Then, in

Section 3, statistics tests on the features indicating problem severity will be performed among systems. In order to provide further implications of the features and recommend thresholds to label faulty systems, the statistical distribution of the features are estimated by the kernel density estimation. Finally, Section 4 will show statistics of the fault detection results as well as a couple of case studies, illustrating the effect of operational faults on system efficiency and occupancy comfort.

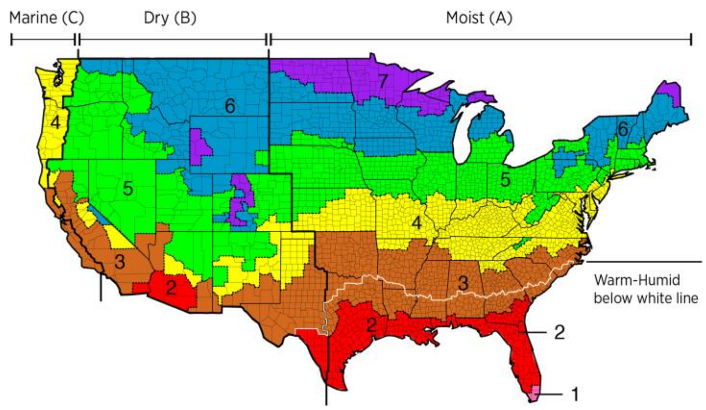

Figure 1: International Energy Conservation Code climate zones and moisture regimes (International Code Council *et al*., 2012). Climate zones: 1~7 in different colors. Moisture regimes: marine, dry, and moist from west to east.

2. INNOVATIVE DATA PREPROCESSING PROCEDURES

Preprocessing procedures are indispensable in order to perform correct and accurate statistical tests for fault detection. Once raw thermostat data is queried from the database, four preprocessing procedures will be conducted sequentially, namely data cleansing, labeling modes of operation, feature extraction, and identification of poor tracking periods. In brief, data cleansing removes data points with sensor faults and time periods where the thermostat is offline. Then the mode labeling transforms raw data into a more useful dataset by defining three system operation modes. Afterwards multiple useful data features are extracted from each operational mode. Finally, poor tracking periods are identified from the cooling tracking mode, one of the three operation modes, by using an unsupervised machine learning method.

2.1 Integrity Verification: Data Cleansing

The raw thermostat data is event-based, which means that the database is updated only when a new event occurs. For example, when the indoor/outdoor temperature changes more than a quantized amount, the cooling/heating setpoint is changed, or the system starts/stops. The event-based dataset records the event and corresponding time, and takes up less digital storage space than the uniformly sampled time series data. Sometimes, however, sensor integrity issues and network communication issues can occur (e.g. the sensor is unplugged, the thermostat goes offline or otherwise fails to communicate data). These issues could strongly affect the analytical process. For example, if a setpoint change event is not recorded, then the thermostat may seem to control the indoor temperature to value different from the supposed setpoint; or if a cooling off event is missed, then the system may appear to continue running for a long time. Therefore, after the raw data is queried, the first preprocessing step is to cleanse the data and remove these issues. This algorithm uses a combination of filters and logical tests to identify and remove these data.

2.2 Data Partitioning and Classification: Labeling Modes of Operation

After the raw data is cleansed, the mode labeling algorithm is applied to transform the raw operational data (cooling, heating, off) into a more useful dataset based on mode: regulating mode, tracking mode, and free response mode (Rogers *et al*., 2020). Note that both heating and cooling have respective regulating and tracking modes.

- In the regulating mode, a system cycles on and off to maintains a relatively constant indoor temperature around the setpoint. The space being cooled or heated is assumed to be in a pseudo steady-state condition.
- In the tracking mode, a system remains powered on to reach the setpoint and exhibits transient behavior. Typically, the cooling tracking mode is activated after a drop in cooling setpoint or during high cooling load; the heating tracking mode is activated after a rise in heating setpoint or during high heating load.

- In the free response mode neither setpoint is active. A free response mode may occur after a rise in cooling setpoint or a drop in heating setpoint, or when both cooling and heating loads are low such that the indoor temperature remains between setpoints for an extended period.

Figure 2 provides an example of labeling modes of operation. In Figure 2a, the cyan color shows the cooling regulating mode when the indoor temperature is fluctuating and maintained relatively constant, and the red color shows the cooling tracking mode when the indoor temperature drops significantly. In Figure 2b, the green color shows the free response mode when indoor temperature rises above the heating setpoint and the orange color shows the heating regulating mode when the indoor temperature drops to the heating setpoint.

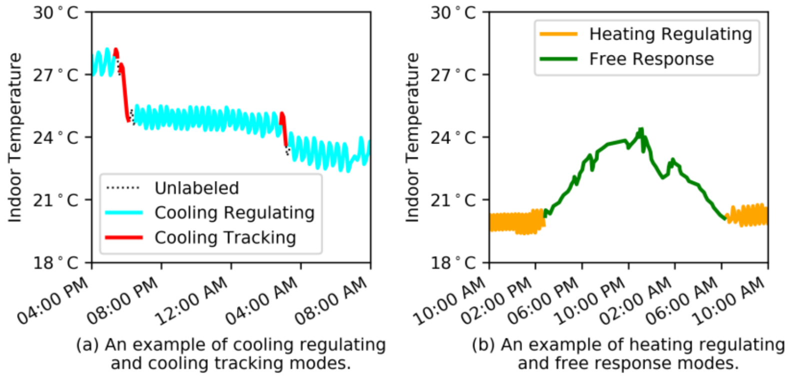

Figure 2: An example of labeled modes of operation. Subplot (a) shows the cooling regulating and cooling tracking modes, and subplot (b) shows the heating regulating and free response modes.

2.3 Feature Generation: Extracting Features from the Cooling Tracking Mode

Within the operating modes introduced above, this paper studies the poor transient behavior, corresponding to the cooling tracking mode activated during high cooling load. Note that even when the cooling tracking mode is activated by a drop in cooling setpoint, a system can sometimes exhibit poor transient behavior if the cooling load is too large for the system. The features listed in Table 1 are extracted from the cooling tracking periods. Among all of the features, the first three are calculated within each cooling tracking period, and will be applied to identify the poor transient behavior; the fourth and fifth features are comprehensive indicators averaged over all poor tracking periods for each system, and will be used to characterize the problem severity.

Table 1: Supporting features for the cooling tracking mode

Symbol	Feature name	Definition
$T_{i,inc}$	Indoor temperature increase [°C]	The maximum indoor temperature increase*/** in a cooling tracking period.
Δt_{inc}	Increase time [hr]	The time required to reach the maximum indoor temperature increase.
$\dot{T}_{i,inc}$	Indoor temperature increase rate [°C/hr]	The rate at which indoor temperature increases; defined as $\dot{T}_{i,inc} = T_{i,inc}/\Delta t_{inc}$.
$\overline{DH}$	Average degree hour [°C·hr]	The integral of the difference between the indoor temperature and the cooling setpoint, during a time segment exhibiting poor transient behavior, averaged over the whole cooling season; defined as: $\overline{DH} = \frac{1}{N}\sum_1^N \int_0^{24} I \cdot \max[0, (T_{id} - T_{sp,cool})]\, dt$; where N is the number of days in a cooling season; I equals 1 in poor tracking periods, and 0 in other cases.
$\bar{T}_{i,max}$	Average maximum indoor temperature [°C]	The average of a fixed number of highest $T_{i,max}$ in all poor tracking periods** after removing a few extreme cases.

Notes: * A searching algorithm is applied to find the maximum increase in a time series.
** If a poor cooling tracking period is longer than 24 hours, then it will be segmented with one period a day. Generally, there is at most one poor tracking period each day, and the maximum indoor temperature occurs in the afternoon when cooling load is the highest. Please see Figure 7 and 8 in case studies for reference.

During normal cooling tracking periods activated by a decrease in cooling setpoint, the indoor temperature should decrease (or increase a very small amount) after cooling starts, such that both the value of the indoor temperature increase and the temperature increase time should be very small. For the poor tracking periods, however, both of these two features could show very high values.

2.4 Behavior Recognition: Identification of Poor Tracking Periods

In this step, the features extracted above will be analyzed to identify all poor transient behavior of a system. In total four types of transient behavior are common in the cooling tracking mode. Recall that a cooling tracking period is just one single cooling on-cycle. Figure 3a shows normal transient behavior (the most common), where the cooling system starts after a drop in setpoint and remains on until reaching the new setpoint. Figure 3b shows poor transient behavior, where the indoor temperature increases over 5℃ before returning, despite the cooling system operating continuously for nearly 24 hours. Both Figure 3c and 3d show interesting transient behavior where the indoor temperature first increases precipitously after the cooling system turns on. The behavior in Figure 3c may be caused by lack of insulation on the return air duct in the attic, such that warm air is initially blown into the house when the fan starts after a long downtime; the behavior in Figure 3d may be caused by the internal heat load of the thermostat itself on the sensor, such that indoor temperature seems to rise as soon as the fan starts (after cooling starts) and the air circulation direction of the room changes.

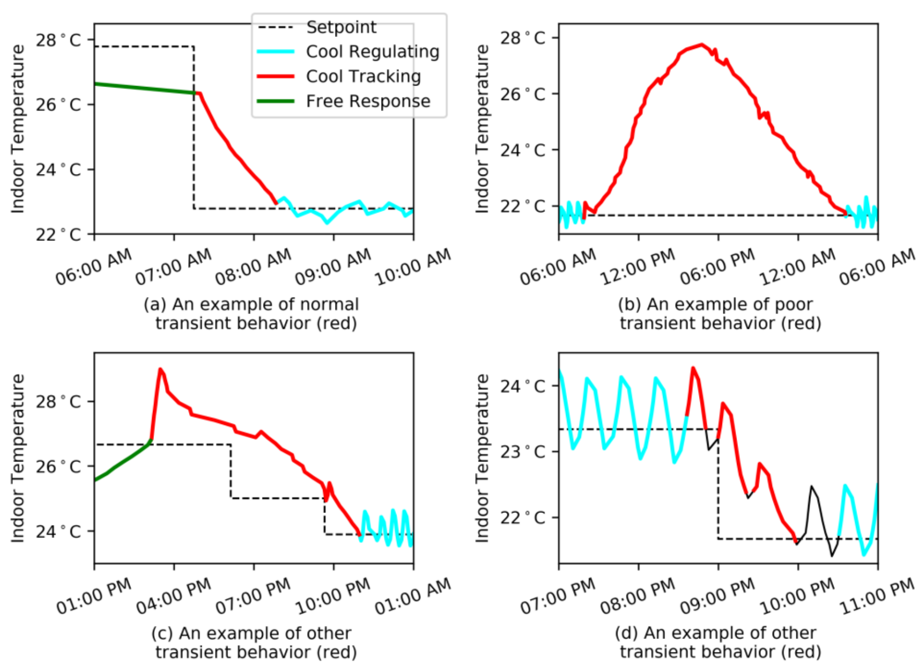

Figure 3: Four main types of transient behavior exhibited in the cooling tracking mode (red color).

Three features, namely indoor temperature increase ($T_{i,inc}$), increase time (Δt_{inc}), and increase rate ($\dot{T}_{i,inc}$), are used together to separate the different causes of poor transient behavior. As a first step, normal transient behavior should exhibit $T_{i,inc} \approx 0$, and hence these normal periods can be eliminated by a simple range filter, e.g., $T_{i,inc} > 0.56$℃ (1°F). Distinguishing between the types of undesirable transient behavior, however, is more difficult. Poor transient behavior could exhibit long Δt_{inc} and low $\dot{T}_{i,inc}$, or vice versa. Figure 4a shows the kernel density estimation of all tracking periods after removing those identified to be normal, with darker regions having more data. The data forms two groups, shown by Figure 4b. The cluster on the left could only correspond to the poor tracking periods due to its long increase time, and the other on the bottom could only correspond to other types of behavior due to its fast increase rate. Only data between two groups in the lower left region has some ambiguity. However, based on an assumption that if a system has some confirmed poor tracking periods, then the ambiguous ones are more likely to be poor tracking periods as well, such that the hierarchical clustering method can be applied to group the two behavior for each system.

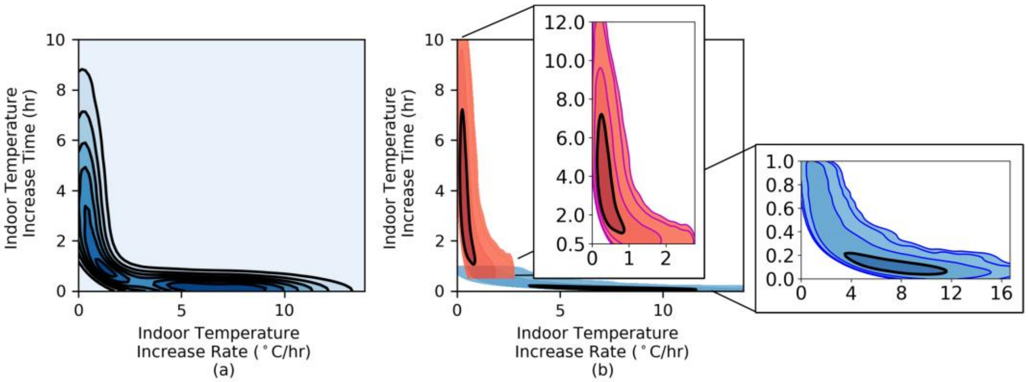

Figure 4: (a) Kernel density estimation of the remaining tracking periods after the normal ones are removed. (b) The data forms two groups. The group in red corresponds to poor transient behavior, and the group in blue corresponds to other transient behavior. The black circles show the core region (50% of mass) of each group.

In this study, Ward's agglomerative hierarchical clustering method (Ward and Joe, 1963) is applied to build a hierarchy of clusters from the transient data of each system. This method starts with each data point in its own cluster. Then as the algorithm moves up the hierarchy, it seeks to merge pairs of clusters which can minimize the variance of the clusters. In order to exactly find the two clusters of behavior, some generated data from the two black circles in Figure 4b is added into the real data. Note that the black circles correspond to the core regions of each cluster, taking up 50% of the mass, with known true labels. Also, features on both axes are normalized such that the Euclidean distance is applicable. By this means, the algorithm iterates over each system to label the tracking periods mixed with generated data. Since the two clusters are defined by expertise and experience, this approach can be regarded as setting soft thresholds between the two behaviors. After checking the results, the method is found to be stable and robust, and can correctly label the data of either type of behavior. Therefore, all cooling tracking periods labeled with poor transient behavior can be separated from the other behavior.

3. STATISTICS-BASED FAULT DETECTION METHOD

This section presents the proposed statistics-based fault detection method. In order to compare system performance to the entire population and identify outlier behavior, the statistical distribution of two features, namely average degree-hour above setpoint and average maximum indoor temperature, will be investigated among all systems by means of kernel density estimation. These two features could strongly indicate the existence and the severity of operational faults, and thresholds for identifying faulty systems will be recommended

3.1 Statistical Distributions of Features

Once all poor tracking periods are identified, a statistics-based fault detection algorithm can be applied using two additional features, namely average degree hour above setpoint and average maximum indoor temperature. The average degree hour above setpoint ($\overline{DH}$, unit: [℃·hr]) averages the area between indoor temperature and cooling setpoint for only all poor tracking periods (see Figure 3b as an example) each day in the whole summer cooling season, which represents the system effectiveness and occupant comfort. For instance, a system with $\overline{DH} = 12$℃·hr may on average have indoor temperature 3℃ above setpoint lasting for 4 hours every day in the summer, even though cooling runs in full power. The average maximum indoor temperature ($\overline{T}_{i,max}$) is calculated by averaging ten highest indoor temperatures during poor tracking periods, after first removing the five most extreme instances in the cooling season. Thus, this feature represents the most severe instances of occupant discomfort. For instance, a system with $\overline{T}_{i,max} =$ 30℃ will have indoor temperature rising over 30℃ on average for at least 15 days in the summer, even though cooling runs in full power. These two metrics characterize the severity of the detected problem.

To exemplify the distributions of the two features, approximately 10,000 residential single-stage cooling systems in 2A IECC climate zone (see Figure 1) in Florida are queried with data from June 1st to September 30th in 2019. Among them, 904 systems have been identified with more than 15 (a hard threshold) poor tracking periods. The kernel density estimation of the average degree hour above setpoint and average maximum indoor temperature are shown in Figure 5. From Figure 5a and 5b, most systems have average degree hour above setpoint less than 15℃·hr and average maximum indoor temperature less than 30℃. From the 2-D distribution in Figure 5c, one can find that generally $\overline{DH} > 8$°C·hr along with $\bar{T}_{i,max} > 27$℃ is abnormal.

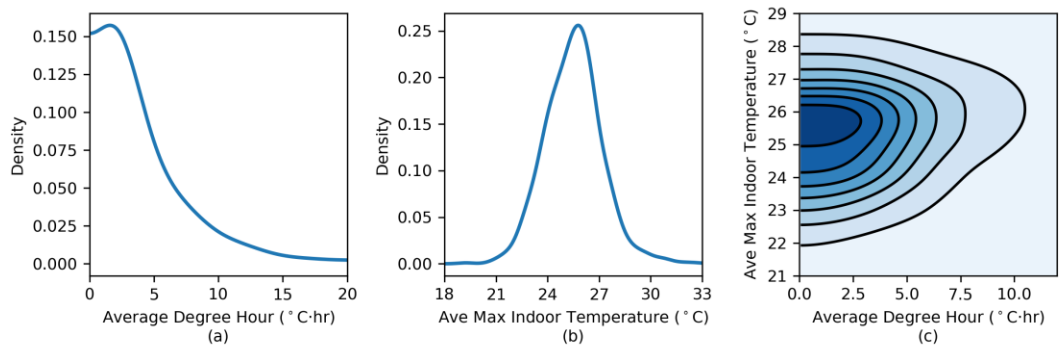

Figure 5: Kernel density estimation of (a) the average degree hour above setpoint, (b) average maximum indoor temperature, and (c) both features together, for all 904 systems identified with more than 15 poor tracking periods.

3.2 Thresholds Recommendation for Fault Detection

Although high $\overline{DH}$ and high $\bar{T}_{i,max}$ are not equivalent to faults, they can strongly indicate the existence or severity of faults. We hope to use the distributions of these two metrics to set thresholds for fault and estimate fault severities. Practically the real numbers of faulty systems are unknown and the exact boundary between faulty and fault-free systems is indeterminate. Furthermore, all systems exhibiting poor transient behavior could have some level of operational faults. Nevertheless, to be conservative, in this study the thresholds are adjusted such that about 5% systems with the poor transient behavior are classified as faulty. Note that approximately 9% systems are identified with poor transient behavior, so this threshold will label about 0.5% among all systems to be faulty. The threshold is flexible and subject to change based on the service companies' preferences. The study finally takes 80% quantile of the $\overline{DH}$ and $\bar{T}_{i,max}$ in the dataset as thresholds, respectively 6.9℃·hr and 26.7℃, calculated from the estimated probability density function in Figure 5a and 5b. Any systems with both features above thresholds are flagged. Two case study examples are shown in the next section.

4. RESULTS AND DISCUSSION

Using the approach outlined above, systems that exhibit faulty behavior are flagged. These faults could be related to either capacity degradation faults or undersizing issues. In this section, general fault detection results are summarized, and two typical cases are presented, with each representing one type of common behavior. The results demonstrate the potential of large data fault detection methods for residential HVAC systems using cloud-based thermostat data.

4.1 Summarization of Fault Detection Results

Figure 6 briefly summarized the fault detection results. Figure 6a shows how faulty systems are flagged layer by layer. The Venn diagram in Figure 6b shows a total of 181 systems are flagged by each feature using the proposed thresholds, and the 68 systems at the intersection of the two groups are labeled as faulty. The next three scatterplots illustrate the behavior of these 68 labeled faulty systems in the 2019 summer cooling season. Figure 6c shows that in most of these homes the indoor temperature often reaches to around 29℃ although the cooling setpoint is usually set to around 23℃, and there are some extreme systems having very high indoor temperature and degree hour above setpoint. Figure 6d compares the previously defined degrees hours with the degrees hours when the indoor temperature is 1.1℃ (2°F) above setpoint. The latter feature can be calculated by the equation in Table 1 assuming the setpoint increased by 1.1℃ (2°F). The result shows strong linear relationship, indicating higher degree hours means both higher temperature and longer time. Occupants living in a high-degree-hour conditioned space have to endure high indoor temperature well above the setpoint value they selected for several hours every day. Finally, Figure 6e shows that most faulty systems spend between 400 and 2000 hours with poor tracking during the cooling season. No particular relationship can be found between maximum indoor temperature and total time on poor tracking due to the difference in setpoint values for each system.

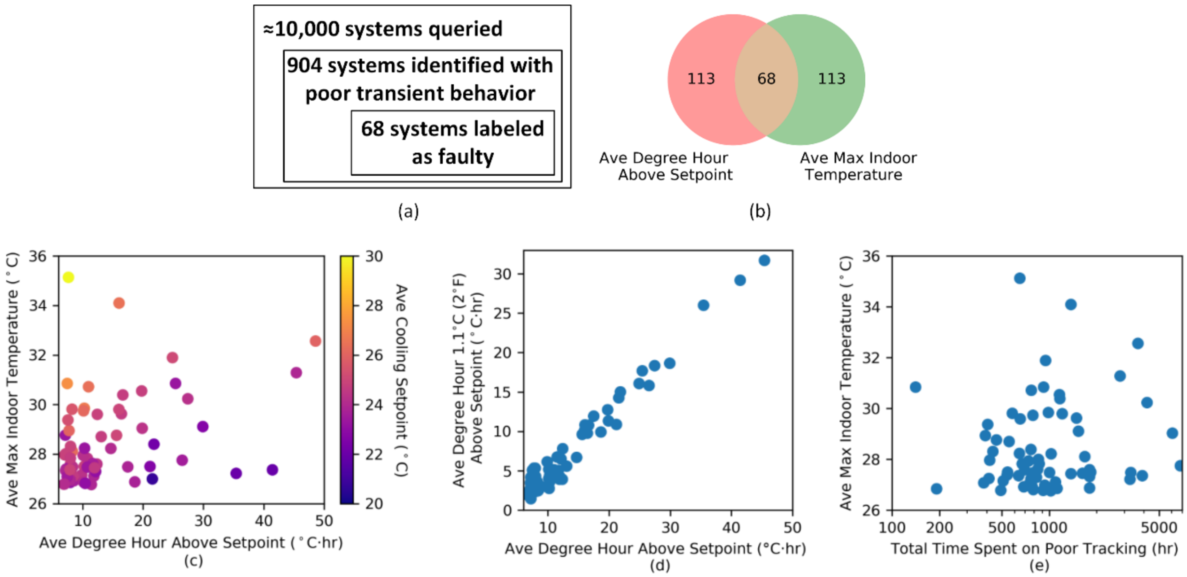

Figure 6: Illustration of the statistics-based fault detection results. (a): General statistics. (b): A Venn diagram showing the numbers of flagged systems. (c) to (e): Statistics of the 68 faulty systems in the summer cooling season.

4.2 Case Study I: Significant Time above Setpoint, High Maximum Indoor Temperature

Figure 7 displays a part of daily operation of a selected faulty system, recorded from June 10th to June 14th. Note that this is the most common behavior among all labeled faulty systems. The first plot records the indoor temperature variation and cooling setpoint changes with modes labeled in red, cyan and green color. The second plot records the cooling load factor (i.e. on/off status) of this single-stage cooling unit. The third plot records the outdoor temperature variation. From this figure, the system frequently shows long periods of poor transient behavior, and the indoor temperature can spike from 24℃ to above 30℃ when the outdoor temperature approaches 32℃ in the afternoon. Typically, every day the system operates all the time from the sunrise to sunset, until the outdoor temperature drops below 26℃. It works very little during the night, because the cooling setpoint is above the outdoor temperature and the house is cooled passively by the ambient environment.

Statistics shows the average degree hour above setpoint is 25.4℃·hr and average maximum indoor temperature is 30.8℃. These numbers could be understood in the following way: the occupants in the house on average experience 3.2℃ above setpoint every day for 8 hours, and the maximum indoor temperature in a day approaches 30.8℃ on average for at least 15 days in summer. Clearly the comfort level is very low, and the system capacity does not meet the cooling load.

4.3 Case Study II: Significant Time above Setpoint, Low Maximum Indoor Temperature

Another example shown in Figure 8 also has many long periods of poor tracking and even have one poor tracking period lasting for several days (e.g., the period from September 8th to September 14th). The average degree hour above setpoint is 46.4℃·hr, much higher than the former example. This case, however, is very different from the former one in that the occupant comfort is not totally lost. The average maximum indoor temperature is 25.3℃, and the cooling setpoint is adjusted 19.5℃ on average when the system exhibits poor transient behavior. Because of the low indoor temperature, this example is *not* labeled as faulty. Nonetheless, this behavior is very common, characterized by an occupant driven issue in addition to possible capacity degradation issues.

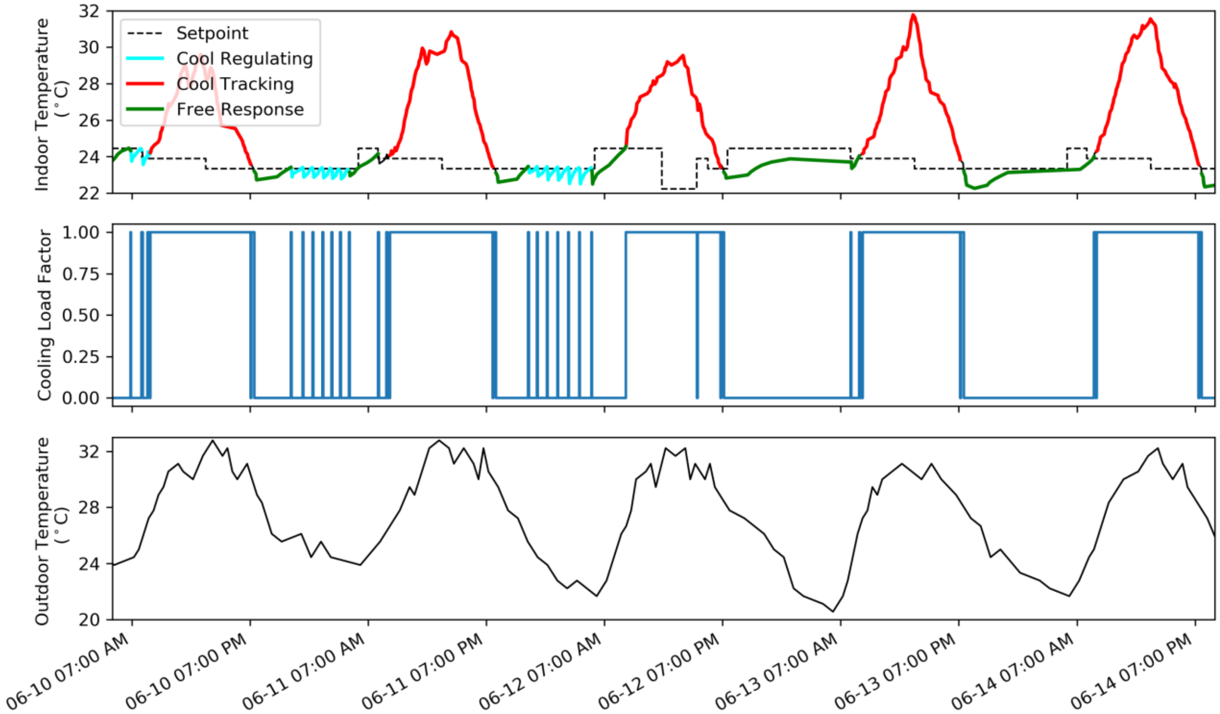

Figure 7: Daily operating condition of system I with labeling modes of operation, from June 10th to June 14th. Red: poor cooling tracking periods; cyan: cooling regulating periods; green: free response periods; dotted line: cooling setpoint.

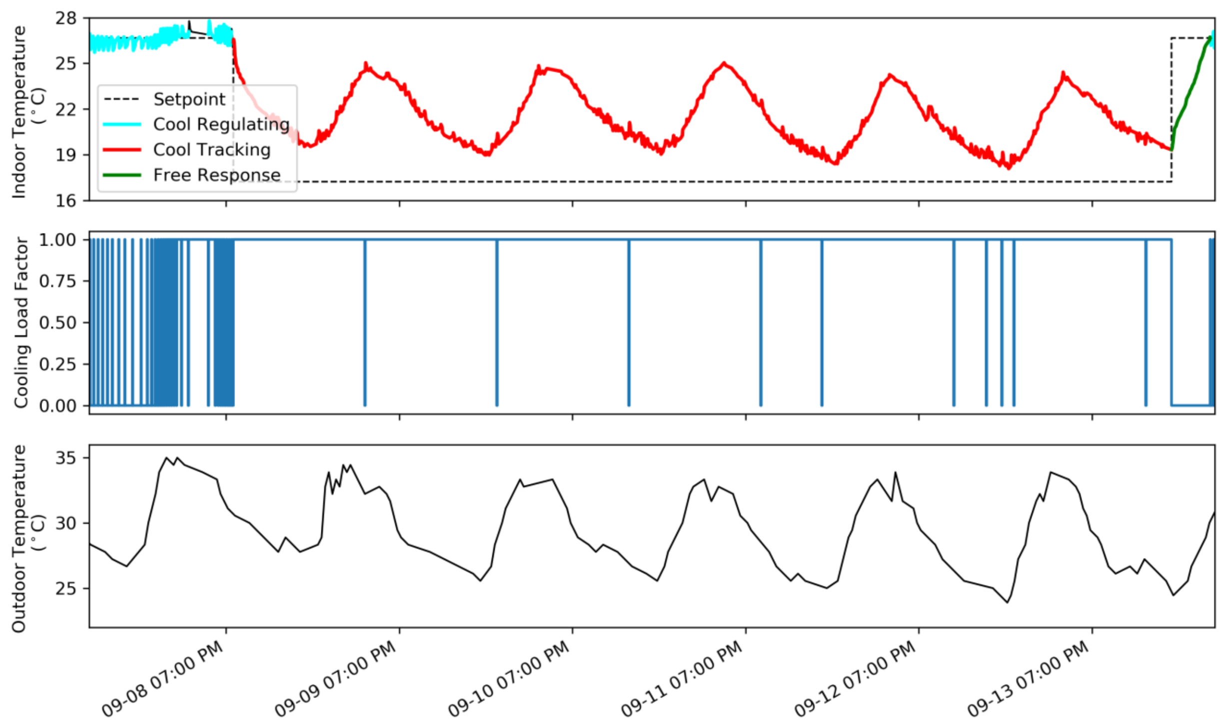

Figure 8: Daily operating condition of system II with labeling modes of operation, from September 8th to September 14th. Red: poor cooling tracking periods; cyan: cooling regulating periods; dotted line: cooling setpoint.

Figure 8 captures a segment of the occupant driven issue. On the evening of September 8th, the occupant deliberately lowered the cooling setpoint to 17.2℃ (63°F) in order to receive more cooling, even though he or she understood that the indoor temperature might never reach the setpoint. From the figure, the system precools the home at night to approximately 19℃, and during the daytime the indoor temperature can be well-controlled below 25℃. In other words, the occupants were forced to decrease the setpoint because he or she had realized that the system capacity was not large enough, and if the system did not operate during the nighttime, the indoor temperature would probably rise above 27℃ in every afternoon. Additionally, we speculate that nobody was at home before and after the displayed poor tracking period, so the occupant could adjust the setpoint at 26.7℃ (80°F) to reduce cooling and the associated electric bill. However, this precooling method is not always effective and is symptomatic of faulty equipment. A better solution for the home owner will be to contact service companies and request maintenance.

5. CONCLUSIONS

By means of cloud-based smart thermostat data of thousands of residential HVAC systems, the proposed fault detection method can successfully identify faulty systems from analysis of their transient behavior, and infer the problem severity using specific data features. The flagged faulty systems exhibit low cooling capacity compared to the load, which is the result of system degradation, improper sizing, or improper commissioning, and the occupants either experience discomfort or are forced to compensate by artificially adjusting the cooling setpoint.

This paper only introduces two features indicating severity of capacity degradation fault. Other features extracted from the cooling tracking mode can potentially indicate additional faults observed only from the transient behavior. For instance, indoor temperature increase ($T_{i,inc}$) and increase time (Δt_{inc}) can be applied to diagnose problems such as lack of insulation in the house attic, thermostat misplacement issues, and smart thermostat internal heat load issues. The potential of large data fault detection methods requires both domain expertise and sound statistical analysis.

REFERENCES

Do, H., & Cetin, K. S. (2019). Data-Driven Evaluation of Residential HVAC System Efficiency Using Energy and Environmental Data. *Energies, 12*, 188.

EIA. (2015). *Residential Energy Consumption Survey (RECS).* U.S. Energy Information Administration.

Ham, W., Klein, M., Tabatabaei, S. A., Thilakarathne, D. J., & Treur, J. (2016). Methods for a Smart Thermostat to Estimate the Characteristics of a House Based on Sensor Data. *Energy Procedia, 95*, 467-474. doi:https://doi.org/10.1016/j.egypro.2016.09.067

International Code Council, Building Officials, Code Administrators International, International Conference of Building Officials, & Southern Building Code Congress International. (2012). *International energy conservation code.* International Code Council.

Jain, M., Gupta, M., Singh, A., & Chandan, V. (2019, 3). Beyond Control: Enabling Smart Thermostats for Leakage Detection. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., 3*, 14:1--14:21. doi:10.1145/3314401

Kim, W., & Katipamula, S. (2018). A review of fault detection and diagnostics methods for building systems. *Science and Technology for the Built Environment, 24*, 3-21. doi:10.1080/23744731.2017.1318008

Neme, C., Nadel, S., & Proctor, J. (1999). Energy savings potential from addressing residential air conditioner and heat pump installation problems.

Proctor, J., & Downey, T. (1999). Transforming routine air conditioner maintenance practices to improve equipment efficiency and performance. *Proceedings of the 1999 international energy program evaluation conference*, (pp. 1-12).

Rogers, A. P., Guo, F., & Rasmussen, B. P. (2019). A review of fault detection and diagnosis methods for residential air conditioning systems. *Building and Environment, 161*, 106236. doi:https://doi.org/10.1016/j.buildenv.2019.106236

Rogers, A. P., Guo, F., Martinez, J., & Rasmussen, B. P. (2020). Labeling Modes of Operation and Extracting Features for Fault Detection with Cloud-Based Thermostat Data. *2020 ASHRAE Annual Conference.*

Turner, W. J., Staino, A., & Basu, B. (2017). Residential HVAC fault detection using a system identification approach. *Energy and Buildings, 151*, 1-17. doi:10.1016/j.enbuild.2017.06.008

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American statistical association, 58*, 236-244.