Large Scale Analytics for Residential HVAC systems using Cloud-Based Smart Thermostat Data

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INTRODUCTION

Predictive and preventive maintenance through fault detection and diagnosis (FDD) plays a significant role in mitigating the unnecessary expenditure of energy in residential HVAC systems. Traditionally, FDD of residential split systems warrants the installation of additional sensors on the equipment making it cost-ineffective to be implemented on a large scale especially for mass produced residential systems. The following study provides an alternative FDD approach wherein a large number of systems will be analyzed using only limited amount of sensor information from each system. The data required for such a large scale analysis is the data aggregated by smart thermostats that upload event-based usage data unto a cloud. Analyzing smart thermostat data has a number of benefits for not just the home occupants but the manufacturers as well.

Motivations for FDD using Smart thermostat data

- Disadvantages of Traditional FDD methods
  - Usually designed for one large commercial system
  - Requires installation of additional sensors
  - Requires knowledge of steady-state conditions and access to fault-free data
- Advantages of Large Scale Data Analytics using Smart Thermostat Data
  - No need to install additional sensors
  - Ubiquitous installation of smart thermostats in residential buildings
  - Ease in querying data from thousands of systems
  - Faults detection is done by comparing features of different systems

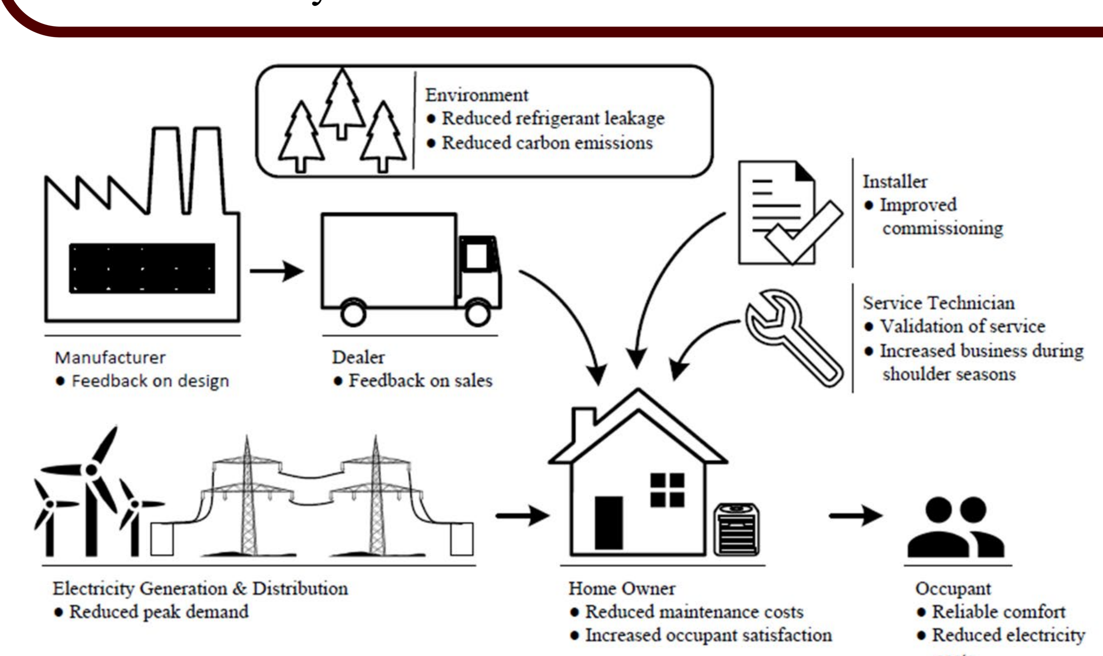

Figure 1: Benefits of using FDD for residential HVAC systems [1]

STEPS IN THE FDD PROCESS

Step 1: Thermostat data uploaded unto the cloud is retrieved and cleansed.

- Removal of thermostat communication issues
- Removal of sensor integrity issues

Step 2: Data is partitioned into modes of operation.

- Regulating mode: System is cycles on and off maintaining a constant temperature.
- Tracking mode: System is operating continuously to reach a desired setpoint.
- Free response mode: System is neither actively cooling or heating.

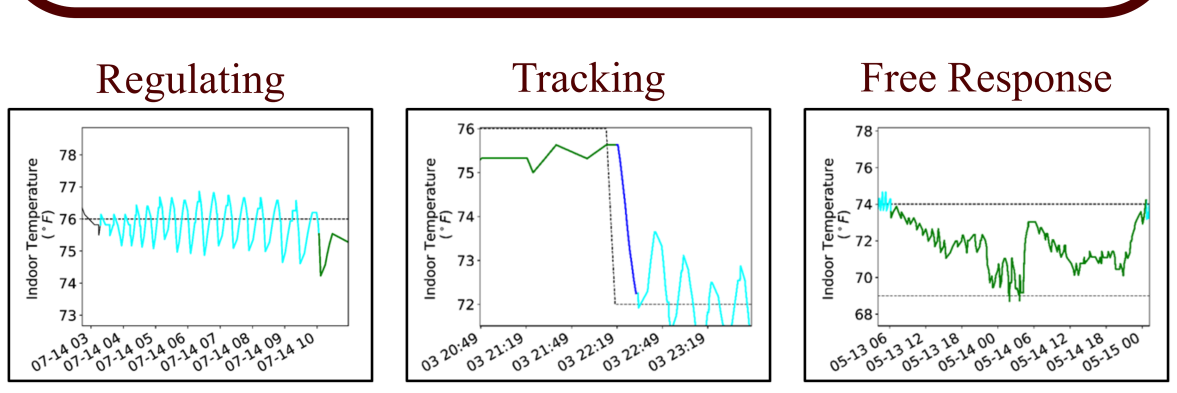

Figure 2: Modes of operation of a air-conditioning system [2]

Step 3: Interesting features are extracted from each mode. Few examples include,

- Temperature difference between indoor and outdoor (°F), indoor humidity ratio
- Regulating: Cooling effort (%) (product of duty factor and load factor), cycling frequency ($cycles/hr$), average setpoint error (°F)
- Tracking: Average degree hour above setpoint ($°F \cdot hr$), average maximum indoor temperature (°F), indoor temperature change rate ($°F/hr$), daily cooling/heating hours (hr)

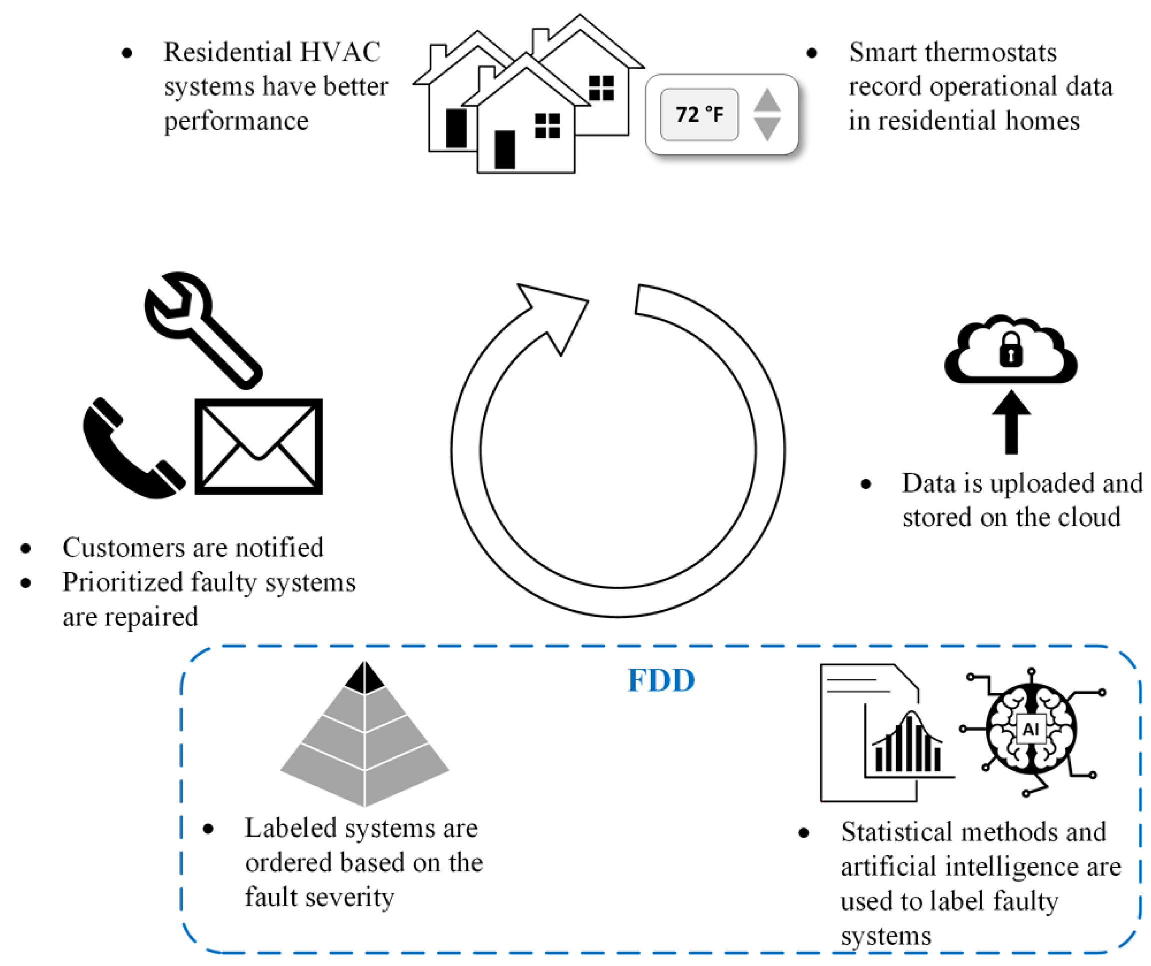

Figure 3: General process of fault detection with smart thermostat data [5]

Step 4: Features of systems are compared against each other to identify anomalies. Few of the faults detected are:

- **Setpoint Tracking Failure Detector**: Identifies systems with faulty transient behavior. System is unable to track a new setpoint efficiently. Diagnosed to be a case of severe capacity loss, improper sizing or installation problems [4].
- **Inadequate Capacity Detector**: Analyzes features extracted from the regulating mode to detect systems with severe capacity inadequacy [8].
- **Abrupt Change Detector**: Examines the time series of features to determine points (if any) of sudden changes in system capacity [3].
- **Degradation Trend Detector**: Examines the time series of features to identify trends, if any, of gradual degradation of system capacity [7].
- **Control Problems Detector**: Identifies control problems by building distribution of features extracted from the regulating mode and identifying systems that lie at the extremes [5,6].

Figure 4 shows the flowchart with each of the steps in the FDD process. *Figure 5* is an example of a faulty system identified using the control problems detector. Notice how the features of the system lie far away from the contour of the population distribution.

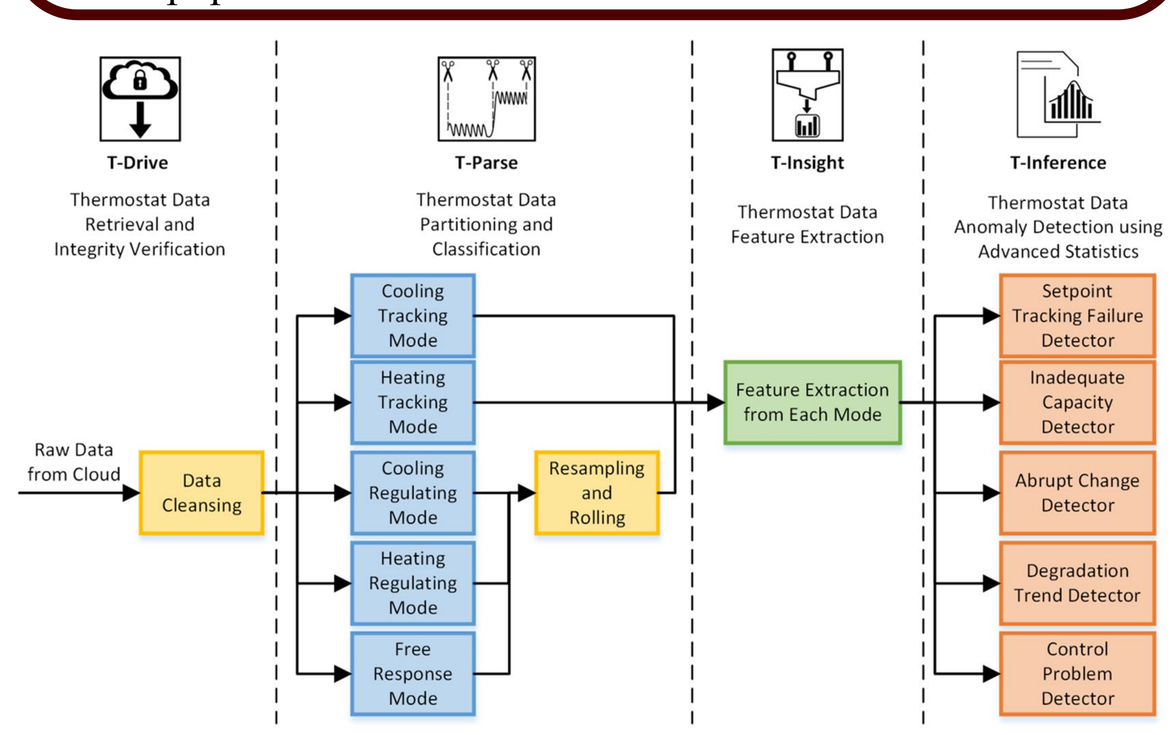

Figure 4: Flowchart of the whole FDD process

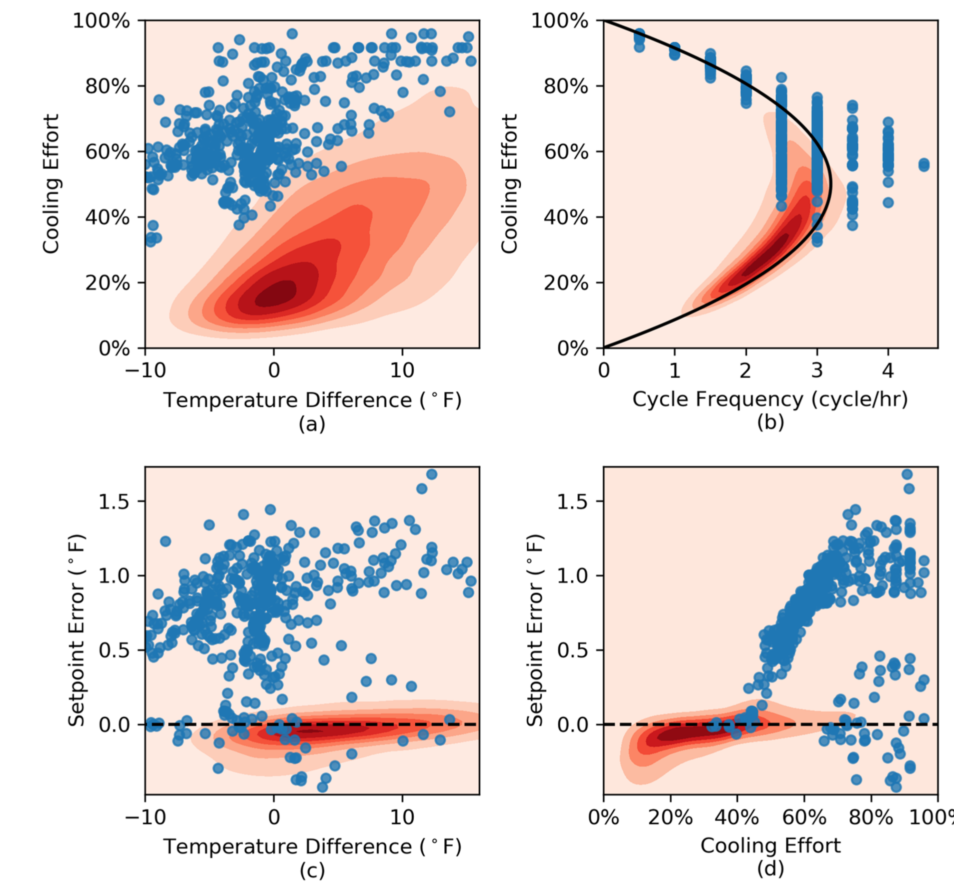

Figure 5:. The blue points in the scatterplots are features of a faulty system. The contours show the population distribution. Darker regions correspond to a higher concentration of points. [6]

SYSTEM IMPACT AND SEVERITY

Metrics were developed to estimate the impact of systems on energy consumption and thermal comfort of occupants. Subsequently, a combination of energy and thermal comfort impacts was used to determine a severity index for the system based on which systems are ranked and prioritized for repair.

- **Energy Impact**: The energy consumption of the given system as well as the average system operating in the same climate region were modelled. Energy impact of the given system was estimated as the relative difference in total cooling hours of the given and the average system [9].
- **Thermal Comfort Impact**: Average thermal discomfort of the indoor and outdoor environment of the house was estimated based on the Predicted Mean Vote (PMV). Thermal Comfort impact was estimated as the ratio of mean level of discomfort felt by occupant living in the indoor environment over the mean discomfort level they would have felt if they were living outside [9].
- **Severity Index**: The change in temperature to make the house completely comfortable was estimated. The relative difference between the total cooling hours of the given and the average system under comfortable indoor conditions is the severity index [9].

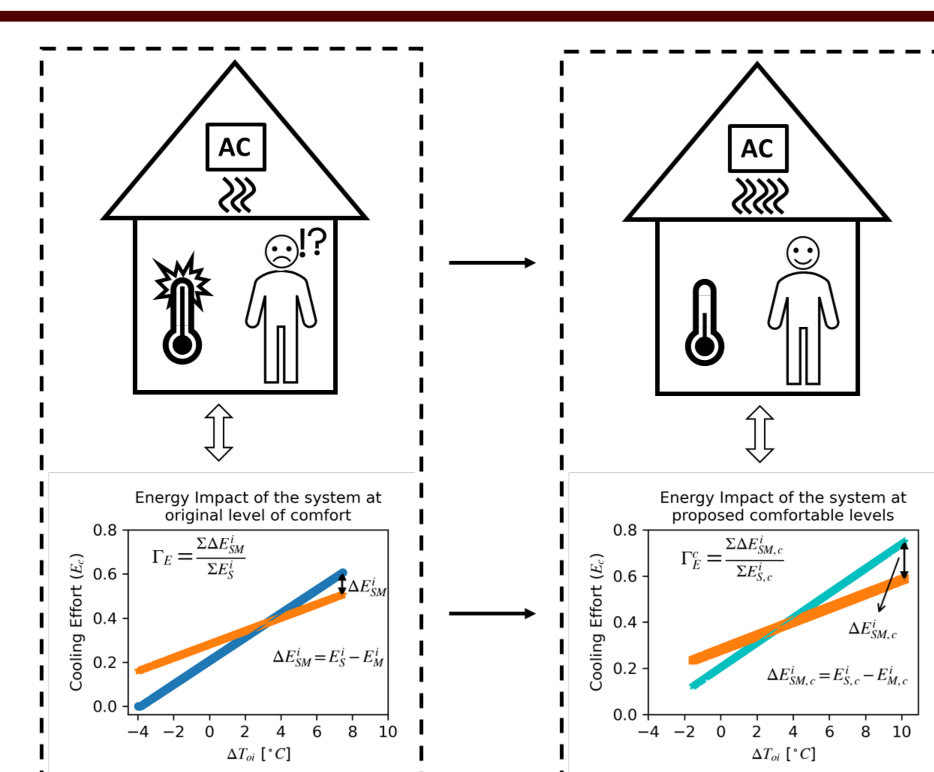

Figure 6: Change in performance of the system when the indoors are made completely comfortable. The orange points are from the model of the average system. The points in blue and cyan are from the model of the given system. [9]

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