PACMAN : Predicting AC Consumption Minimizing Aggregate eNergy Consumption

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Certificate

This is to certify that the thesis titled **"PACMAN: Predicting AC Consumption Minimizing Average eNergy Consumption"** submitted by **Milan Jain** for the partial fulfillment of the requirements for the degree of *Master of Technology* in *Computer Science & Engineering* with specialization in *Mobile and Ubiquitous Computing* is a record of the bonafide work carried out by him under my guidance and supervision in the Mobile and Ubiquitous Computing group at Indraprastha Institute of Information Technology, Delhi. This work has not been submitted anywhere else for the reward of any other degree.

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Abstract

Buildings account for a significant proportion of overall energy consumption across the world. Heating Ventilation and Air Conditioning (HVAC) typically consumes a major proportion (e.g. 32% in India) of the total building energy consumption. While centralized HVAC systems are more prevalent in developed countries, separate room level Air Conditioners (ACs) are a commonplace in developing countries, such as India. Poor building insulation in developing countries, together with an option to easily control room level air conditioning, presents a major opportunity for energy conservation in these countries. We propose PACMAN - a novel approach for predicting the energy consumption of room level AC. PACMAN involves learning a thermal model of the room from historical usage and combines this model with the weather forecast for user's location to guide the user towards optimized AC settings in order to balance user comfort and energy efficiency. Empirical validation was performed using a real world study, conducted across 7 homes in India, with collective data for a duration of 2200 hours in total. PACMAN achieved more than 90% accuracy in predicting the energy consumption across different ACs, room types and set temperatures used during the data collection. We further describe a prototype realization of the proposed PACMAN system towards achieving reduced AC energy consumption with better feedback and control.

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Chapter 1

Research Aim and Motivation

Energy crisis is a major issue across the globe. Governments, around the world, are concerned about energy crisis, as electricity demand is rising at an alarming rate. Of this total electricity demand, International Energy Agency (IEA) estimated the contribution of buildings to be one-third[1]. Buildings also contribute to CO_2 emissions which is one of the major sources of pollution in the environment[1].

While energy crisis is a global issue, conditions are even worse in developing countries, such as India, when compared to developed countries. Even being the third largest electricity producer, 25% of the population in India have no access to electricity at all along with the shortage of 9% during peak demands[2]. Of all the electrical appliances, Heating, Ventilation and Air Conditioning (HVAC) contributes a significant proportion (30-50%) of the total energy consumption across both residential and commercial buildings[3,4,5] [16]. However, most of the developing countries have a higher prevalence of room level ACs in residential buildings. Possibility of room level control, together with building's substandard thermal insulation make decentralized ACs, an attractive target for energy conservation in residential buildings, which consume significant amount of electricity. According to a previous study carried out globally in 2005 by IEA, residential buildings contribute 29% in aggregate energy consumption across the globe[6]. They also contribute 21% directly and indirectly to global CO_2 emission[6]. While the savings at an individual home level may seem insignificant but, when scaled up to millions of homes across the globe, will help us to face challenging energy demands.

On the other side, Centralized air conditioners (AC) in a residential building involves division of conditioned space into multiple zones, each consisting of multiple rooms serviced together by independent fan units. Difference in occupancy levels, together with higher possibilities for leakage of cooling, across rooms within a zone make optimal control for a central AC system

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[1] http://bit.ly/1m2mXyG

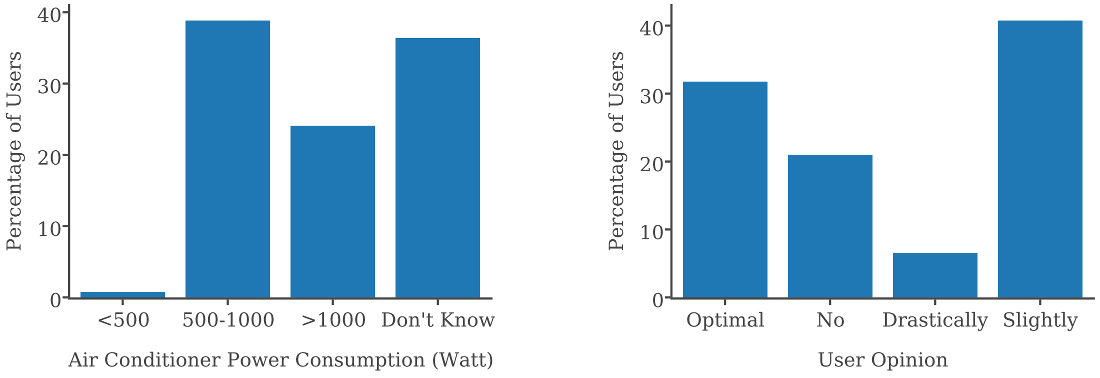
[2] http://bit.ly/1oWwuHz

[3] http://bit.ly/1icjKIJ

[4] http://bit.ly/1ow8fjp

[5] http://bit.ly/1ol1tv6

[6] http://bit.ly/1mhY4yC



(a) Power consumption estimate

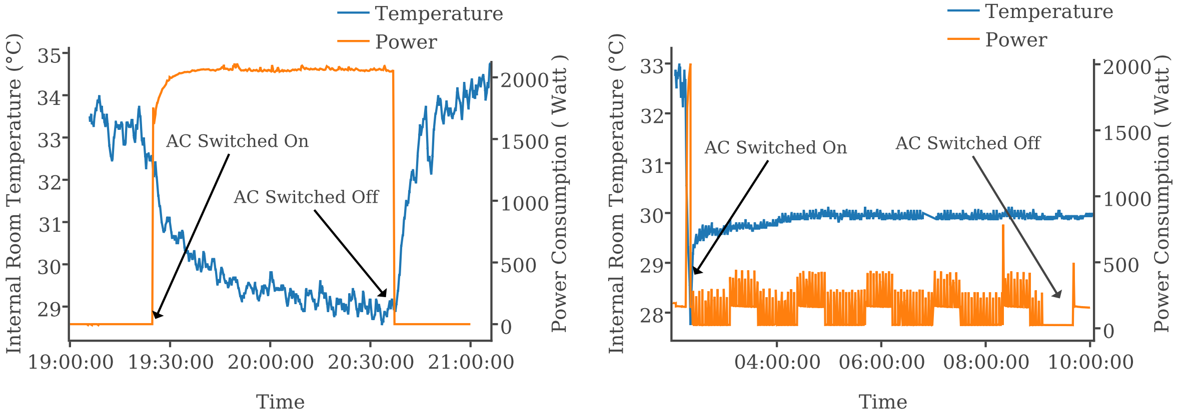
(b) Expected usage

Figure 1.1: Results from the survey of 1800 people in Urban India,discussed in Jain et al. [12], illustrating (a) perceptions about AC power consumption and (b) opinion on scope for reduction.

difficult.

However, lack of understanding among the users to optimize the energy consumed during an AC usage (Time duration from the time AC is switched on to the time it is switched off), results in significant wastage. A survey conducted across 1800 people in urban India [12] observed two interesting facets of this energy wastage. First, many of the users (more than 76% of those surveyed) underestimate the power consumption of ACs (see Figure 1.1a for detailed breakup). Secondly, majority of users (more than 50% of those surveyed) believe that there is a scope to save energy during their AC usage when compared to their current usage (see Figure 1.1b for detailed breakup). Previous study [15] has observed that occupants, who are unaware of their electrical consumption, add up to one-third to their electricity bills. However, real time and appliance level feedback about energy consumption together with steps on how to achieve energy efficiency is largely missing today.

An interesting extension of current commercial AC control systems is a feedback system that guides the user to achieve the desired comfort level while still being able to attain energy efficiency. Specifically for AC, such a feedback system should accurately predict the energy consumed as per the user's desired set temperature and inform her on possibilities of energy savings by increasing the set temperature by a few degrees. It is important for prediction to be accurate so that the user trusts the system. Thus for accurate prediction, the system should account for outside weather conditions together with the learned thermal model from the historical usage. Figure 1.3 presents AC energy consumption per hour at various set temperatures (25-29)°C used across all the ACs during our data collection. Ideally, energy consumption should increase with a decrease in the set temperature. However, as can be observed, it varies depending upon the thermal environment in the room, and external weather conditions. Thermal environment for a room in turn needs to account for quality of insulation, occupancy count and human activities being undertaken. Correspondingly, accurate prediction of AC energy consumption requires a



(a) 16°C set temperature with average external temperature at 28 °C.

(b) 28°C set temperatuer with average external temperature at 28 °C.

Figure 1.2: Temperature and power consumption for AC usages with different set temperature and external temperature. Higher set temperature results in significant savings with compressor being turned off for most of the time.

thermal model of the room environment, together with accounting for AC settings and external weather conditions.

In this work, we focus on real time feedback about AC usage in order to optimize the energy consumption. Commercial products for optimization of AC energy consumption, such as Nest[7], learn user settings over a period and subsequently control AC to reduce energy wastage. However, such a system lacks feedback to the user, about the impact of their current settings on the energy consumption, to potentially motivate change in behavior for setting up slightly higher set temperatures. As an illustration of possible energy savings with varying set point temperatures, Figure-1.2 presents room temperature and power consumption at different set points and external weather conditions as collected during real usages within different homes during our data collection. Figure-1.2a present the data with set point at 16°C whereby AC compressor remained ON all throughout the usage from 7:25 - 8:40 PM. However, when the set temperature was 28°C, it was quickly achieved in the desired room, and thereafter AC fans were enough to maintain the temperature, allowing the AC compressor to remain off. Overall, with set point at 28°C, a total of 20 units of electricity were saved over the duration of 10 hours of operation illustrated in Figure-1.2b.

Motivated from the energy saving opportunities, presented by the large number of room level ACs being used in India, we propose PACMAN, to forecast AC energy consumption based on its set temperature and weather forecast for the user's location. PACMAN estimates AC energy consumption without using any power measurements, by accounting for variation in room temperature during historical usage and the rated power consumption of the AC. Such temperature measurements can be easily obtained from a room level sensor or even with mobile

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[7] https://nest.com/

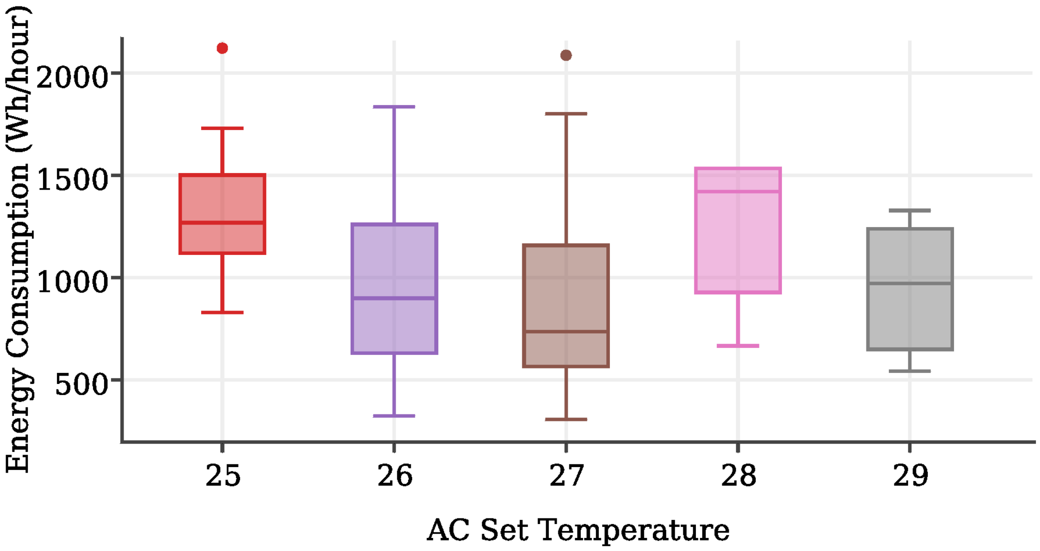

Figure 1.3: Per hour energy prediction at different AC set temperatures across all usages observed during our study.

phones that come with embedded temperature sensors (such as Samsung Galaxy S4[8] and Galaxy Note 3[9]). PACMAN provides access to the real-time room temperature (as communicated by the sensor), weather forecast for the user location and current external temperature (pulled from a weather website) and predicts energy consumption around the desired set temperature as a feedback to motivate the user towards optimally setting the AC temperature. PACMAN updates its model parameters based on each historical usage of the AC, thus providing improved performance with time. PACMAN is evaluated using real data (consisting of both room level temperature and AC power consumption) collected from 6 different ACs used across 9 rooms in 7 homes, for a total duration of 2200 hours.

Rest of this thesis is organised as follows. In Chapter-2, we provide an overview of related work. Chapter-5 exhibits a use case scenario of PACMAN to understand its role in energy conservation followed by PACMAN system and its components and concluded with the implementation details of PACMAN. Chapter-6 evaluates its performance using data from a real world study. In Chapter-7, we discuss various outliers, limitations and future directions for the PACMAN system. Finally, Chapter-8 provides details of prototype realization of PACMAN system, before we conclude in Chapter-9.

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[8] http://global.samsungtomorrow.com/?p=23610

[9] http://bit.ly/1qb5fsi

Chapter 2

Related Work

In this chapter, we present various approaches to provide disaggregated power consumption to the user. We also look into existing techniques to optimize energy consumption by HVAC and personal air conditioners.

Optimization of HVAC systems towards energy conservation has been well studied in the past. Much of this optimization work is done on central HVAC systems, optimizing their operations based on the occupancy and outside weather conditions. Previous studies [1, 8, 9, 14] have used passive infrared sensor (PIR) to detect occupancy and sleeping patterns within the area to control the HVAC systems. Agarwal et al. [2] observed PIR sensors to be inadequate for HVAC control due to error in detecting relatively stationary occupants. Besides direct occupancy monitoring using PIR sensors, indirect sensing techniques such as detecting changes in the concentration of CO_2 levels[1,2], and using logs of wireless access points [3] have also been used to detect occupancy for controlling the centralized HVAC system. However, this line of work does not involve the occupant in the loop for deciding the optimal AC settings. Participatory involvement of occupant to decide optimal AC operations is a core concept, embedded in the proposed PACMAN system.

For decentralized HVAC systems, more commonly used in residential settings, Scott et al. [20] proposed sensors based actuation while Rogers et al. [19] introduced a system to control heating based on calculated thermal comfort in real-time. An automated sensor based HVAC control could have false positives from sensors leading to energy wastage or false negatives leading to user discomfort [4]. Involving the occupant, to decide the optimal control, can further help to balance the user comfort and energy efficiency appropriately.

Several studies have shown the impact of providing the feedback to the users on the energy conservation. Detailed feedback of appliance level energy consumption was observed to result in 5-15% savings in energy consumption [7]. Such an appliance level feedback could be provided by directly monitoring and controlling the plug loads [21] or using a single meter at the mains level.

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[1] http://bit.ly/1mtS7An

[2] http://bit.ly/1rxFwhk

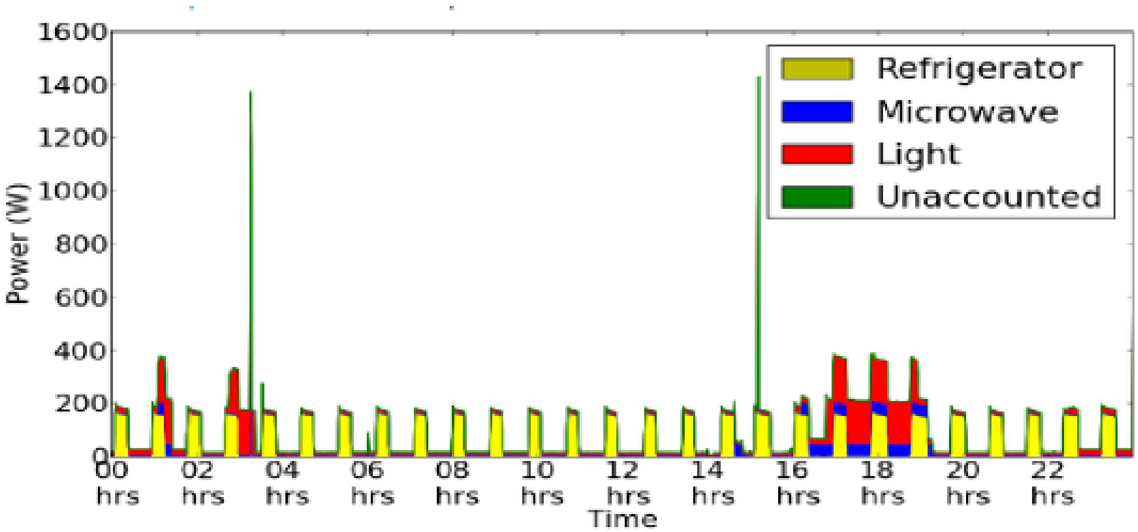

Figure 2.1: Illustration of Nonintrusive Load Monitoring[5]. Using NILM to disaggregate energy consumption by Refrigerator, Microwave and Light from total power consumption.

Main meter data is disaggregated into appliance level consumption[3,4] [11] using machine learning algorithms. Figure-2.1 shows an illustration of Nonintrusive load monitoring where authors developed a Non-Intrusive Load Monitoring Tool Kit [5] to detect refrigerator, microwave and light from aggregate power consumption of the house. PACMAN predicts energy consumption of AC without directly monitoring the energy usage. It leverages the temperature sensor from the room, and outside temperature extracted from a weather website, thus making the overall system both inexpensive and easier to maintain.

Recent work from Rogers et al. [18] is the closest to our work. They proposed MyJuolo system whereby a USB based temperature logger collected room temperature data that was used to learn a thermal model for the room, involving several parameters including leakage rate, heating rate and thermal noise within the room. However, their process requires significant user intervention and involves learning a static thermal model that may not provide accurate predictions with varying operating and weather conditions. In contrast, PACMAN requires minimal effort from the user and updates the learned model with each AC usage, thus optimally accounts for dynamic operating and weather conditions.

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[3] https://plotwatt.com/

[4] https://www.bidgely.com/

[5] https://github.com/nilmtk/nilmtk

Chapter 3

Research Contributions

In this section, we will discuss about novel contributions of our work in the context of existing literature on heating, ventilation and air conditioning(HVAC) systems. Major contributions of this work are:

1. We propose a feedback system PACMAN, Predicting AC Consumption Minimizing Aggregate eNergy Consumption, to forecast energy consumption by AC based on its set temperature, and weather forecast for user's location.
2. We present architecture and implementation details of the system, used to collect room temperature data. We also collected meter data and weather information used in evaluation of PACMAN's performance.
3. We analyse reasons for some of the outliers in prediction accuracy of PACMAN, caused primarily from imperfect applicability of the proposed thermal model, thus requiring inclusion of multiple thermodynamic properties to enrich the current model being learned.
4. Finally, we explain a prototype system realization using PACMAN to provide feedback to the user towards optimal usage of AC.

Chapter 4

Background

In this section, we discuss the thermodynamics involved during the interaction between room and AC. Then we look into the fundamental concept of air conditioner i.e. Vapor Compression Cycle, widely used method for air conditioning. Finally, we present working of an air conditioning unit and its various components.

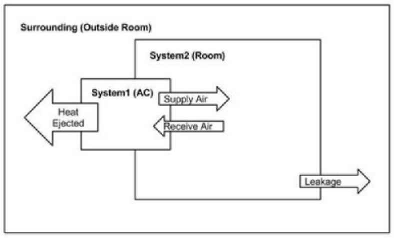
4.1 Thermodynamics of the Room

Li et. al. [13] proposed a model of the Air Conditioning and Refrigeration (AC&R) system used for temperature regulation in enclosed space. They considered room as a system interacting with another thermodynamic system i.e. AC&R. AC&R extracts room air, works (cooling) over it and supply back to the room at desired temperature.

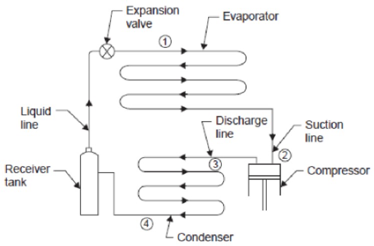
However, our thermal model considers room to be an open space interacting with vicinity around it. Figure 4.1a presents the thermal model for the heat exchange between room, air conditioner, and the surrounding. AC extracts room air at higher temperature, absorbs heat from the air and supplies it back to the room at user desired temperature. AC throws, heat extracted from the air to the vicinity outside the room. AC is a machine which takes room air at higher temperature and provides air to the room at desired temperature plus ejects heat outside the room. The rate at which air conditioner absorbs heat from room air is termed as *Cooling Rate*. Cooling Rate defines the performance of the AC, as lower the cooling rate more the time it will take to cool down the room.

When AC is on, room temperature goes down and to maintain thermal equilibrium between inside and outside room temperature, heat gets added in the room from outside. Source could be windows, walls, open doors, etc. The rate at which heat gets added in the room due to the structure of the building is termed as *Leakage Rate*. Higher leakage rate affects the thermal efficiency of AC as chillness added to the room, leaks to the surrounding environment. Better thermal insulation of the room helps in reducing leakage rate.

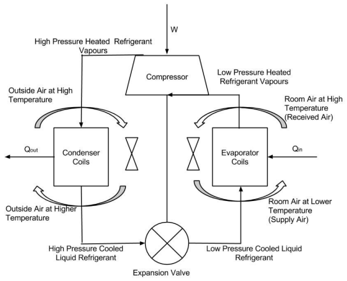
Heat transfers through conduction, convection and radiation. Thus, temperature varies because



(a) Thermodynamics of the Room



(b) Vapour Compression System [17]



(c) Schematic diagram of a Room Level Air Conditioner

of multiple sources, such as number of occupants, human activities, that radiate or absorb heat in the room. These sources are random in nature and varies with time. Variation in room temperature due to random thermal sources is termed as *Thermal Noise*. It creates interference in the working of AC and effect of thermal sources depend on their nature.

4.2 Room Level Air Conditioners

In this section, we discuss the working of a room level air conditioner and its various components. We start from vapor compression cycle, used in ACs.

4.2.1 Vapor Compression Cycles

AC leverages the concept of vapour compression refrigeration cycle which completes four fundamental mechanical processes; (1) Compression, (2) Condensation, (3) Expansion, and (4) Vapourisation. In this section we introduce important terms used in AC and major components in vapour compression system:

- **Referigerant:** Rajput et. al. [17] defined Refrigerant as *"Any substance that absorbs heat through expansion or vaporisation and loses it through condensation in a refrigeration system. These substances absorb heat at one place at low temperature level and reject the same at some other place having higher temperature and pressure. The rejection of heat takes place at the cost of some mechanical work."*
- **Compressor:** Its function is to remove refrigerant's vapours from evaporator and increase the temperature and pressure of refrigerants to a point such that its vapours can be condensed by the condensor.
- **Condensor:** It provides a medium to refrigerant vapours, to pass heat and liquify itself.
- **Expansion Valve:** It controls amount of refrigerant going to the evaporator and reduce pressure its pressure so that liquid will vapourize in the evaporator at the desired low temperature and take out sufficient amount of heat.

- **Evaporator:** It provides a heat exchange medium to transfer heat from room air to refrigerant vapours.

Figure-4.1b presents a vapour compression system. Refrigerant circulates in the system and switches it state from liquid to vapour, vapour to liquid back and forth. Following are the steps invloved in the cycle:

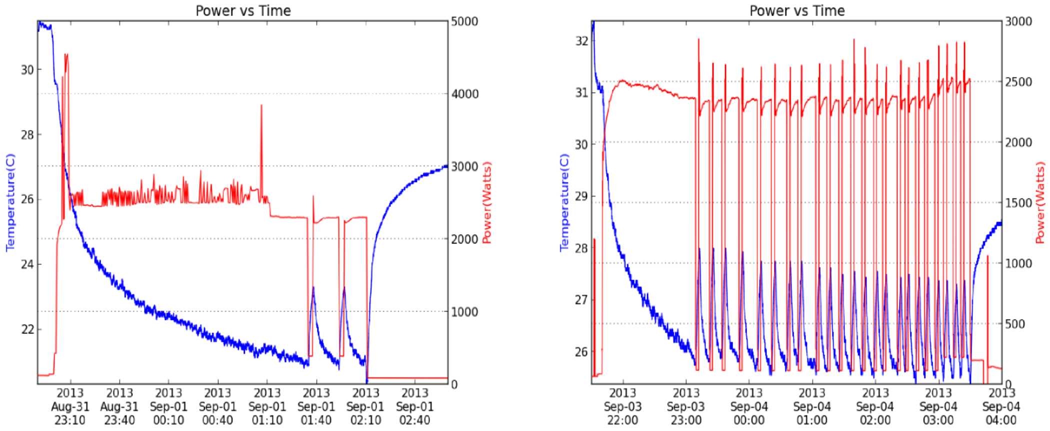
1. Low pressure refrigerant vapours enter the compressor, where it is compressed to increase its pressure.
2. High temperature and high pressure vapours enter the condensor where they are condensed to high pressure liquid referigerant and collected in a receiver tank.
3. From receiver tank, refrigerant vapours pass through expansion valve where they are throttled down to a low pressure and low temperature liquid referigerant.
4. Finally vapours are passed on to the evaporator where it extracts heat from the surrounding and changes to low pressure refrigerant vapours.

4.2.2 Working of Air Conditioner

In this section, we discuss working of a room level air conditioner and its various components. Figure 4.1c presents the schematic diagram of an air conditioning unit. Two fans are present for air circulation, one towards evaporator coils and other towards condenser coils. Fan towards evaporator coils draws air from the room and then it is passed over the evaporator coils containing low pressure low temperature liquid refrigerant. It absorbs heat from the room air and supplies cooler air to the room. Due to heat absorption, refrigerant liquid converts to high temperature refrigerant vapours. These vapours are passed to the compressor for increasing the pressure and temperature for condensation.

Fan towards condenser coils extracts air from the outside environment at high temperature. Extracted air is passed to condenser coils having high pressure and high temperature refrigerant vapours. Air absorbs heat from refrigerant and fan circulates it back to the outside environment at higher temperature thus converting refrigerant vapours to low temperature liquid refrigerant and passed to evaporator coils. Amount of refrigerant passing through evaporator coils is controlled by the expansion valve using the *Set Temperature* of the AC, which is the room temperature desired by the user. This cycle continues till the thermostat senses room temperature, close to the user desired temperature.

A single vapour compression cycle is termed as *Compressor Cycle*. Compressor consumes the maximum power consumption for AC. Power consumption by a compressor depends upon the set temperature. As we decrease the set temperature, volume of refrigerant vapours going into the compressor also increases thus increasing the compressor's power consumption. *AC Usage* is the time user switches on the AC unit, till she switches it off. A single AC usage may comprise of one or more compressor cycles.



(a) Set Point Temperature at 20°C

(b) Set Point Temperature at 26°C

Figure 4.2: Variation at different Set Point Temperature

According to Clausius statement, *"Heat can never pass from a colder to a warmer body without some other change, connected therewith, occurring at the same time"* [6]. Therefore, we need to do some work to extract heat out of the room to the surrounding. Air Conditioner does this job and work done results in energy consumption. Lower the temperature you set in air conditioner, more energy it would consume. Figure 4.2 shows variation in energy consumption based on set point temperature. During our study we found, some temperatures set points were infeasible according to that environment. Room was not able to attain that specific set point temperature because of which compressor remain turned on for whole duration air conditioner was on. This results in higher energy consumption by air conditioner. We will discuss in next section about the savings PACMAN can do by predicting energy consumption based on set temperature and provide updates on what minimum temperature could be achieved in specified time duration at this set point.

Chapter 5

PACMAN

In this chapter, we discuss the design, architecture and implementation details of PACMAN. First we provide an overview of PACMAN through a use case scenario followed by discussion about the architecture and work flow of PACMAN and conclude with the implementation details of PACMAN.

5.1 System Overview

Before getting into the details of PACMAN system, we discuss a use case that envisions it in a real-world setting. Figure 5.1 illustrates the usage scenario. Alice uses PACMAN web interface to input the temperature at which she desires to operate her AC. PACMAN pulls the predicted weather conditions, for the area surrounding Alice's residence, from a weather service. Weather forecast, together with the thermal model of Alice's room is used to predict the energy consumption around the desired AC set temperature.

Alice also has a temperature sensor in her room that is uploading temperature data to a server accessible by PACMAN. This server could be one of the many Internet of Things (IoT) services available today (such as Xively[1]) and the temperature sensor could be one of the many off the shelf available in the market (e.g. Maxim's 1-Wire DS18B20 temperature sensor[2]) or temperature sensor in Alice's smartphone (Samsung Galaxy S4[8], Galaxy Note 3[1]). As the AC is switched off, PACMAN pulls the observed room temperature from the server and outside weather conditions from the weather service, corresponding to the duration when AC was on, to update the thermal model of the room.

Real time room temperature together with current and predicted outside weather conditions are also shown by PACMAN to Alice for better user engagement. Besides the web interface, PACMAN also comes as a smartphone application for easy accessibility by Alice.

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[1] www.xively.com

[2] http://bit.ly/1fdT62x

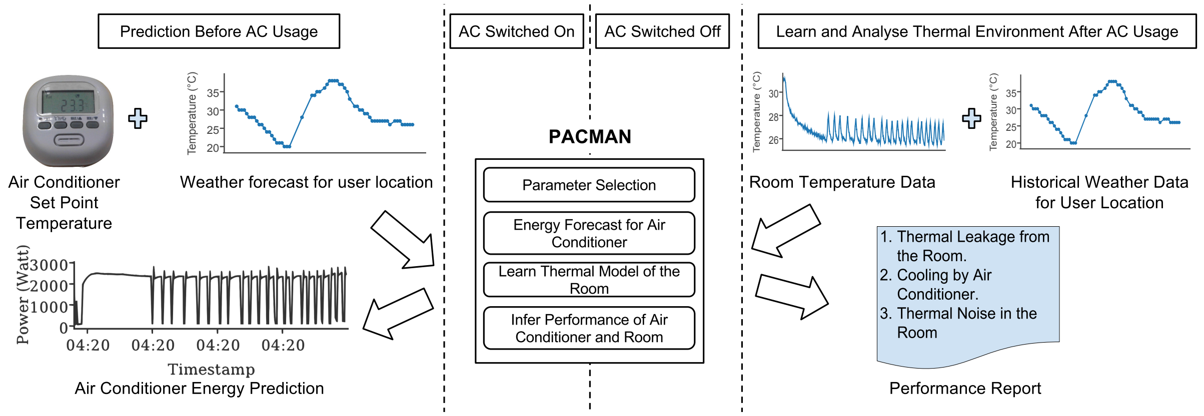

Figure 5.1: Use case of PACMAN: When the AC is switched ON, the set temperature and weather forecast is used with the learned model to predict the AC power consumption. When the AC is switched off, the room temperature data, collected during the past usage, and corresponding external temperature data is used to improve the learning process.

5.2 System Architecture

We designed PACMAN to forecast energy consumption of AC for the user at different set temperatures, inspiring them to be energy conscious. Figure 5.2 presents the architecture of PACMAN, illustrating its various components and interaction between them. Keeping in mind the modularity and extensibility of the system, PACMAN is divided into four major sub-systems;

1. *PACMAN-L* is a learning component that utilizes set temperature, room and outside temperature, during the AC usage, to learn the following thermal parameters for the room:
   (a) **Cooling Rate:** The rate at which AC removes heat from the room.
   (b) **Leakage Rate:** The rate at which heat gets added in the room because of its thermal insulation and structure. Structure includes various factors such as number of windows, area of the room and material used for the walls.
   (c) **Thermal Noise:** Room temperature could also vary due to factors such as occupancy, human activities in the room and heat generated by various appliances in the room. Thermal noise indicates the effect of these sources on the room temperature.
2. *PACMAN-P* is the prediction component providing energy consumption at different set temperatures. When the AC is switched on, PACMAN-P takes as input the set temperature, thermal parameters learned from previous usages and predicted outside weather to then forecast the energy consumption of AC for the current usage.
3. *PACMAN-UI* takes set temperature and user's location as input to generate energy forecast for AC along with the weather forecast information for that location. Further, it also displays room temperature and external temperature in real time. When user switches off the AC, PACMAN-UI also communicates energy consumption for that usage to the user.

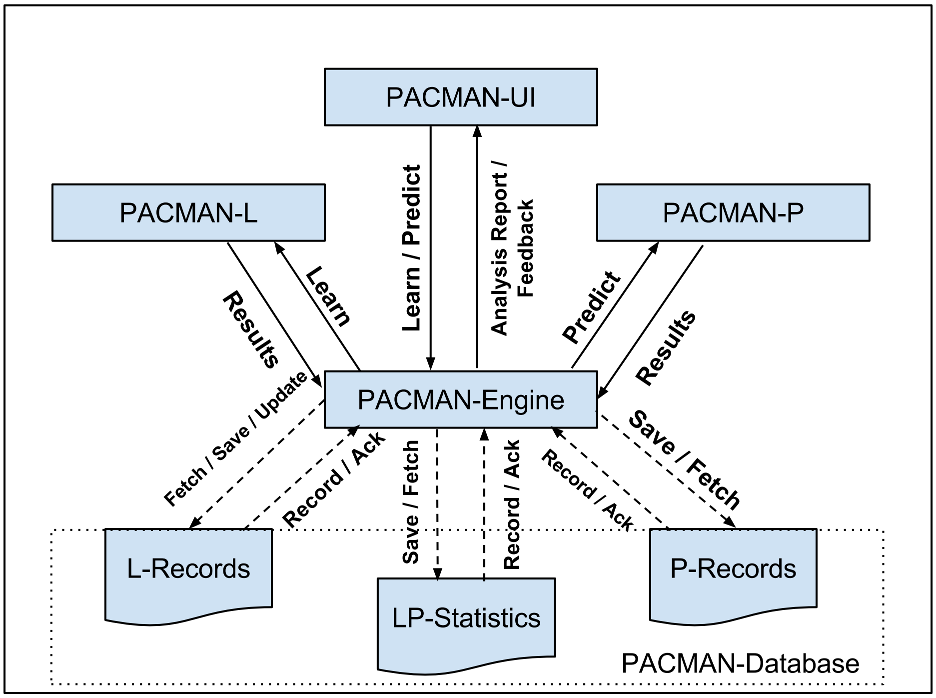

Figure 5.2: PACMAN System Architecture illustrating interaction of different sub-systems, within PACMAN system, with each other.

4. *PACMAN-Engine* is an administrative component that controls other components of PACMAN, as shown in Figure 5.2. It interacts with a weather service to get historical weather data to learn thermal model of the room, and weather forecast for prediction of energy consumption. It also interacts with the IoT server to get room temperature data.

PACMAN-Database manages various records that are used to cache statistics generated by all other components. Thermal parameters learned by PACMAN-L are accumulated in L-Records while P-Records manage prediction statistics such as energy forecast and thermal parameters applied for prediction. LP-Statistics stores analysis, related to accuracy metrics such as prediction error, to enhance the overall performance of PACMAN. PACMAN-Engine is the only system component with the authority to access and manipulate the database.

5.3 System Implementation

PACMAN is implemented in Python while utilizing several libraries supporting machine learning tools (e.g. Pandas and scikit-learn). We now discuss the implementation details for each component of PACMAN, as outlined in Section 5.2.

5.3.1 PACMAN-L

It is the learning component of PACMAN that takes set temperature, collected room temperature data and weather conditions during the AC usage, to learn different thermal parameters i.e. (1) Cooling Rate, (2) Leakage Rate, and (3) Thermal Noise. This component includes multiple modules as explained next.

Usage Parser

After switching off the AC, a usage matrix is generated constituting time annotated room, and outside temperature data measured at mismatched sampling rate. To time align the collected data, this module alters their sampling rate to 1Hz and interpolates the missing value using linear interpolation[3]. Thereafter, it segregates timestamp, room temperature and outside temperature vectors from the usage matrix. Finally, it estimates the duration of AC usage using the timestamp and room temperature vector.

Status Vector Generator

Usage parser module generates a room temperature vector which defines an AC usage, comprising of one or more compressor cycles. We assumed AC to be a two state machine; (1) Compressor On, and (2) Compressor Off. For every usage, this module generates a status vector which is an array of binary numbers (0,1) to present the compressor state at any moment during the AC usage. Status vector, using Equation-5.1, estimates energy consumption for an AC usage where, P_{rated} is the rated power consumption of AC as specified by the manufacturer.

$$E_{cons} = P_{rated} \times \sum \{[1, 1, 0, ...0, 0]\} \tag{5.1}$$

Power Temperature Correlation: We use temperature data to depict AC state at any instant. Figure 5.3 exhibits the correlation between the room temperature and AC power consumption. As the set temperature (27°C) is achieved in the room, the compressor is turned off resulting in an increase in the room temperature. When the room temperature goes beyond a threshold (this threshold varies for different AC), the compressor is again turned on, and the room temperature starts decreasing. Correspondingly, room temperature keeps fluctuating around the set temperature with minimum corresponding to compressor off instance and maximum corresponding to compressor on instance.

Compressor On & Off Temperature learner

AC thermostat temperature, resulting in switching on and off of AC compressor during a usage depends upon AC's control algorithm. However, room temperature, as observed at another

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[3] http://bit.ly/TJwM9j

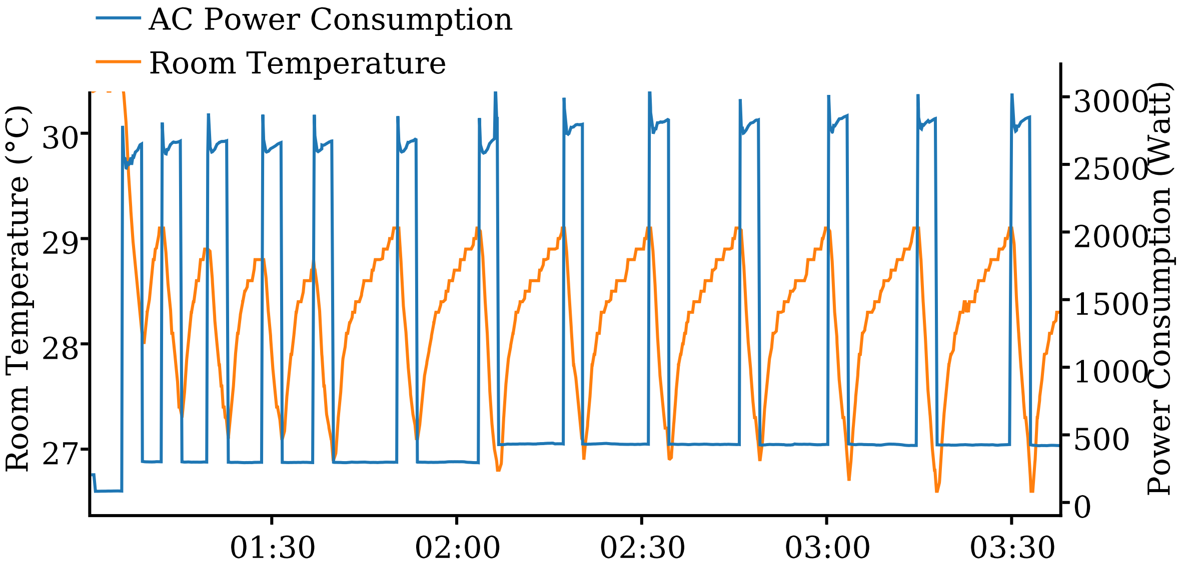

Figure 5.3: Variation of room temperature with AC compressor cycles (set temperature of AC being 27°C)

location in a room, depends upon numerous factors such as number of occupants, activity performed by the occupants, number of windows and doors in the room and material of walls. As a result, the temperature recorded by the sensor deployed away from the AC, corresponding to compressor on or off instance might differ from what the AC thermostat, on which the AC control cycle depends, might observe.

$$\delta^{on} = T_s - \sum_{i=0}^{n} \frac{T_{on}^{i}}{n} \qquad (5.2) \qquad\qquad \delta^{off} = T_s - \sum_{i=0}^{n} \frac{T_{off}^{i}}{n} \qquad (5.3)$$

To learn the correlation between temperature observed by the room sensor and the state of AC compressor, we use the temperature observed during the compressor on and off instances for each cycle from the room temperature vector. As threshold temperature value depends upon control algorithm of AC, δ^{on} i.e. the deviation of compressor on temperature from threshold temperature value and δ^{off} i.e. the deviation of compressor off temperature from the set temperature are modeled using AC set temperature as shown in Equation-5.2 and Equation-5.3 respectively. T_s is AC set temperature, n is the number of compressor cycles and T_{on}^{i}, T_{off}^{i} are compressor on and compressor off temperatures respectively for i_{th} compressor cycle.

Thermal Model

While the room temperature at any instant depends upon numerous factors, we explicitly considered the effect of AC cooling and external temperature for our thermal model. We treated

Algorithm 1: Algorithm to Predict AC Compressor Cycles

```
Input: $T_0$, $T_s$, $t_{duration}$, $\theta$
Output: $T_{Pred}$, $S_{Pred}$
$T_{Pred}^{(0)} = T_0$ ;
for $i = 0$ to $t_{duration}$ do
    $T_{pred}^{on} = T_s - \delta^{on}$ ;
    $T_{pred}^{off} = T_s - \delta^{off}$ ;
    $T_{Pred}^{(i+1)} - T_{Pred}^{(i)} = \alpha \times (T_{Pred}^{(i)} - T_{ext}^{(i)}) + \beta \times S^{(i)} + \epsilon$ ;
    if $T_{Pred}^{(i+1)} \leq T_{Pred}^{(i)}$ then
        if $T_{Pred}^{(i+1)} \geq T_{Pred}^{Off}$ then
            $S_{Pred}^{(i+1)} = 1$ ;
        else
            $S_{Pred}^{(i+1)} = 0$ ;
        end
    else
        if $T_{Pred}^{(i+1)} \leq T_{Pred}^{On}$ then
            $S_{Pred}^{(i+1)} = 0$ ;
        else
            $S_{Pred}^{(i+1)} = 1$ ;
        end
    end
end
```

all other factors as thermal noise in the room.

$$T_{int}^{(i+1)} - T_{int}^{(i)} = \alpha \times (T_{int}^{(i)} - T_{ext}^{(i)}) + \beta \times S^{(i)} + \epsilon \tag{5.4}$$

Equation-5.4 presents PACMAN's thermal model using status vector, room and outside temperature and thermal parameters of the model i.e. (1) Cooling Rate (β), (2) Leakage Rate (α), and (3) Thermal noise (ϵ). $T_{int}^{(i)}$ is the room temperature, $T_{ext}^{(i)}$ presents external temperature, and $S^{(i)}$ depicts AC state, at i_{th} second during the AC usage.

PACMAN generates a feature matrix from room temperature vector and external temperature vector generated by usage parser module. It then computes temperature gradient for every second using room temperature vector to generate output matrix. Thermal parameters corresponding to the usage are learned using linear regression over feature and output matrix.

5.3.2 PACMAN-P

The prediction component of PACMAN captures AC set temperature from the user, together with her location, to forecast AC energy consumption. Using the learned temperature deviations for compressor switching, as explained in Section 5.3.1, this segment predicts the compressor on and off temperature using Equation-5.5 and Equation-5.6 respectively.

$$T_{pred}^{on} = T_s - \delta^{on} \quad (5.5) \qquad T_{pred}^{off} = T_s - \delta^{off} \quad (5.6)$$

We present prediction algorithm (Algorithm-1) to predict status vector for AC, which estimates energy consumption of AC using Equation-5.1.

The algorithm uses optimal thermal parameters, θ (=$\{\alpha, \beta, \epsilon, \delta_{on}, \delta_{off}\}$), current room temperature (T_0), AC set temperature and weather forecast, to predict room temperature and status vectors for the entire usage ($t_{duration}$). $T_{pred}^{(i)}$ denotes predicted room temperature and $S_{pred}^{(i)}$ is the predicted compressor state at i_{th} second. T_{pred}^{0} denotes room temperature at the time AC was switched on. PACMAN-Engine selects optimal thermal parameters from L-Records using optimal parameter selection algorithm illustrated in Algorithm-2.

5.3.3 PACMAN-Engine

We now discuss the administrative component of PACMAN that manages the learning and the prediction sub-systems. It is the only component in the whole framework which is authorized to access the internal database of PACMAN and interact with external weather or temperature server. PACMAN-Engine uses a weather service for weather forecast, historical weather data and real time update of outside temperature.

Accuracy Model

In order to evaluate prediction, PACMAN-Engine provides a set of metrics. We now give a brief description of each metric implemented in PACMAN along with its mathematical definition.

1. *Prediction Error and Accuracy in Energy Consumption:* We evaluate PACMAN performance through prediction error (E_{pred}^{error}) and prediction accuracy (E_{pred}^{acc}) of AC energy consumption. Prediction error is defined as:

$$E_{pred}^{error} = \frac{E_{pred.} - E_{cons}}{E_{cons}} \times 100 \tag{5.7}$$

   while, prediction accuracy as:

$$E_{pred}^{acc} = 100 - |E_{pred}^{error}| \tag{5.8}$$

   where, E_{cons} is the energy consumed by AC and E_{pred} is the energy forecast for the same AC usage. PACMAN-Engine reports prediction error and accuracy to the user, in terms of percentage and stores them in LP-Statistics.

2. *Mean Absolute Deviation(MAD) of Temperature and Status Prediction:* Alignment of temperature and status prediction curve from the actual values is defined by Equation-5.9 and

5.10 respectively.

$$T_{pred}^{mad} = \frac{\sum_{i=0}^{n} |T_{pred}^{i} - T_{act}^{i}|}{n} \tag{5.9}$$

$$S_{pred}^{mad} = \frac{\sum_{i=0}^{n} |S_{pred}^{i} - S_{act}^{i}|}{n} \tag{5.10}$$

3. *True Positives, False Positives, False Negatives, True Negatives:* True positives are the number of time slices in which air conditioner's compressor was correctly classified as being on, false positives are number of slices classified as being on while it was off.

$$TruePositive(TP) = \sum_{t} AND(S_{pred}^{i} = 1, S_{act}^{i} = 1) \tag{5.11}$$

$$FalsePositive(FP) = \sum_{t} AND(S_{pred}^{i} = 1, S_{act}^{i} = 0) \tag{5.12}$$

$$TrueNegative(TN) = \sum_{t} AND(S_{pred}^{i} = 0, S_{act}^{i} = 0) \tag{5.13}$$

$$FalseNegative(FN) = \sum_{t} AND(S_{pred}^{i} = 0, S_{act}^{i} = 1) \tag{5.14}$$

   False negatives are the number of slices where it was classified as off while it was actually on and true negative are the number of slices when it predicted correctly as off.

4. *Precision, Recall:* Precision defines the fraction of number of time slices air conditioner's compressor was correctly predicted to be on to number of time slices compressor was predicted to be on. While recall is the fraction of number of time slices air conditioner's compressor was correctly predicted to be on to number of time slices compressor was actually on.

$$Precision = \frac{TP}{TP + FP} \tag{5.15}$$

$$Recall = \frac{TP}{TP + FN} \tag{5.16}$$

5. *F-Score:* The harmonic mean of precision and recall.

$$F - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5.17}$$

Thermal Parameter Selection

To forecast energy consumption of AC, prediction algorithm (Algorithm-1) need thermal parameters as one of the inputs. PACMAN-Engine stores thermal parameters learned from each AC usage, in L-Records of PACMAN-Database. L-Records, together with thermal parame-

Experimental Setup			**Air Conditioner Technical Specifications**			**Room Specifications**			
#ID	**#Days**	**Used Set Temperatures**	**Model**	**Tonnage**	**Rated Power (Watts)**	**Floor Area (sq.mt)**	**Window Width (meter)**	**Occupancy**	**Floor Ratio**
1	15	26, 27, 28	O-General AXZB18GNL-W	1.5	2180	20.06	2	1-2	2/2
2	9	26	O-General	1.5	2180	13.2	2	2-3	2/12
3	9	25, 26, 27, 29	O-General	1.5	2180	14.5	2	1-2	2/12
4	13	25, 26, 27	Hitachi RAU518HTD	1.5	1570	20.06	2	1-2	5/12
5	41	26, 27, 28	Haier HW-18L2H/2013	1.5	1950	20.06	2	1-2	5/12
6	9	25, 26, 27	Carrier Durakool GWRAC 018DR002	1.5	1950	13.2	2	3-4	6/12
7	12	26, 27, 28, 29	LG L-Crescent 1.5TR 5Star	1.5	1600	20.06	2	1-2	7/12
8	9	16, 18, 20, 26, 28, 29, 30	Hitachi RAV518HTD	1.5	1575	20.06	2	1-2	9/12
9	10	18, 26, 27	Voltas 4501468/2012 Platinum	2	1984	42.2	3.5	1-2	9/12

Table 5.1: Summary for each room from where data was collected. Second column represents number of days we collected the data, third column shows various set temperatures used during the study. AC technical specifications are as supplied by the manufacturer. Room specifications, that impact thermal modeling, includes occupancy denoting number of occupants for the room and floor ratio representing proportion of room's floor number to total floors in the building.

ters, contain one more column which is termed as score. After every prediction, we evaluate PACMAN performance based on accuracy in energy forecast. Based on the achieved accuracy, PACMAN-Engine updates the previous score of the row in L-Records using Equation-5.18.

$$score = score + \begin{cases} +2, & \text{if } 90 < E^{acc}_{pred} \leq 100 \\ +1, & \text{if } 80 < E^{acc}_{pred} \leq 90 \\ +0, & \text{if } 70 < E^{acc}_{pred} \leq 80 \\ -1, & \text{if } 50 < E^{acc}_{pred} \leq 70 \\ -2, & \text{if otherwise} \end{cases} \tag{5.18}$$

Score of a thermal parameter symbolizes its performance when used for energy forecast. With every newly learned usage, a score of zero is initialized to thermal parameters. Further, PACMAN-Engine uses Algorithm-2 to select optimal thermal parameters for AC energy prediction. The algorithm selects five top scores having the same phase and the same set temperature from the L-Records. Phase depicts whether current room temperature is less than or more than average external temperature forecast. A set of room temperature and external temperature, E_{cond}, presents thermal environment of the room. We then calculate euclidean distance (dist) between every record from the selected L-Records and current room and external temperature. Minimum. amongst the calculated euclidean distances, represents the closest thermal environment, from the historical usages, for the current AC usage. E^{prev}_{cond} is an array of a set $\{T_{int}, T_{ext}\}$ for each of the selected L-Records. E^{curr}_{cond} depicts current environmental condition and IEDist is an array having euclidean distance of each parameter from E^{curr}_{cond}.

Algorithm 2: Algorithm to Select Optimal Thermal Parameters

```
Input: pValue, $T_s$, $T_{ext}^{mean}$, $T_{int}^0$
Output: $\theta$
lrecords = select top five score from L-Record where phase = pValue and $T_{set} = T_s$ ;
$E_{cond}^{prev}$ = select $T_{int}^i$, $T_{ext}^{mean}$ from each record in lrecords;
$E_{cond}^{curr} = \{T_{int}^0, T_{ext}^{mean}\}$ ;
for $i$ in $E_{cond}^{prev}$ do
    dist = Euclidean distance{$E_{cond}^{prev}$[i], $E_{cond}^{curr}$};
    IEDist = IEDist.add(dist)
end
index = indexOfMin(IEDist);
$\theta$ = lrecords[index];
```

Record Update

PACMAN-Engine maintains a single database that comprises of three tables; (1) L-Records, (2) P-Records, and (3) LP-Statistics to cache intermediate information by various segments. We implemented PACMAN database in MySQL.

L-Records maintain information such as leakage rate (α), cooling rate (β), thermal noise (ϵ), compressor on temperature deviation (δ^{on}), compressor off temperature deviation (δ^{off}) learned for an AC usage. It also contains meta information such as AC usage duration, initial room temperature and score, for every AC usage. PACMAN-Engine interacts with L-Records to get thermal parameters for the prediction segment. Similarly, it makes an entry of learned thermal parameters in L-Records for every usage.

P-Records contain metadata information such as initial external temperature (T_{ext}^0), initial room temperature (T_{int}^0), AC set temperature (T_{set}) and a pointer to thermal parameters in L-Record that were used for energy forecast. Prediction segment returns a vector of predicted room temperature and compressor status using which PACMAN-Engine estimates energy forecast of AC and minimum achievable temperature to store them in P-Records.

LP-Statistics keep information related to prediction error and accuracy. PACMAN-Engine analyzes predicted and actual usage to generate statistics evaluating prediction performance of PACMAN. Finally, it updates these statistics and various parameters of accuracy metrics in LP-Statistics of PACMAN-Database.

Chapter 6

Evaluation

We conducted a real world study across nine different rooms in seven homes. The study was started in August, 2013 and persisted for approximately three months. During our data collection, we collected room temperature, power consumption and external temperature data. Data collection from each home was done in different time intervals across three months. Table-5.1 summarizes environment of the nine rooms, with their AC specifications, from which the data was collected.

6.0.4 Experimental Setup

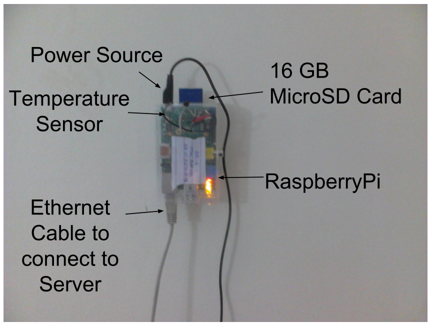

Figure 6.1: Installed Raspberry Pi for Data Collection

A temperature sensor from Maxim[1], with accuracy of 0.5°C, was interfaced with a single board computer[2] to record room temperature data at 1Hz. Figure 6.1 presents labeled diagram of a system used for data collection and uploading it to the server. Collected data was posted to a server over HTTP interface. For each home, we collected power consumption data from a modbus enabled electricity meter with a sampling rate of 1Hz. Each home had a three phase power supply with a clear understanding of which phase was supplying power to the AC that we were monitoring. Correspondingly, it was easy to extract the AC power consumption from the phase level power consumption monitored at the meter level using simple transient based methodology [11]. Figure 6.2a illustrates AC power extraction from phase level power consumption from one of the usage instance in one of the homes. External temperature was recorded using Wunderground API[3] that provided two readings of historical weather information for every hour and one read-

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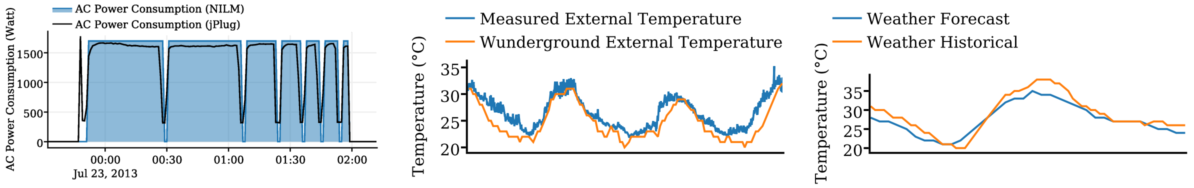
[1] http://bit.ly/1fdT62x

[2] http://www.raspberrypi.org/

[3] http://www.wunderground.com/



(a) AC power extraction from aggregate phase power measured at the meter level

(b) Comparison of recorded external temperature on campus and pulled from weather service

(c) Comparison of weather forecast and historical weather as extracted from weather service

Figure 6.2: Validation of different datasets used for the empirical evaluation of PACMAN.

ing of weather forecast every hour. During the course of study, we recorded average external temperature to be 28°C, with the minimum at 25°C and maximum at 33°C.

6.0.5 Data Validation

Datasets used as proxy, e.g. weather data from weather service as a proxy for external temperature, are validated for their accuracy before using them for evaluation purpose. Figure 6.2a validates power consumption extraction for an AC, using the meter data. During this experiment, AC power consumption was separately monitored using jPlug [10]. AC power consumption as extracted from meter data and as observed directly were observed to be similar.

To validate the accuracy of external temperature data as provided by weather service, we recorded external temperature from our own temperature sensor for a day. For the same duration, historical weather temperature was also extracted from the weather service. Figure 6.2b compares both the dataset confirming that the historical temperature provided by the weather service is close to the actual external temperature as observed by us. The mean absolute deviation[4] of 0.35°C was observed between the actual temperature and historical temperature from the weather service.

Since PACMAN takes weather forecast, from the weather service, for the prediction of AC energy consumption, the energy prediction accuracy directly depends on the accuracy of weather forecast. To validate the accuracy of forecasts provided by the website, we collected both the forecasted temperature and actual temperature for the duration of 34 hours, as shown in Figure 6.2c. Mean absolute deviation[4] of 0.83°C was observed between the forecasted and actual temperature, as reported by the weather service.

6.0.6 Analysis of AC Energy Prediction Accuracy

We now present the details of AC energy consumption prediction accuracy of PACMAN. We evaluate the prediction accuracy of PACMAN for each room (with different combination of room and AC specifications), each set temperature across different homes and ACs, and across

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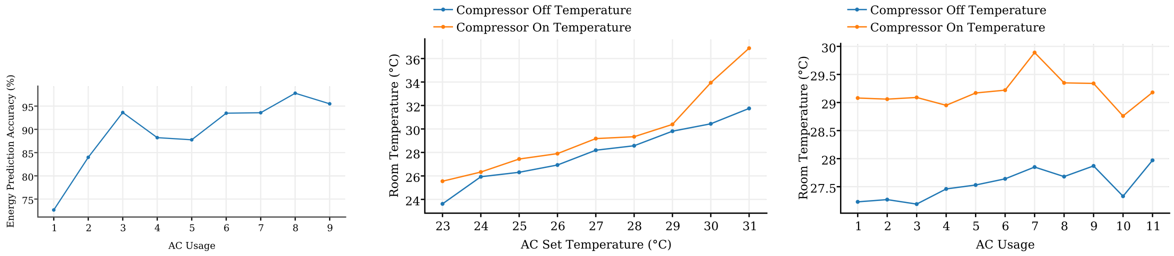
[4] http://bit.ly/TJzIm6



(a) Usage wise accuracy in energy prediction across all ACs at set temperature of 27°C.

(b) Average compressor on and off temperature for different AC set temperatures

(c) Variation in compressor on and off temperature at set temperature of 27°C across different usages for Room-1.

Figure 6.3: Variation in compressor on and off temperatures across different set temperatures and usages.

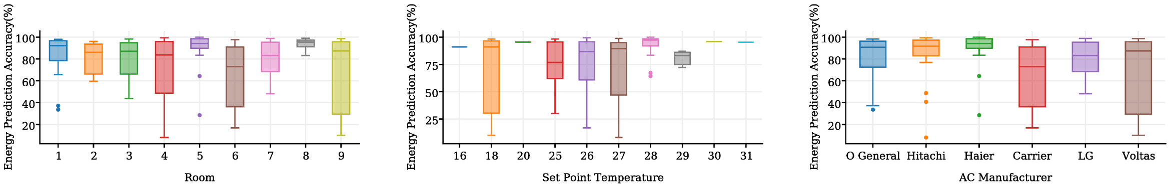
different AC manufacturers to understand the general applicability of PACMAN across diverse usages.

Room level comparison

Figure 6.4 presents box plot for room level prediction accuracy in energy forecast of AC usage across all the 9 rooms that were studied. Maximum prediction accuracy across all the rooms was observed to be more than 96%. Average prediction accuracy across all the rooms was observed to be at least 70% except for the two rooms, Room-6 and Room-9, that showed poor prediction accuracy for some of the usage instances. Overall prediction for Room-6 and Room-9 drops because the thermal noise for these rooms is not accurately accounted for in our thermal model. For example, Room-9 was a dining hall with a large open space resulting in significant thermal noise and interference, leading to poor prediction accuracy for several usage instances. It had minimum accuracy of 10% in AC energy consumption forecast.

AC Set Temperature Based Evaluation

During our experiment, users set AC at various set temperature, as shown in Column 3 of Table-5.1. Figure 6.4b summarizes accuracy in energy prediction of AC usage based on different set temperatures, for all the rooms. Across all the set temperatures, average and maximum prediction accuracy was observed to be at least 66% and 87% respectively. There were only a small number of usages at some of the set temperatures thus resulting in smaller variation in prediction accuracy for such temperature settings. Set temperature of 18°C was used only for Room-8 and Room-9. Since prediction accuracy for Room-8 was consistently very high (as can be observed in Figure 6.4), poor accuracy levels at 18°C can be attributed to poor thermal model learned for Room-9. Similar argument can also be extended for set temperatures of 18, 25, 26 and 27 °C as these set temperatures were used by Room-6 and Room-9, which gave poor room level accuracy. Taking away these two rooms, prediction accuracy for PACMAN was consistently observed to be more than 80% across all set temperatures.



(a) Comparison across different rooms

(b) Comparison across different set temperatures

(c) Comparison across different manufacturers

Figure 6.4: Comparison of AC Energy Prediction accuracy based on different influencing parameters - room (for thermal properties), set temperature (being directly used in the prediction model) and AC manufacturer (possibly leading to different control mechanisms).

AC Manufacturer Based Evaluation

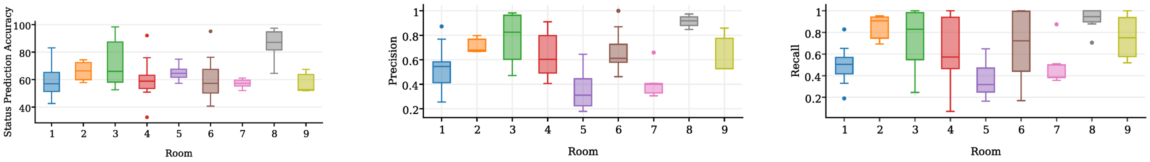
Figure 6.4c illustrates energy prediction accuracy based on variations in model of ACs used in our experimentation. Room-9 and Room-6 had Voltas and Carrier air conditioners respectively thus resulting in poor prediction accuracy for these manufacturers (mostly attributed to poor thermal model learned for the room). Leaving these two manufacturers, PACMAN performs reasonably well across different manufacturers with average and maximum prediction accuracy to be at least 80% and 97% respectively.

Performance Improvement with Usage

PACMAN scoring based best fit model selection, as explained in Algorithm-2, should ideally result in improved performance prediction with increasing number of usages. This was further validated from the collected data as well. Figure 6.3a shows the prediction accuracy for different usages at 27°C, when averaged across all the homes. If, for one of the homes, AC was used at 27°C only three times, it is counted in averaged data for the first three usages only. Maximum number of usages at 27°C across all the homes was 9. Improvement in prediction accuracy with increasing usages validates the adaptive nature of PACMAN approach, making it better than other static model based systems, proposed earlier [18].

Status Prediction Accuracy:

It denotes number of times status was predicted accurately. It is 100 minus mean absolute error in predicting compressor status at each second. Figure-6.5a presents apartment wise box plot of status prediction accuracy at each second. As compressor on and off temperature depends upon thermal conditions around temperature sensor in the room, it was diffcult to model is precisely. Therefore, status predition accuracy shows variations for each apartment. We will discuss about compressor on and off temperature modelling later in this section.



(a) Room wise accuracy in status prediction across all ACs.

(b) Room wise precision across all ACs.

(c) Room wise recall across all ACs.

Figure 6.5: Performance evaluation of PACMAN based on (a) Status prediction accuracy (b) Precision (c) Recall.

Precision and Recall:

Precision denotes number of times compressor status was predicted "On" accuractely out of total number of instances it was predicted to be "On". Figure-6.5b presents precision in predicting compressor "On" status for each apartment. Recall denotes number of predicted compressor "On" instances to the number of actual compressor "On" instances. Figure-6.5c shows recall in predicting compressor "On" status for each apartment. Due to low accuracy in predicting compressor on and off status, preditcted and actual internal room temperature were not time aligned thus reducing its accuracy, precision and recall. We will discuss about these challenges later in the thesis.

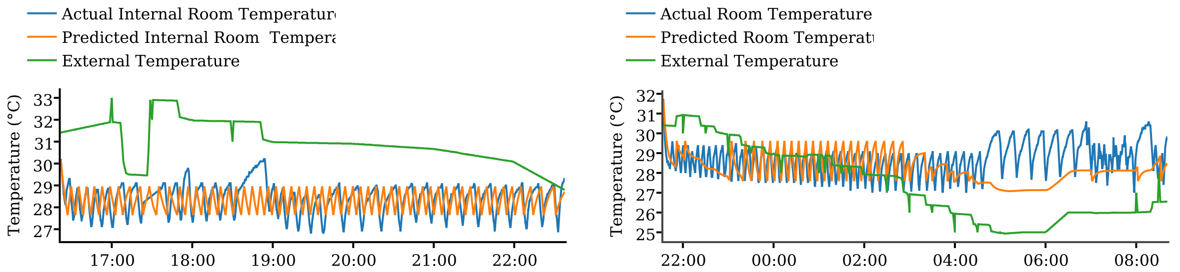
Chapter 7

Discussion

PACMAN is a feedback system for the prediction of energy consumption and is principally designed for room level ACs. It anticipates AC energy consumption followed by anatomization of AC usage to guide users towards energy conscious utilization of AC and its optimal settings. Prediction accuracy of PACMAN depends upon how well the thermal model can be learned which in turn depends upon parameter selection and proximity of chosen parameters from present thermal environment. We now analyse reasons for some of the outliers in prediction accuracy of PACMAN, caused primarily from imperfect applicability of the proposed thermal model, thus requiring inclusion of multiple thermodynamic properties to enrich the current model being learned.

As is clear from Equation-5.2 and Equation-5.3, prediction accuracy of AC energy consumption also depends on using correct compressor on and off temperature. These on/off temperatures may vary based on different manufacturers and the location where the room temperature is sensed for learning purposes. Currently, PACMAN predicts compressor on and off temperatures statically, before it initiates room temperature prediction. However, thermal noise in the room will impact the sensed room temperature and hence would result in varying compressor on/off temperatures for different usages, as was also observed in our data collection. Figure 6.3b presents average compressor on and off temperature, across all ACs, based on AC set temperature. It shows that difference between compressor on and off temperature varies from 0.4°C to 5.13°C depending upon the thermal environment in the room. Further, compressor off temperature, that should ideally be close to AC set temperature, differs from set temperature by 0.44°C to 1.93°C across different set temperatures. Figure 6.3c presents usage wise variation in compressor on and off temperature for Room-1 at set temperature of 27°C. Large variation in compressor on and off temperatures, for the same AC set temperature, motivates the need to further enrich the proposed model.

Thermal noise, introduced by some unaccounted factors in the room, distorts temperature cycles (resulting from compressor cycles) generated by the AC. Figure 7.1a presents an illustration of one such scenario observed during our data collection. During the time durations 17:23 - 17:39 and 18:31 - 18:52, temperature variation in the room deviates from the normal cyclic pattern



(a) Thermal noise distorting cyclic pattern in room temperature from 17:23 - 17:39 and 18:31 - 18:52

(b) Phase change as external temperature becomes lower than room temperature.

Figure 7.1: Illustration of outlier usages resulting in reduced AC energy prediction accuracy

observed during other times. This deviation from cyclic pattern could be attributed to the addition of some thermal noise (e.g. door/window being left open), thus making temperature prediction (hence energy consumption) inaccurate. In the scenario, where external temperature is lower than the AC set temperature, the compressor should ideally turn off. PACMAN prediction model, accounting for variation in external temperature, will also work as per this ideal scenario. However, if there are sources of additional thermal noise in the room, the compressor may still continue running, thus resulting in poor prediction accuracy. Figure 7.1b illustrates one such scenario observed during our data collection drive. Beyond 01:00 AM, external temperature dropped lower than room temperature and correspondingly PACMAN model predicted compressor to be off resulting in room temperature variation as per the thermal model. However, in reality, the compressor switching pattern continued (resulting in a cyclic pattern of room temperature). As a result, AC energy consumption prediction accuracy for this usage was reduced to 8%.

Variations in room temperature measurement depend upon numerous factors such as number of occupants, human activities, number of doors & windows together with whether they are open or closed and thermal appliances present in the room. However, annotating each factor would make the model overly complex along with making it cumbersome for the user to accurately report each of these parameters as and when they change. Therefore, while compromising on the accuracy in some of the usage instances, we simplified the thermal model requiring only set temperature to be reported by the user. Placement of temperature sensor in the room also impacts the prediction accuracy as its temperature measurement would depend upon thermal conditions surrounding the sensor. We deployed temperature sensor in some open space within the room while also accounting for aesthetics in the room to ensure its presence is not discomforting to the user.

Chapter 8

Realization of PACMAN

In this chapter, we explain realization of a prototype system using PACMAN for providing feedback to the user towards optimal usage of AC. Our prototype is based on a wireless protocol i.e. Z-Wave. Before looking into the architecture, we discuss, wireless technoogy Z-Wave followed by working system architecture to control Room AC based on Z-Wave. We then conclude this section with the implementation details of the proposed architecture.

8.1 Z-Wave Overview

Z-Wave is a low bandwidth half duplex wireless communication protocol which is designed for home automation. Z-Wave uses a low power wireless technology, designed to control remote applications. Z-Wave is primarily designed for low bandwidth communication and it works in a frequency range of around 900 MHz. Z-Wave was designed by Danish startup called ZenSys that was acquired by Sigma Designs in 2008. Z-Wave is a proprietary wireless protocol designed specifically for residential control. Figure-8.1b represents network stack for Z-Wave which consist of five layers. Each Z-Wave network may include up to 232 nodes and consist of controllers and slave devices. Nodes are capable of retransmit and forward messages allowing multipath network in an established network. Radio Specifications are as follows [1]:

- **Bandwidth:** 9,600 bit/s or 40 kbit/s, fully interoperable
- **Modulation:** GFSK
- **Range:** Approximately 100 feet (or 30 meters) assuming "open air" conditions, with reduced range indoors depending on building materials
- **Frequency band:** The ZWave Radio uses the 868.42 MHz SRD Band (Europe) the 900 MHz ISM band: 908.42 MHz (United States) 919.82 MHz (Hong Kong) 921.42 MHz (Australian/New Zealand).

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[1] http://www.z-wave.com/

Z-Wave creates a mesh network and nodes are part of that network. Majorly, there are only two type of nodes i.e. controller and slave nodes. Hierarchy for type of devices in a Z-Wave network is as follows:

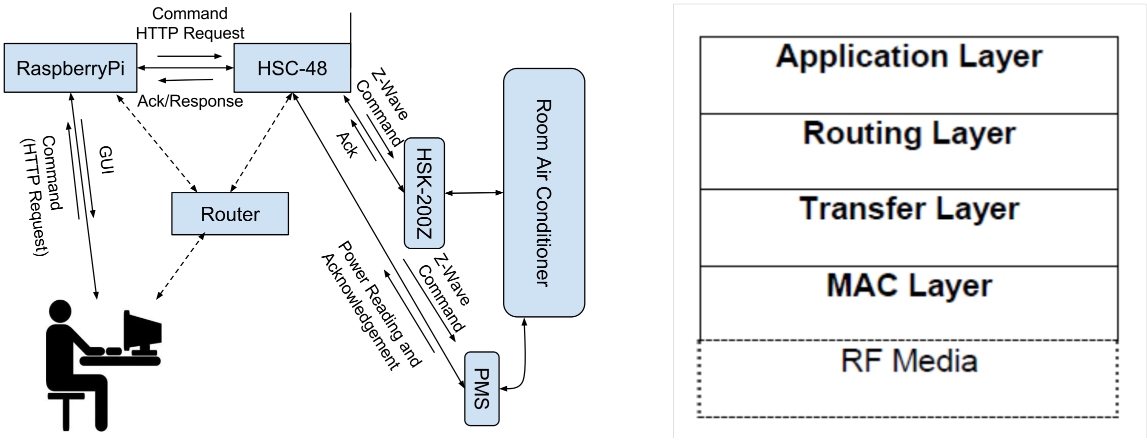
1. **Controller Nodes:** Controller Nodes are those Z-Wave devices that initiates communication between the devices. Commands are distributed in various command classes. Commands are sent over Z-Wave network to slave devices to perform some action or report about their current status. Controllers are of two types:
   - **Portable Controller:** As the name suggest, portable controllers are designed to change their position in the Z-Wave network. They are generally battery powered devices and mainly used in portable applications. Example: Remote Controller
   - **Static Controller:** Fixed controller that never changes its position. Z-Wave network is generally created by a static controller that are also known as primary controller.
   - **Static Update Controller(SUC):** Static controller receives notifications from the primary controller regarding all the changes taking place in the network's topology. It is capable of sending network topology updates to other controllers and routing slaves upon request.
2. **Slaves:** A Z-Wave device has very little information about the network and follow commands sent by the controller. These devices are not having any capability to include/exclude nodes to Z-Wave Network.
3. **Home ID & Node ID:** The Z-Wave protocol uses a unique identifier called Home ID to separate networks from each other. Home ID is a 32-bit unique identifier which is preprogrammed in all controller devices. Node IDs are used to address individual nodes in the network. It is an 8-bit value assigned to slave nodes by the controller.

8.2 System Architecture

In this section, we discuss architecture of proposed system and its implementation details. Figure 8.1a presents various components of the realized system together with the interaction amongst them and with the user.

8.2.1 System Components

Our architecture includes two Z-Wave sensors, one to measure power consumption of AC and other to control AC using the remote application (Ex. Web Interface, Mobile Application). Some of the system components involved in the architecture are:



(a) System architecture of Z-Wave based AC actuation and temperature monitoring system. User involvement is through a web server hosted by the single board computer.

(b) Z-Wave Stack

Figure 8.1: System Description

1. **Z-Wave Controller (HSC-48):** It is a Z-Wave[2] gateway manufactured by HomeScenario[3] that acts as a primary controller to create Z-Wave network. Within the system, it functions as an interface between WiFi and ZWave networks. It supports a maximum range of 30m indoor line of sight, sufficient for residential purpose.

2. **Z-Wave Based Sensors:**

   (a) **Power Monitor Switch:** It is a Z-Wave based power module for monitoring power consumption of AC and switching it on or off. It can work with a maximum load of 3000 Watts.

   (b) **HSK-200Z (IR Sensor):** HSK-200Z, manufactured by HomeScenario, is an IR sensor capable of emulating buttons of any IR based remote. It was used to provide user with a capability to control their AC remotely, besides allowing the system to automatically control the set temperatures.

8.2.2 System Implementation

A Single Board Computer (SBC) was used as a web server for hosting an application for user interface. The web server provided used with access to real time AC power consumption, room temperature and weather updates. Following is a sequence of communication between various components that result in the realization of PACMAN architecture using the prototype system:

1. SBC hosts an application for the user, which provides an interface, to input the desired set temperature for the AC and user's location, for weather forecast information. Using this

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[2] http://www.z-wave.com/

[3] http://www.homescenario.com/home/index.html

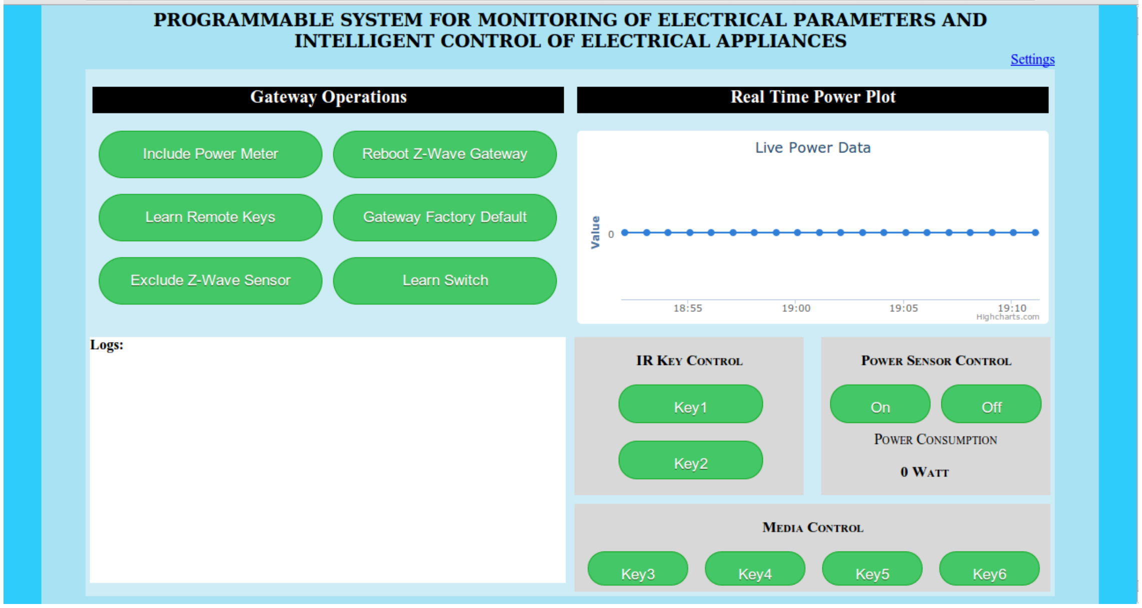

Figure 8.2: User Interface to monitor AC power consumption and control AC remotely

information together with PACMAN learned model from past usages, a predicted energy consumption at different set temperatures is displayed.

2. User can then select from any of the set temperatures and corresponding message is relayed to the AC using HSK-200Z. Message relay occurs via HSC48 that takes the command on WiFi and encodes it as a Z-Wave command before broadcasting it to the Z-Wave network, for the end node.

3. As the AC is switched on, power monitor starts reporting its power consumption to SBC via the HSC48 gateway. Accordingly, SBC provides real time power consumption together with real time updates of room temperature (as reported by the attached temperature sensor) and external temperature (as pulled from the weather service).

4. When AC is switched off (as reported by Power monitor or HSK-200Z), PACMAN uses the temperature data from the past usage to update its model for future usages.

Web interface from current realization can easily be extended for mobile phones as well.

8.2.3 User Interface

We also developed an user interface to interact with Z-Wave based system and remotely send commands to AC. Figure-8.2 presents screenshot of the user interface. Using this interface, user can configure Z-Wave sensors, AC remote keys according to his comfort level. Plot provides power consumption of AC in real time to the user. Power reading is reflected in the bottom left corner of the interface from where user may actuate AC also. Log section in bottom right corner of the interface is to display error messages and acknowledgments to the user.

Chapter 9

Conclusion

In this thesis, we present PACMAN system to forecast energy consumption for room level ACs. The proposed system includes participatory involvement of the users by providing predicted energy consumption at different AC set temperatures thus motivating the user to set optimally the AC temperature realizing both user comfort and energy efficiency. Extensive study, conducted across nine rooms in seven different homes, validated the high prediction accuracy for PACMAN system, across ACs with different manufacturers and with different set temperatures. A prototype system implementation is presented, illustrating the simplicity of the hardware system required for real world realization of PACMAN based AC control system. We outline different scenarios in which the proposed system fails to predict the energy consumption accurately for an AC usage, motivating the future work required towards enriching the thermal model proposed in this thesis based on which AC consumption is predicted.

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