Engineering and Analysis of System Support for Partitionable Resources

by

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I, hereby declare that the investigation presented in the thesis has been carried out by me. The work is original and has not been submitted earlier as a whole or in part for a degree/diploma at this or any other Institution/University.

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List of publications arising from the thesis

Journal

1. Gopinath Karmakar, Ashutosh Kabra, and Krithi Ramamritham, "Maintaining Thermal Comfort in buildings: feasibility, algorithms, implementation, evaluation", *Real-Time Systems, The International Journal of Time-Critical Computing Systems*, Volume 51, No. 5, pp. 485-525, 2015, Springer USA.

Chapters in books and lecture notes

1. S. Ghaisas, G. Karmakar, D. Shenai, S. Tirodkar and K. Ramamritham, "SParK: Safety Partition Kernel for Integrated Real-Time Systems", Book Chapter: *Lecture Notes in Computer Science (LNCS), 2010, Volume 6462, From Active Data Management to Event-Based Systems and More*, Pages 159-174, 2010, Springer-Verlag Berlin Heidelberg, Germany, 2010.

Conferences

1. Gopinath Karmakar, "Building Comfortability and Computation Schedulability: A Comparative Study", *In Proceedings of the IEEE PES Conference on Innovative Smart Grid Technologies (ISGT2015)*, February 2015, Washington DC, USA.

2. Gopinath Karmakar and Ashutosh Kabra, "Energy Aware Thermal Comfort-Band Maintenance Scheduling under Peak Power Constraint", *In Proceedings of the IEEE Recent Advances in Intelligent Computational Systems (RAICS 2013)*, pp 122-127, December, 2013, Trivandrum, India.

3. Gopinath Karmakar, Ashutosh Kabra, and Krithi Ramamritham, "Coordinated Scheduling of Thermostatically Controlled Real-Time Systems under Peak Power Constraint," *In Proceedings of the 19th IEEE Real-Time and Embedded Technology and Applications Symposium (RTAS 2013)*, pp 33-42, April 2013, Philadelphia, USA.

4. Gopinath Karmakar, Ashutosh Kabra, R K Patil and Krithi Ramamritham, "Partitioned Environment for Programmable Controller in Safety Applications", *In Proceedings of the 17th IEEE International Conference on Emerging Technologies & Factory Automation (ETFA 2012)*, 2012, Krakow, Poland.

Other

1. Gopinath Karmakar, "Scheduling of TCEDs under Peak Demand Constraint and Adaptive D-R Control", *In 10th Microsoft Research (MSR) India annual Symposium TechVista 2015 PhD Poster session*, January 2015, Bangaluru, India.

ओम अज्ञान तिमिरान्धस्य ज्ञानाञ्जन शलाकया।
चक्षुर्मिलितं येन तस्मै श्री गूरवे नमः ॥

"Om ajnana-timirandhasya jnananjana-salakaya

caksur-unmilitam yena tasmai sri-gurave Namah"

I offer my respectful obeisances to my Guru(s) who opened my eyes with the lighted torch of knowledge from the darkness of ignorance.

Dedicated to

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Abstract

Limiting peak-loads and reduction in energy consumption are two important considerations in the design of smart-home/smart-building control systems. A smoother load profile benefits both utilities and the consumers in terms of improved grid stability and quality of service (fewer occurrences of load-shedding, brownouts and blackouts). Building loads are dominated by thermostatically controlled electrical devices (TCE devices or TCEDs) such as air-conditioners (ACs) and heaters. In order to maintain the peak demand within limit, these loads must be scheduled to deliver the desired thermal comfort by maintaining the temperature of a given space or zone within a band acceptable by consumers. We refer to this desirable temperature band as *comfort band*. Reduced and flattened peak in power demand benefits the utilities by way of reduced investment in costly generating stations (oil/gas-fired and hydro) suitable for meeting peak power requirements. Utilities, therefore, penalize the consumers with very high electricity tariff for peak power consumption. Today, many commercial buildings are subjected to very high tariff under peak demand pricing. In the near future, residential buildings are also likely to be subjected to such electricity pricing schemes.

TCE devices like air-conditioners, refrigerators and room-heaters do not need human intervention for their continuous operation. As long as the desired thermal comfort is maintained, user will not be concerned about *when* they consume the energy required to perform their assigned functions. Under un-coordinated individual thermostat control, it is possible that all these TCEDs run simultaneously during some time intervals. This can result in higher peak power demand. Since TCE devices do not run continuously and follow a cyclic ON-OFF pattern, coordinated scheduling of TCEDs can reduce the peak demand.

The cyclic ON-OFF operation of TCEDs makes them suitable to be modeled as periodic

tasks. Here, within one duty-cycle, the time duration for which a TCE device remains ON is equated with the execution time requirement C_i within a period $P_i = (C_i + L_i)$ where, L_i is the time duration for which the device remains OFF. Once modeled as periodic tasks, as suggested by existing literature, it is logical to look into the real-time domain and apply existing policies to schedule TCEDs in order to maintain peak demand within limit.

Even though the algorithms from real-time domain appear to be suitable for scheduling TCEDs due to their periodic duty-cycle, we find that existing policies are not suitable for the coordinated control of TCED loads, as is. We have shown with example that there are major differences between a real-time (RT) task and a TCED modeled as periodic task, referred to as TCED task. A real-time task is considered schedulable if it receives C_i units of CPU-time within its period P_i irrespective of *when* it receives this C_i within P_i. But, in case of a TCED task, these parameters are dynamic. This is because execution of such device depend on the existing temperature of the zone controlled by them. Therefore, in order to maintain temperature of a zone controlled by a TCED, it is important *when* power is allocated to a TCED within its duty-cycle. Further, the loads must be managed taking into account important practical issues, especially, i) considering mandatory *restart-delay* in scheduling compressor-driven TCEDs, ii) avoiding undesirable switching (ON/OFF) of electrical appliances (to improve efficiency of the equipment and reduce failures), and iii) accounting for the effect of periodic scheduling decisions, taken in discrete time, on the maintenance of thermal-comfort. In view of this, we critically examine the similarities and the differences between real-time tasks and TCED activities before presenting our solution to address the above issues.

A task needs CPU to execute and a TCE device needs electrical power to run. Based on this analogy, we attempt mapping the problem of allocating electrical power (to TCE devices) to allocating CPU (to computational tasks). This is done in order to explore the possibility of adopting suitable policy from real-time domain to schedule allocation of power to TCEDs so that they maintain the desired temperatures of their respective zones under peak demand constraint. Our analysis first shows how the problem of scheduling m out of n TCE devices can be mapped to the problem of scheduling n tasks on m processors. Then we show the limitations of existing policies from real-time domain in scheduling TCEDs for maintaining the desired thermal comfort under peak demand constraint. We find that though there are similarities between them, dissimilarities are also many. For example, in real-time task scheduling there is no time restriction when a task can be restarted after it is preempted, i.e., there is no notion of restart delay. In this work, it has been shown that existing art of using the concept of task blocking time in handling restart delay constraint is not adequate. This restricts the applicability of traditional real-time policies in coordinated scheduling of TCEDs for maintaining peak demand within limit without compromising the thermal comfort.

We present a new Thermal Comfort-band Maintenance (TCBM) algorithm whose design is motivated by the above considerations. Based on our empirical study of the functioning of ACs, we developed a conceptual model of power consumption and maintenance of thermal comfort. From the insights gained from this study, a basic feasibility analysis technique is proposed for maintaining thermal comfort-band under peak power demand constraint. The feasibility analysis is then extended to consider the practical aspect of ensuring mandatory *restart delay* to make coordinated scheduling of TCE devices implementable in real-world application. Driven by the goal of maintaining the comfort-band with minimal number of switching of power between appliances, we presented the TCBM approach for selecting the subset of appliances to power at a given point in time.

In order to evaluate the performance of TCBM algorithm against the candidate scheduling algorithms from real-time domain, simulation studies as well as real-world implementation were carried out. The results from simulation and prototype implementation demonstrate that our algorithm is superior to the existing algorithms for scheduling building electrical load in terms of maintenance of thermal comfort and reduced number of undesirable switching.

The energy consumption of a TCED not only depends on how much change in zone temperature it brings, but also on the values of the initial temperature T_1 and the final temperature T_2. In other words, choice of comfort band has a role to play in the energy consumption of a TCED. We have shown that even for the same comfort-band width $(T_1 - T_2)$, the energy consumption varies for different combinations of T_1 and T_2. We analyze the effect of comfort-band variation in energy consumption. We develop a theoretical model and show how variation in comfort-band leads to energy-efficiency and propose an adaptive demand-response control by suitable adjustment of the comfort-band. Implementation in a prototype system shows that by means of shifting/adjustment of comfort-band even by a small variation of 0.5^0C can result in significant reduction in energy demand. Energy consumption of TCEDs is affected by change in ambient temperature because variation in ambient conditions cause change in the thermal characteristics of a TCED. Further, peak demand limit for a certain demand charge may not be the same throughout the day. Utilities offer/impose TOD (time-of-day) charge in order to influence the consumption pattern of consumers to strike balance between the power generating capacity and the demand with a goal to achieve a flattened peak demand. So, in order to reduce electricity bill, consumers may need to adapt to the time varying peak demand limit and/or may like to limit energy consumption during some period of the day due to time-of-day (TOD) charges. Therefore, we propose an adaptive demand response (D-R) technique in dynamic energy pricing/availability scenario. Our study shows that if users are informed, they can participate in demand response (D-R) control by means of shifting/adjusting the comfort-band in the event of i) varying ambient temperature, and ii) dynamic peak demand limit.

Parameters and Notations

Parameter	**Notation**
No. of TCE Devices	n
Power Requirement of $i^{th} AC$	W_i
Peak Power Demand Limit	W^P
Peak Processing Power of CPU	K^P
Temperature in i^{th} Zone	T_i
Ambient Temperature	T_a
Upper value of comfort-band	T^U
Lower value of comfort-band	T^L
Warming slope of i^{th} TCED	S_r^i
Cooling slope of i^{th} TCED	S_f^i
Time for T_i to reach T^L from T^U or the Execution Time of i^{th} AC modeled as RT task	C_i
Time for T_i to reach T^U from T^L or the Laxity of i^{th} AC modeled as RT task	L_i
Scheduling Decision Interval	I^S
Min. T_i to switch-ON a TCED	B^U
Preferred T_i to switch-OFF a TCED	B^L
Restart Delay	R^d

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Chapter 1

Introduction

Rapidly growing energy demand and the dependency on *dirty* (Fossil fuel) energy sources to meet the gross as well as peak demand have raised concerns over poor quality of service (occurrences of black-outs, brown-outs and load shedding), depletion of energy resources and its impact on the environment. Use of information and communication technology with power system engineering has a key role to play in mitigating these concerns and it motivated us to address a few of them as introduced in this chapter. We also formulate the research problem, discuss the background and related work followed by the major contributions of this thesis in this Chapter.

1.1 Motivation

Energy Challenges: Power utilities need to address a number of challenges, which include i) energy conservation, ii) optimal deployment of expensive resources, iii) diversification of generation and its integration with the grid, and iv) dynamic demand-response (D-R).

Further, about 20% of the generating capacities exists in a power grid to meet the peak demand, which is used only 5% of the time[1]. Therefore, flattening of peak demand is another important energy-challenge. In order to meet the peak demand, mainly quick-responding oil/gas fired generating sources and hydroelectric plants are brought in. This is because they can be started within minutes and ramped up and down quickly to meet spikes in demand or sudden changes in the loads. While oil/gas turbine sources are inefficient and costly, the hydro generating sources have their own impact on the environment in terms of submergence of land, impact on wild life and causing or aggravating flood situations. In order to achieve a flattened peak consumption profile, a suitable demand-response (D-R) program is required.

Smart Energy: We need to follow the path of *smart energy* to meet the energy challenges. Smart Energy suggests use of technology for reducing consumption [2][3], inclusion of renewable sources like solar and wind power[4][5], flattening of peak demand[6][7], energy storage[8] and use of information and communication technology with power system engineering[1][9] to reduce power outages and load-shedding.

Reduction in peak demand and overall energy consumption by means of efficient control of building loads is an active area of research. This is because i) peak energy consumption has an impact on upfront capital costs and hence on energy tariffs, ii) a smoother load profile improves grid stability and quality of service (less occurrences of blackouts, brownouts & load shedding), and iii) global contribution from buildings towards energy consumption, both residential and commercial, has steadily increased reaching figures between 20% to 40% in developed countries [10].

1.2 Our Focus: Demand-Response (D-R) Management under Peak Constraint

In developing countries like India, energy consumption in buildings is rapidly growing and the HVAC (Heating, Ventillation and Air-Conditioning) market in India is mainly characterized by the use of air-conditioners[11]. In urban India, according to a study conducted by Tata Power, air-conditioning in commercial and residential buildings together makes almost 40% of the electricity consumption in the utility's consumer base [12]. It may be noted here that in India, building air-conditioning is dominated by window/split air-conditioners. This is due to the initial investment cost involved in centralized HVAC system. Other than air-conditioners and room-heaters, the next significant fraction of home as well as large buildings' energy demand comes from refrigerators. All these equipments are thermostatically controlled electrical devices, which we refer to as *TCEDs or TCE devices*. These building loads can contribute towards increase in peak electricity

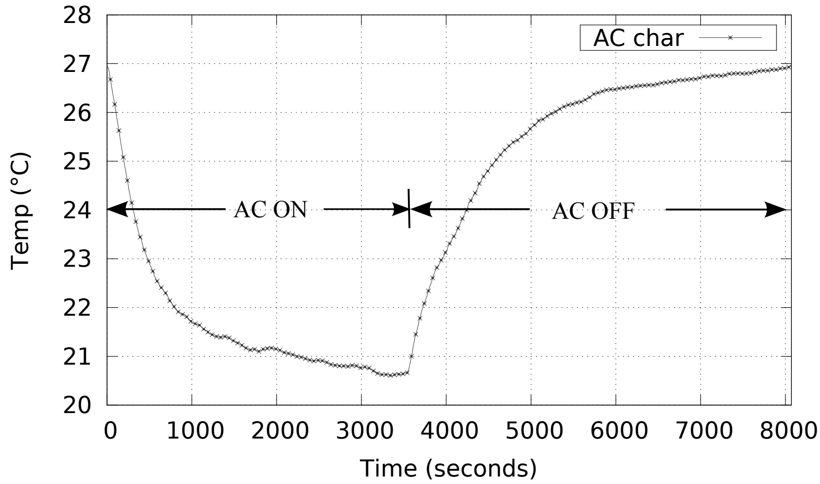


Figure 1.1: Experimentally Obtained Thermal Characteristics of an AC

demand during certain times of the day. For example, in summer evenings, when most of the office-goers reach home are likely to turn on the ACs causing increase in peak power demand.

The Figure 1.1 depicts the experimentally obtained operating characteristics of an AC, a representative TCED. It can be observed from Figure 1.1 that a TCE device does not run continuously, but follows a pattern of ON-OFF cycles. Since thermostat controlled electrical device do not run continuously, coordinated scheduling of these devices can reduce the peak demand subject to the condition that it does not compromise the thermal comfort requirement of the consumers. It may be noted here that a thermostatically controlled electrical device like AC, room-heater and refrigerator maintains the temperature of its zone within a band, usually within $\pm 1^0 C$ of the set temperature. We refer to this temperature-band as *comfort band* or *CB*.

Further, the thermal characteristics of a thermostat controlled device varies depending on the changes in the ambient temperature, heat loads and heat losses. Therefore, the energy consumption and efficiency of a device for maintaining a particular temperature is not static. It leaves a scope for looking into the possibility of energy saving by means of dynamically adjusting the operating regions (in terms of operating temperature-band) of these devices.

Efficient demand-side control of building loads for reduction in peak demand and energy consumption generated interest in researchers[13]. Consumers' participation in the demand-response (D-R) control has the potential for flattening peak demand and reducing energy consumptions. Utilities attempt to influence customers to participate in D-R control by levying financial penalties for consumptions beyond peak limit and offering time-of-day (TOD) charges i.e., different rates for energy consumption during different time slots of the day. This can also lead to varying peak demand limit in a day.

In this work, we focus on thermostatically controlled electrical devices in a building/home. Our primary aim is to formulate an efficient demand-side management policy in terms of when a TCED load needs to be scheduled. The cyclic ON-OFF operation as shown in Figure 1.1 makes TCE devices amenable to such demand management.

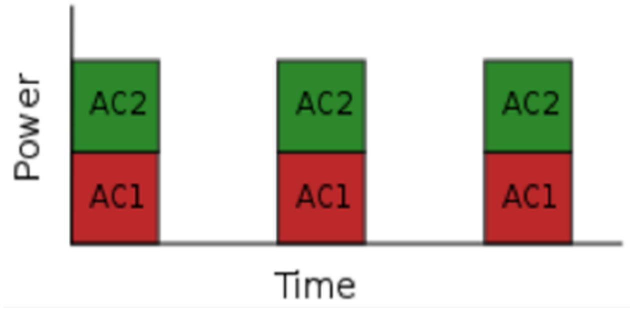
1.3 Problem Statement

In this section, we present three key aspects of the research problem addressed by this thesis viz., i) Coordinated scheduling of TCEDs and maintenance of peak demand within limits, ii) Analysis of existing policies and insights from the real-time domain in solving the problem of maintaining thermal comfort under a given peak demand constraint and iii) Consumers' participation in demand-response (D-R) under varying ambient conditions, time-of-day (TOD) charges and dynamic variation in peak demand limit.

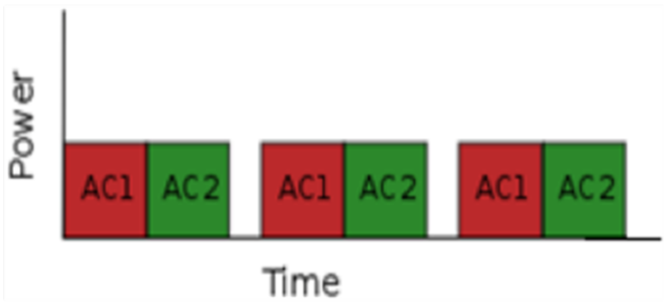
1.3.1 Peak Demand Constraint and TCED scheduling

Under un-coordinated individual thermostat control, it is possible that all the TCEDs in a building/home run simultaneously during some time intervals. This can result in higher peak power demand. Said differently, coordinated scheduling of TCEDs can reduce the peak demand.

Let us consider the case of an office room fitted with 2 ACs. The usual practice is to switch on both the ACs immediately after entering the room. Now, both the ACs work for some time, the temperature of the room comes down and then both the ACs go off. Subsequently, both the ACs start again, when the room temperature goes high and the process continues. It can be observed from Figure 1.2a that under un-coordinated operation of ACs, the peak power requirement is that due to two ACs. But, if the ON-time of the ACs are staggered, the peak power requirement can come down to 50%, as



(a) High peak demand due to un-coordinated Scheduling



(b) Reduced peak demand under Coordinated Scheduling

Figure 1.2: Peak Demand Reduction by Coordinated Scheduling

shown in Figure 1.2b. But, it must be ensured that the desirable thermal comfort of the consumer(s) is maintained while ACs are scheduled.

Reduced and flattened peak in power demand benefits the utilities by way of reduced investment in costly generating stations (oil/gas turbine and hydro) suitable for meeting peak power requirements. Utilities, therefore, penalize the consumers with very high electricity tariff for peak power consumption.

Today, many commercial buildings are subjected to very high tariff under peak demand pricing [14]. In India, Central Electricity Authority (CEA) initiated the process of introducing Time Of the Day (TOD) tariff[15] for large commercial consumers. The CEA has also suggested TOD tariff at the retail level for domestic consumers. Therefore, in the near future, residential buildings are also likely to be subjected to such electricity pricing scheme. Electricity-bills for industrial sites and other bulk consumers like academic institutions typically contain usage charge and demand charge. For example, electricity tariff structure by Mahavitaran (Maharashtra State Electricity Distribution

Company Ltd.)[16] for a bulk consumer like Indian Institute of Technology, Bombay, has both the components; *usage charge* and *demand charge*. Usage charge is proportional to the amount of energy consumed over a period, typically a month. Demand charge is related to *peak* demand (kVA), which is based on the average peak demand over an N minute interval (slot), typically 60 minutes, within the billing period M, typically 1 day. The demand charge is made prohibitively high so that i) it is commensurate with the high peak-power generation cost and ii) it acts as a deterrent so that consumers take initiative to limit their consumption within the contracted peak demand.

The need for flattening of peak demand and the possibility of achieving it by co-ordinated scheduling of TCEDs motivated us to find an answer to the following question.

- *What should be the appropriate scheduling policy to operate TCE devices so that peak demand limit is not exceeded without compromising thermal comfort?*

1.3.2 Are Algorithms from Real-Time (RT) Domain Applicable in Demand Management?

The cyclic ON-OFF operating nature of TCEDs makes them suitable to be modeled as periodic tasks. Therefore, literature on real-time task scheduling and management is a good source to get insights. The work on real-time scheduling is extensive and has been enriched by researchers over four decades since the seminal work by Liu and Layland[17] in 1973.

Not surprisingly, existing literature [18] [19] [6] [20] suggests modeling TCED loads as real-time tasks and applying traditional scheduling policies like EDF (Earliest Deadline First)[17] and LSF (Least Slack-time First)[21]. Here, within one duty-cycle, the time duration for which a device remains ON is equated with the execution time requirement C_i within a period $P_i = (C_i + L_i)$ where, L_i is the time duration for which the device remains OFF. But, we find that scheduling algorithms from the real-time domain are not suitable for scheduling TCED loads, because of the following features of these algorithms, which are not appropriate for most of the electrical appliances used in a home/building.

- A task is considered schedulable if it receives C_i unit of processor time (equivalent to power-ON time of an appliance) every P_i, the period of a task, irrespective of

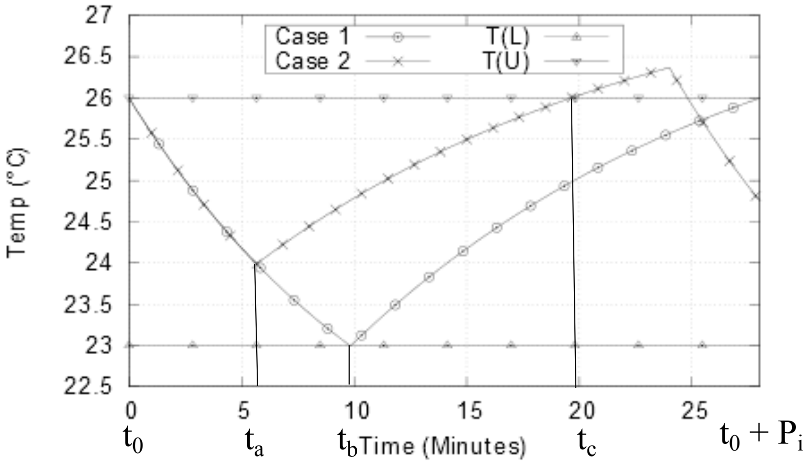


Figure 1.3: TCED Operation vs Real-Time Task Model

when it receives C_i within P_i.

- They do not account for environmental parameter feedback in taking scheduling decisions.

We now show that in order to schedule thermostatically controlled electrical devices, it is not just enough to allocate power for C_i units of time within P_i; it is also important *when* this C_i is allocated within P_i. It can be seen in Figure 1.3, that if the TCED task is executed (powered-ON) continuously for C_i units of time at the beginning of its period from t_0 to t_b, the environmental temperature T_i remains within the comfort band. But, if the task is preempted after its execution till t_a and is powered-ON for the remaining execution time just at the end of the period $[t_i, t_0 + P_i]$, T_i goes beyond the upper limit T^U of the comfort band $[T^L, T^U]$.

Thus, whereas traditional real-time scheduling algorithms consider the deadline D_i, maximum laxity L_i and duty cycle P_i as constants for a task, in the case of TCE devices these parameters are dynamic, because execution of such devices depend on the existing temperature of the very environment controlled by them. From Figure 1.3, it can also be observed that for the same TCED task, the duty cycle should change dynamically from P_i to $(t_c - t_0)$ when preempted at $t = t_a$. Also, the maximum Laxity L_i changes from $(t_0 + P_i - t_b)$ to $(t_c - t_a)$. Note that the duty-cycle of a TCED is related to the plant state variable (temperature). In case of real-time task there is no notion of duty-cycle, because real-time schedulability analysis deals with constant values of WCET (C_i) & P_i

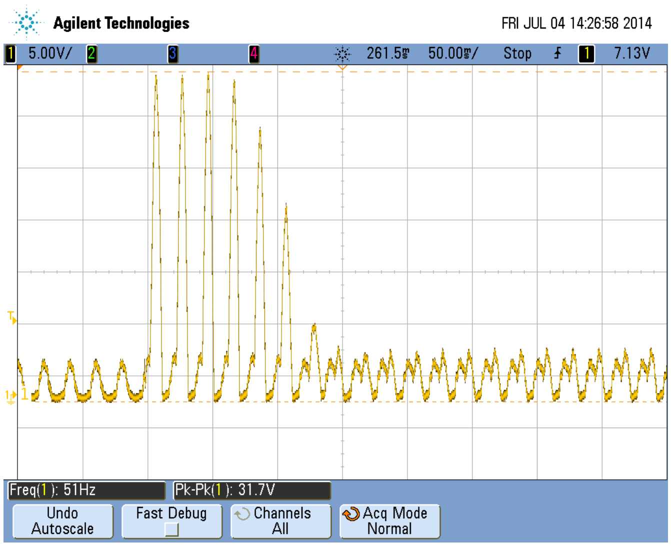


Figure 1.4: High starting current of AC on every switch-ON

and not concerned with plant state variable. Therefore, in case of TCED tasks these parameters are required to be calculated dynamically in order to apply any scheduling algorithm effectively. Further, zone temperature T must be taken into consideration while making preemption decisions. For example, so as not to violate the need for maintaining $T_i \leq T^U$ of AC A_i, another AC A_j, whose zone temperature T_j is $< T^U$ might have to be preempted to divert power to A_i. It calls for a environmental parameter (temperature here) feedback mechanism in real-time scheduling and feasibility analysis, which is absent in existing art.

Therefore, we conclude that real-time schedulability analysis is unsuitable in handling TCE devices, as is.

Furthermore, in order to make any algorithm for scheduling TCE devices useful in real-world applications, the following important practical requirements must be taken into consideration.

1. A delay of about 3 minutes is mandatory before a compressor driven TCE device can be switched on again once it is switched off. This delay allows the pressures in the system to equalize so that the compressor does not start under a load. If restart-delay is not provided, the compressor may not start due to an overload or it can even damage the equipment.

2. Minimum switching of TCE devices, except for resistive heat loads, is desirable

because of the following reasons.

- Switching-ON of inductive TCED loads (ACs, refrigerators, etc.) involves high starting current as shown in Figure 1.4, captured by oscilloscope. It causes additional energy consumption, and
- device failure is accelerated due to excessive switching.

3. Scheduling decisions take time and therefore introduce delays in a reactive system.

This led us to *critically study the similarities and differences between a TCED task and a real-time task* (discussed in Chapter 2) for further insights.

1.3.3 Peak Demand Constraint, QoS and Need for Adaptation

The objective of any TCE device A_i, is to maintain the temperature T_i of the zone Z_i under its control within a desirable thermal *comfort band* $[T^U, T^L]$. Under peak power constraint, not all devices may be able to run concurrently at any point of time. Therefore, under peak power demand constraint, we need to switch power between the devices intelligently, while ensuring that the desired temperature is maintained by each. Suppose W_i denotes the wattage of device A_i and W^P denotes the Peak Power Limit, then the devices that can be powered at any point of time will be governed by the following constraints:

$$\forall t, \sum_{i=1}^{n} x_i(t) \times W_i \leq W^P \tag{1.1}$$

$$T^L \leq T_i \leq T^U \tag{1.2}$$

Where, $\forall i$, $x_i(t) \in \{0, 1\}$. $x_i(t)$ represents the state (1 = ON and 0 = OFF) of the i^{th} device at time t.

While the desired temperature band of the environment provides thermal comfort to human beings or meets the environmental temperature requirement of equipment (controllers, servers etc.) or food items in case of refrigerator, a common term *comfort band* is used in the rest of this thesis.

Energy Consumption and comfort band

An important fact pertaining to the operation of any TCE device is that its *energy efficiency* depends on its operating temperature band. Here, we define the energy-efficiency of an AC as the time it remains ON for bringing down the zone temperature by 1^0C. It can be observed from Figure 1.1, for example, that the time required for the AC to bring down the temperature 24^0C to 23^0C is much less compared to the time required for bringing down the temperature from 23^0C to 22^0C. In other words, the AC will consume more power in bringing down the temperature from 23^0C to 22^0C than from 24^0C to 23^0C though, in both the cases temperature is brought down by 1^0C only. Therefore, judicious selection of the operating region of a TCE device can improve energy-efficiency.

The quality of service (QoS) requirements of consumers are related to i) maintenance of thermal comfort and ii) achieving the thermal comfort at minimum cost. As discussed (Section 1.3.3), change in thermal characteristic has an effect on the energy consumption. Therefore, it will also have an effect on schedulability of TCEDs under peak demand constraint.

Given a peak demand limit, any scheduling policy needs to meet the QoS requirement of consumers under the following conditions.

- Change in thermal characteristics of TCED due to change in ambient temperature, heat loads and losses, and
- dynamic variation in peak demand limit.

So, we need to find answers to the following questions.

- *What will be the effect of changed thermal characteristics on Schedulability of TCEDs?*
- *How one can maintain consumption within specified limits under dynamic peak demand constraint?*
- *What is the correlation between energy consumption and comfort band? What is the scope for adjustment in comfort band in real-world applications so that energy-efficiency is improved?*

1.4 Background and Related Work

In recent years, control of HVAC related building equipments has drawn considerable attention of the researchers. Two distinct trends can be observed in this area of research viz., i) Model Predictive Control (MPC)[22][23][24][25][26], a white box approach of thermal modeling of building and ii) reactive control based on thermal parameter feedback.

A comprehensive survey of the literature on the theory and application of MPC to HVAC control system is presented in [22]. MPC has an advantage of using a system model for anticipatory control actions over corrective control. But, reactive control has an advantage of simplicity and is adequate for residential and small commercial buildings [27][28]. In order to attain energy efficiency, control algorithms need to be tailored to the physical properties of the target building. Thermal model of a building is necessary to design an optimal controller to achieve balance between thermal comfort and energy consumption. A variety of MPC approaches can be found in the literature. Modeling and control of a centralized cooling system and an MPC scheme for minimizing energy consumption is presented in [29]. The authors proposed a non-linear model of the overall cooling system. In [30], the authors proposed an aggregation-based model reduction method for thermal models of large buildings. Using an electrical circuit analogy, they presented the building thermal model as an RC-network, with large number of coupled linear differential equations. The idea of modeling building thermal behavior is utilized in implementation of controllers in [3]. The authors demonstrated significant achievements in reducing total and peak energy consumption. MPC mainly uses the system model for anticipatory control rather than corrective control. But, it is a complex and computation intensive approach.

In order to provide electrical energy reliably and efficiently, flattening peak power demand, improvement in energy efficiency and optimum demand-supply matching are most important among the major goals of smart grid.

Research on flattening or reduction in peak demand spans over the gamut of work from minimizing peak demand through buffering of renewable resources [8] to the use of model predictive control in building HVAC system [3][31]. Our focus is on i) reactive control of thermostat controlled electrical devices viz., air-conditioners, refrigerators and room-heaters which consume about 30% to 50% of residential and commercial energy consumptions [10] and ii) improving energy efficiency under peak demand constraint. While MPC approach aims at minimizing peak demand, our analysis guarantees maintenance of thermal comfort under a given peak power limit.

Elasticity in terms of energy-demand by resistive heating components in common domestic loads viz., washing machine, tumble dryer, dishwasher, oven, water heater, space heater has been identified in [7]. It has been shown that peak demand can be reduced by allowing less power in the heating element for longer time in order to generate the same heating requirement. But, air-conditioner and refrigerator, which contribute most to the energy consumption in a home/building do not offer any significant elastic component in their operation.

Reduction in peak power demand using a global scheduler in home/building has been addressed in [32], [6] and [28]. Peak-power reduction by means of scheduling appliances using a combination of admission & curtailment control has been discussed in [32], but it does not discuss schedulability. The authors categorized home appliances into two types viz., i) *real-time*, which consume power as they desire, and ii) *schedulable*, which can be turned on at a later time. What they refer to as schedulable are in fact *deferrable* appliances like washing-machines and dishwashers. We show that TCEDs, which cyclically goes on and off are also schedulable without compromising thermal comfort. The authors assume that the home energy management controller (EMC) will use learning algorithms to obtain consumer's usage pattern. They propose that in order to reduce peak demand, power budgeting can be planned by the EMC based on the usage pattern. A comprehensive study on power usage in residential buildings has been discussed in [6] and Least Slack First (LSF) is proposed for background load scheduling. Lazy scheduling approach is proposed in [28] to control HVAC&R (heating, ventilation, air-conditioning & Refrigeration) devices, but it does not guarantee meeting the peak demand constraint in the event when more than m tasks (permitted under peak demand constraint) become critical. Furthermore, none of these work addresses the important practical issue of mandatory restart-delay, which must be considered in scheduling TCE devices.

Given a peak demand constraint, power is available only for m out of n TCE devices. Therefore, peak demand can be maintained if the TCE devices are scheduled so that at any point of time only m devices run without compromising the desired thermal comfort. The problem of scheduling m out of n TCEDs can be directly mapped to the problem of scheduling n tasks on m processors. So, we looked into the work in the area of multiprocessor task scheduling. Work [33] on multiprocessor task scheduling began about a decade back in 1994. A comprehensive review of research in this area can be found in [34]. We find that global EDF policy [35] and the gang-EDF policy [36] followed by it, appear to be highly suitable for scheduling TCEDs under peak power constraint. This is because, both these works deal with the problem of scheduling n tasks on m processors.

Most of the work related to building HVAC system control deals with the centralized air-conditioning system with zone temperature control by variable air volume (VAV) units. In [2] & [37] the authors discuss on-off control of VAV units of the individual zones of a large HVAC system by detecting occupancy. It offers energy saving mainly by means of switching off VAV units of the un-occupied zones. In [38], the authors demonstrated significant savings in energy by sensing occupancy and sleep pattern. The smart thermostat uses sensors to infer when occupants are away, active, or sleeping and turns the HVAC system off as much as possible without sacrificing occupant comfort. The authors proposed hybrid approach of pre-heating a home: Slow heating with high-efficiency equipment saves energy if occupants return home according to a predictable pattern. If they return earlier, low efficiency fast heating equipments are used so that thermal comfort requirement is not compromised. While these schemes offer significant reduction in energy consumption, our work shows that there is further scope for saving energy by means of judicious selection of operating regions of the TCEDs.

Demand-response (D-R) control is another important area of research in the field of smart building/home. Fairness in allocation of power to air conditioners is proposed in [39] against real-time pricing based on demand-response criteria when the demand exceeds the supply. The disadvantage of this scheme is that either i) some of the customers can obtain their requested cooling or, ii) all are proportionally unhappy based on their energy demand (calculated for requested temperature set point). The potential for DR from residential customers has been studied in [13]. It shows that DR can be achieved from house-hold customers through use of predictable price signal and using remote load control. We have shown that shifting/adjustment of comfort band by a small 0.5^0C

can result in significant reduction in energy demand. Our study shows that if users are informed, they can participate in DR control by means of shifting/adjusting the comfort band.

Predicted Mean Vote (PMV) [40] captures individual thermal preference adopted by ASHRE [41]. It provides 7-point numerical thermal comfort level derived from air temperature, mean background radiant temperature, air velocity, humidity, basic metabolic rate of a person and clothing insulation. Given these variables, it predicts the mean value of a group of people's votes in a 7-point ASHRE thermal sensation scale.

The 'thermovote' solution in [42] takes care of the individual preferences in addition to the possible errors in PMV estimation due to likely error in measurement of parameters like occupant's activity, perceived airflow and radiant heat for each space. We look at this work as complementary to ours where the desired comfort band (an input to TCBM algorithm) can be obtained using 'thermovote'. The PMV model is extended by [27] and the authors proposed Predicted Personal Vote (PPV) model to allow per-user personalization as against average comfort level in PMV model. PPV vote function has two components, PMV component and personal component. They suggest to reduce the overall building temperature to a value lower than normal in winter and to a value higher than normal in summer. Personal comfort can be provided by judicious control of the personal thermal controller (radiant heater in winter, fan in summer) based on the occupants preference. But, during summer, simply deploying a fan may not be enough to provide preferred thermal comfort of an individual and in winter, it is likely to call for a low capacity window/split AC, which may not be economical. Further, in developing countries, use of centralized HVAC system is not common in office/commercial buildings and educational institutions for their large initial investment cost. That is why our focus is on providing a low cost solution to thermal comfort using a simple technique like TCBM in controlling multiple ACs.

1.5 Main Contributions of the Thesis

Following our discussions so far, the main goal of this work is to limit power consumption within the peak demand limit by means of efficient control of thermostatically controlled electrical (TCE) loads (devices) in a building without compromising the thermal comfort of the users. In order to achieve this, we propose a centralized control of TCE devices as part a building power management system (BPMS). The BPMS will work under a given or mutually agreed peak demand limit. The job of a BPMS is to schedule the TCE devices in a coordinated manner so that the peak demand does not exceed the given limit while maintaining consumers' thermal comfort. The other goals are to i) develop a technique to cope with the changes in the ambient temperature, heat loads & losses, which affect the cooling/heating characteristics of the TCEDs maintaining temperature of their respective zones and ii) formulate a dynamically adaptive control scheme to keep power consumption within limit under a varying peak-demand constraint.

This main contributions of this work are summarized as follows.

- We discussed the cyclic operating characteristics of TCE devices and the possibility of reducing and maintaining peak demand by co-ordinated scheduling of these devices, in Chapter 1. The cyclic operation makes a TCED device suitable for modeling it as a real-time task. Therefore, we looked into the rich source of existing scheduling techniques from real-time domain.

  We refined the concepts of Laxity (L_i), Deadline (D_i) and Period (P_i) to make them cognizant of the environmental parameter (temperature T_i) controlled by a TCE device. This set the stage for adapting scheduling algorithms from the real-time literature for TCED scheduling.

  We presented our initial observations on some of the limitations of policies from real-time domain in scheduling TCEDs. We concluded that real-time scheduling policies are not suitable for TCEDs, as is. This lead us to critically examine the similarities and differences between real-time task and operation of TCED, which is discussed in Chapter 2.

- In order to gain insights, we studied the operation of AC as a representative TCE device and developed a conceptual model of it as a special class of real-time tasks. The model is corroborated by an empirical study of the thermal characteristics of ACs, which demonstrates that the temperature of the environment controlled by an AC rises exponentially, when the device is switched OFF and falls exponentially when it is switched ON. The insights gained from the theoretical analysis and subsequent empirical studies are presented in Chapter 3. The exponential nature of the characteristic equations underlies the design of the TCBM algorithm as well as the analysis of feasibility of maintaining the specified comfort band under peak demand constraint.

- We presented a new algorithm TCBM (Thermal Comfort Band Maintenance) in Chapter 4 for scheduling TCE devices. Design of the TCBM algorithm is driven by the goal of (i) maintaining the comfort band under peak power demand constraint and (ii) minimizing the number of instances switching of power between the TCEDs.

  Important practical requirement of mandatory *restart delay* in scheduling compressor-driven devices (ACs and refrigerators) is also taken into consideration in our design of TCBM.

  We also analyzed the feasibilty of powering a set of devices for maintaining thermal comfort band under peak power demand constraint using TCBM. With the help of this technique, it will be possible to determine, at the time a user sets the desired comfort band, whether comfort band can be maintained given a peak power constraint.

- In order to evaluate the performance of TCBM with candidate scheduling algorithms from real-time domain, a comparative study, involving simulation as well as prototype implementation is carried out (presented in Chapter 4). This study demonstrates the superior performance of our algorithm compared to approaches adapted from the literature.

- Scheduling of TCE devices need dynamic adaptation because, i) their thermal characteristics can change due to changes in the ambient conditions and ii) variations in heat loads and losses. Further, dynamic variation in the peak demand limit calls for an adaptive D-R mechanism if one has to maintain power consumption within specified limits.

  In order to develop technique for energy-efficient application of TCBM amenable to demand-response control of TCEDs, we studied energy-consumption by TCEDs and its dependency on the selection of comfort band, which is formulated in Chapter 6. Based on the results of this study, an adaptive demand-response technique is proposed to deal with changing ambient as well as varying peak demand constraint. The result of a real-world implementation demonstrates the potential for consumer's participation in D-R by shifting/adjusting comfort-band.

- One of the assumptions in our basic feasibility analysis was that the zones controlled TCEDs are thermally decoupled. But, in practice it may not always be true. So, we carried out experimental study on the applicability of TCBM in thermally coupled zones and established its suitability to coupled zones also. The results are presented in Chapter 6. Our study also demonstrates the robustness of TCBM under external disturbances like manual switching ON/OFF of TCEDs for a short duration.

- We focused on AC as a representative TCE device in our analysis as the same will be applicable to any other thermostatically controlled electrical devices like heaters and refrigerators. This is because, all these devices follow the same basic principles of heat transfer in their operations. Analysis of TCBM scheduling for heating loads is also carried out in Chapter 6 to substantiate this claim. Further, in a home/building there are TCEDs (e.g., ACs and refrigerators), which have different comfort-bands. Applicability of TCBM in coordinated scheduling of devices with different comfort-bands is also presented.

In this chapter, we presented the research problem addressed by this thesis along with the background and motivations behind it. We brought forward the research questions related to the building load (TCED) management for which we sought answers. The presentation of our work carried out mainly to find answers to those questions forms the rest of this thesis.

Chapter 2

Allocation of Computational Power versus Allocation of Electrical Power

A task needs processing power to execute and an electrical appliance needs electric power to run. A periodic task needs C_i units of CPU-time every period P_i for its execution to meet the deadline. We discussed in Chapter 1 that some electrical appliances, especially thermostatically controlled electrical devices (TCED), exhibit cyclic ON-OFF operation to maintain the required temperature of their respective zones, whose thermal environment they control. A TCE device remains ON for C_i units of time within its duty-cycle P_i. This similarity tempts us to model the operation of a TCE device as a periodic real-time task and apply existing policies in scheduling them so that the power requirement of these devices does not exceed the peak demand limit. In this chapter, we critically analyze the capabilities and the limitations of scheduling policies from the real-time domain to attain desired thermal comfort within designated spaces or zones, which we term as comfortability.

2.1 The Analogy

The processing power K of a CPU can be expressed as the number of instructions it can execute per unit time. Let K_i denote the processing power requirement of task T_i so that it completes its execution if CPU is allocated to it for C_i units of time. Let W_i denote the electric power required by a TCED A_i to run and it runs (receives power W_i) for C_i

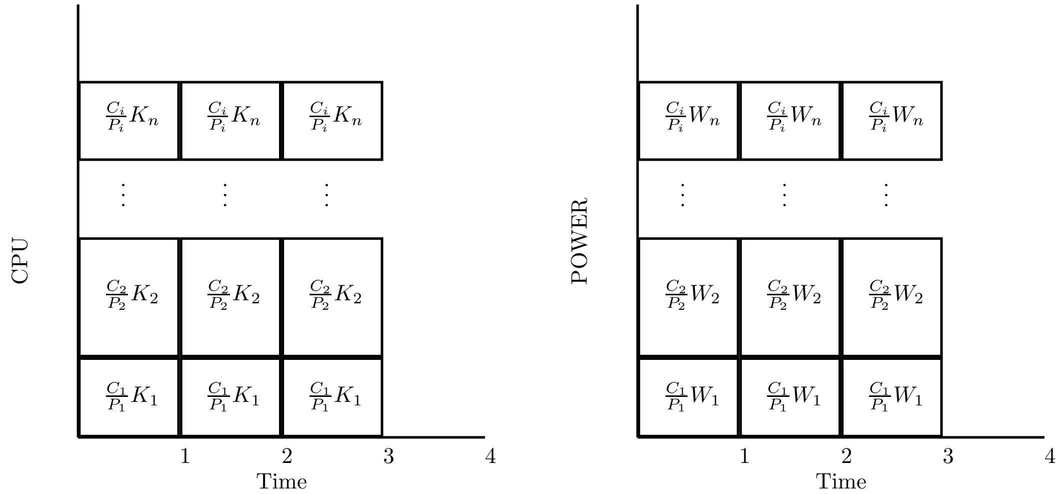


Figure 2.1: Peak Processing resource Vs Power Resource

time within its duty-cycle to maintain the temperature of its zone.

Now, a computational task needs C_i units of CPU-time every P_i. Therefore, the processing power requirement of a computational task per unit time is

$$\frac{C_i}{P_i} \times K_i \tag{2.1}$$

Similarly, the power requirement of a TCED task per unit time can be expressed as

$$\frac{C_i}{P_i} \times W_i \tag{2.2}$$

Under peak power demand constraint of W^P, it is required that at any point of time, the sum of electrical power drawn by the devices in a building/home is limited to W^P. In other words, peak demand constraint will not be violated if the following condition is satisfied.

$$\sum_{i=1}^{n} \frac{C_i}{P_i} \times W_i \leq W^P \tag{2.3}$$

In practice, an electrical equipment can not run with any arbitrary fraction of its rated power. Assume peak demand constraint allows power only to m out of n TCEDs at a time. Therefore, in order not to violate peak demand limit, we need to power $m \leq n$ devices at any time t so that the following condition is satisfied.

$$\forall t \quad \sum_{i=1}^{n} x_i(t) \times \frac{C_i}{P_i} \times W_i \leq \sum_{i=1}^{m} W_i \tag{2.4}$$

where, i) $\forall i,\ x_i(t) \in \{0, 1\}$ and $x_i(t)$ represents the state (1 = ON and 0 = OFF) of the i^{th} equipment at time t, and ii) sum on the right side is obtained from the first m equipments arranged according to the descending order of their power requirement.

Therefore, Equation 2.3 is a generalization of the Equation 1.1, which defines the peak demand power constraint.

Similarly, if the peak processing power of CPU/CPUs is limited by K^P, then at any point of time only a fraction of n tasks can be executed so that the following condition is satisfied.

$$\sum_{i=1}^{n} \frac{C_i}{P_i} \times K_i \leq K^P \tag{2.5}$$

The analogy between the availability of peak electric power to a set of appliances and the peak processing resource available to a set of computational task is depicted in Figure 2.1.

From Figure 2.1, it can be observed that power as a resource can be partitioned to feed electrical appliances with cyclic operating profile in a manner similar to partitioning processor as a resource to periodic tasks.

In practice, a processor can execute only one task at any point of time. In other words, not more than one task can be executed by a single processor at the same instant, even if they individually need only a fraction of processing capacity per unit time. Lets assume that there are n tasks and the number of available processors is $m(< n)$. In this case, only m tasks can run at a time. Now, if n tasks are to be scheduled using m processors, the necessary condition is

$$\forall t \ \sum_{i=1}^{n} y_i(t) \times \frac{C_i}{P_i} \times K_i \leq \sum_{j=1}^{m} K_j \tag{2.6}$$

where, i) $\forall i,\ y_i(t) \in \{0, 1\}$ and $y_i(t)$ represents the state (1 = EXECUTING and 0 = NON-EXECUTING) of the i^{th} task at time t and ii) j is chosen such that K_j is one of the m out of n tasks with highest processing requirement.

Equations 2.4 and 2.6 establish that allocation of power available for m out of n TCE devices under a given peak demand constraint is analogous to allocating time of m available processors to n computational tasks at any time-instant.

Research in the area of multiprocessor task scheduling is rich [34] with initial work [33] about a decade back in 1994. We find that global EDF policy [35] and the gang-EDF policy [36] followed by it, appear to be highly suitable for scheduling TCEDs under peak power constraint. This is because, both these works deal with the problem of scheduling n tasks on m processors and it can be directly mapped to the problem of scheduling of m out of n TCEDs. We will use global EDF as a representative scheduling policy from real-time domain in our subsequent discussions in this chapter.

For simplicity of exposition, in the rest of our discussion in this chapter, we will assume a simpler case where power requirement all the TCEDs are same and equal to W. For such a system, the Equation 2.4 can be reduced to

$$\forall t \quad \sum_{i=1}^{n} x_i(t) \times \frac{C_i}{P_i} \leq m \tag{2.7}$$

where, $x_i(t) \in \{0, 1\}$.

Likewise, if we consider an uniform multiprocessor system, the necessary condition for scheduling n tasks on m processors can be derived from Equation 2.6 as follows.

$$\forall t \quad \sum_{i=1}^{n} y_i(t) \times \frac{C_i}{P_i} \leq m \tag{2.8}$$

where, $y_i(t) \in \{0, 1\}$.

It can be observed that Equations 2.7 and 2.8 are exactly the same. Therefore, it is logical to consider global EDF [35] policy (which deals with uniform multiprocessor scheduling) for coordinated scheduling of TCEDs under peak demand constraint.

However, as discussed in Chapter 1, one of the major differences between a computational task and a TCED task is that in case of a computational task, preemption has no effect on its execution time or period. But, in case of a TCED task, its execution time C_i and the period P_i are dynamic and depends on *when* it is preempted. In Chapter 1, we also established how preemption without considering the feedback of environmental parameter (temperature) can affect thermal comfort. Therefore, we analyze the ability of scheduling policies from the real-time domain to attain desired thermal comfort in the zones (controlled by single or group of devices) by means of coordinated scheduling of TCEDs. This provides the background and rationale for our new algorithm Thermal

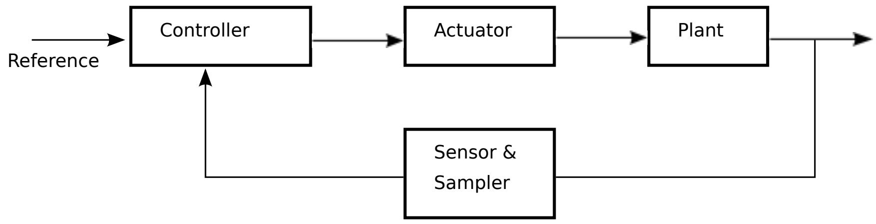


Figure 2.2: Traditional Control Loop

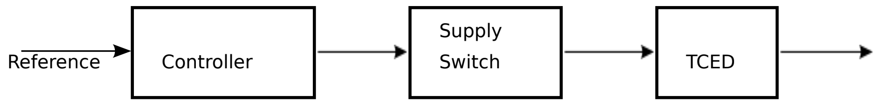


Figure 2.3: TCED (When modeled as periodic task) Control Loop

Comfort-Band Maintenance (TCBM) for scheduling TCEDs presented in Chapter 4.

2.2 The Differences

In this section, we identify and explain with example, the key differences between real-time task scheduling and the power allocation to TCEDs. We take the example of a system of n AC units maintaining the temperature of n thermally de-coupled zones. We assume that a centralized controller replaces individual thermostat controllers of the ACs and maintains temperatures of the the n zones within the desired comfort band (CB).

First, let us re-visit the functioning of a typical feedback controller. As shown in Figure 2.2, the main components of a feedback control loop are i) sensor & sampler, ii) controller and iii) actuator. The sensor output, which provides the plant state variable (temperature T_i in our case) is sampled at a particular frequency. The controller either i) polls the sampler periodically or ii) gets an interrupt when the sample is ready. After receiving the state variable, the controller starts computation (e.g., execution of control logic/interlocks or processing of some special control technique say, Kalman Filter) and sends output to the actuator. The job of the controller is to complete the computation within a given time after it receives the sample, so that the plant state variable does not deviate from its set point to an unacceptable value within that period. After appropriate control analysis, the value of the real-time task period P_i is chosen from the suitable sample frequency. So far as the computation time is concerned, the design requirements of a controller are as follows.

- The controller shall complete the execution of computation task on or before the next sampling time, which defines the deadline $D_i(\leq P_i)$.

- The controller shall schedule the computation tasks in such a way that each task completes execution before its deadline.

TCE devices, a special class of cyber physical electrical systems modeled as real-time tasks, are different from the traditional controller tasks we discussed. This is because a TCED task actually models the plant, which is AC in our case. Note that the time an AC takes to bring down the temperature from T^U (upper limit of the comfort-band) to T^L (lower limit of the comfort-band) becomes its execution time C_i and the time for the zone temperature to rise from T^L to T^U, when the AC is off, becomes its laxity L_i.

In order to differentiate between the two, we refer to the traditional controller task as *computational task* and the other ones as *TCED tasks*. The two fundamental differences between a computational task and a TCED task are as follows.

- When a computational task executes, the plant state variable does not change. To be precise, control requirement demands that the computation task execution time should be short enough not to cause any significant change in the plant state variable. In contrast, when a TCED task executes, it keeps on changing the state variable.

- The worst case execution time (WCET) of a computation task is time invariant, i.e., the CPU-time requirement of a computational task has no dependency on *when* CPU is given to it, within its period. In contrast, a TCED task does not bring uniform change in state variable per unit time of its execution due to the exponential nature of its thermal characteristics. Therefore, the energy-requirement of a TCED varies based on *when*[1] power is given to it, within its duty-cycle. It also makes the execution time C_i and period P_i dynamic as discussed in Chapter 1.

[1]Here, *when* refers to the then zone temperature, whose current value determines the rate of heat transfer

Table 2.1: Computational Task versus TCED tasks

	Computational task	TCED task
Resource	CPU	Power
Unit of Resource	Number of instructions a CPU can execute in one time-unit	Watt
Execution time C_i	Task computation time	ON-time
Period P_i	minimum inter-arrival time (suitable sample frequency)	Duty-Cycle
Preemption criterion	Priority based on deadline/period (sampling frequency)	Priority based on zone temperature T_i
Decision maker	Computational task scheduler	TCED task scheduler
Decision-making variable	Plant state variable	Time
Peak power demand	Peak power is not a concern in making scheduling decision	Peak demand limit is the reason for scheduling TCED

How the exponential thermal characteristics and the dynamic C_i and P_i of a TCED task affects comfort-band is discussed in Section 2.3.3. Table 2.1 summarizes the similarities and the differences between real-time *computational tasks* and TCED tasks.

We observe that the modeling of electrical devices as real-time tasks, in effect, attempts to do away with the sensor-sampler feedback in the control loop. The controller simply needs to keep track of the ON-time and period of the TCEDs as shown in Figure 2.3. Note that the controller needs no feedback as the ON-OFF commands to TCEDs are sent by itself and therefore, it can keep track of the execution time of TCED tasks. The logic behind it is that once the periodic operation of a TCED within a particular comfort-band $[T^L, T^U]$ is modeled as a real-time task, it is expected that there is no need for temperature feedback, so long as the feasibility analysis guarantees execution of every

TCED task within its deadline and they are scheduled according to the applicable policy.

It may be noted here that if the zone temperatures are not maintained simply by scheduling TCED tasks, then we will need a master controller on top of the TCED task scheduler. The master controller may take feedback of the plant state variable and modify the TCED task parameters like priority and worst-case execution time dynamically. By doing so, it should be possible to maintain the desired zone temperature by scheduling the TCED tasks according to the adopted policy from the real-time domain. But, it calls for an analysis on how environmental parameter feedback can be accounted for in schedulability analysis.

2.3 Real-Time Policies and TCED Scheduling

The idea behind modeling TCE devices as real-time tasks originated from the need for reduction in peak demand[43] by applying real-time scheduling policies in controlling them. But, traditional controller in a control loop is not concerned with the electrical power requirement of plant equipment like air-conditioner as mentioned in Table 2.1. Its only concern is to maintain zone temperature within the desired comfort-band $[T^L, T^U]$. So, we focus mainly on the schedulability of TCED task in the context of peak demand constraint.

In this section, we discuss how and why real-time scheduling policies can fail in scheduling TCE devices for maintaining comfortability in building. We find that restart-delay requirement of TCED as well as maintenance of comfort-band of the zones may not be guaranteed by traditional real-time scheduling techniques.

2.3.1 System Model

We consider a system of n ACs installed in a building. But, peak power demand constraint allows only m out of n ACs to run at a time. ACs can be considered as a representative TCED, because all these devices work under the same basic principle of heat-transfer [44]. So, analysis carried out on AC system will also be valid for heating and refrigeration system.

2.3.2 Restart Delay Constraint

Restart delay is an important requirement in scheduling TCE devices like air-conditioners and refrigerators. A delay of about 3 minutes is mandatory before a compressor driven TCE device can be switched on again once it is switched off. This delay allows the pressures in the system to equalize so that the compressor does not start under a load. If restart-delay is not provided, the compressor may not start due to an overload or it can even damage the equipment. But in traditional real-time scheduling policies there is no notion of restart-delay. Once a task is preempted, it can be restarted the moment it receives CPU-time.

Multiprocessor Task Scheduling and Restart Delay

Here, with the help of an example we discuss the analogy between computational task scheduling and coordinated scheduling of TCE devices. Further, we show how real-time task scheduling can violate the requirement of mandatory restart-delay.

Coordinated scheduling of n TCEDs with available power for m TCEDs is analogous to scheduling n tasks on m processors, as discussed in Section 2.1. For simplicity of exposition, we assume here that power requirement of each TCE device of the given is same. Therefore, for TCE devices of equal wattage, application of global EDF [35] scheduling comes as a natural choice as it deals with schedulability of n tasks on m uniform processors. We divide the available power into m logical power sources and schedule the allocation of power to n TCE devices. With the help of a simple example, we now compare multiprocessor task scheduling with scheduling of power-allocation to TCEDs. We take a system of two real-time tasks $\tau_1(7,5)$ and $\tau_2(4,3)$, which are scheduled on two processor as shown in Figure 2.4a. It may be noted that a task is represented here as $\tau_i(P_i, C_i)$, where C_i is the execution time and P_i is its period. $D_1(7,5)$ and $D_2(4,3)$ are two TCE devices, where D_1 runs for 5 units of time and D_2 runs for 3 units of time within their respective duty-cycle of 7 and 4 units of time. We assume that power required to run both these devices is available. We logically divide the power requirement of D_1 and D_2 into two separate power sources. It can be observed from Figure 2.4b that scheduling of $D_1(7,5)$ and $D_2(4,3)$ on two separate logical power sources is exactly similar

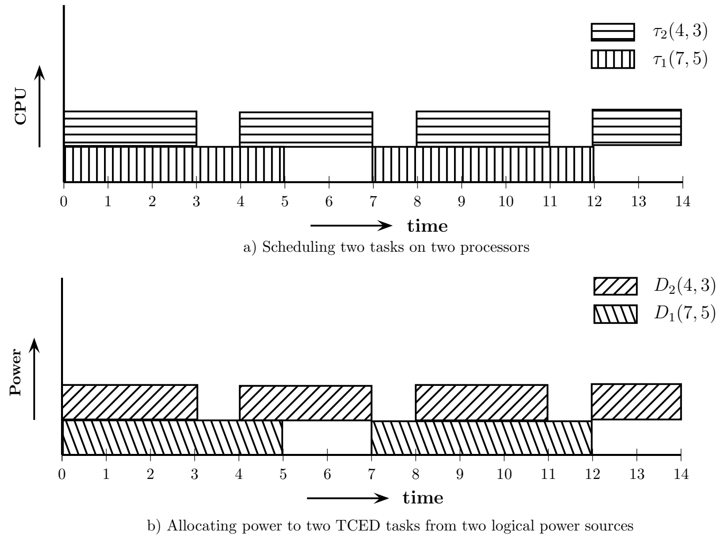


Figure 2.4: Computational Task Scheduling vs TCED Scheduling

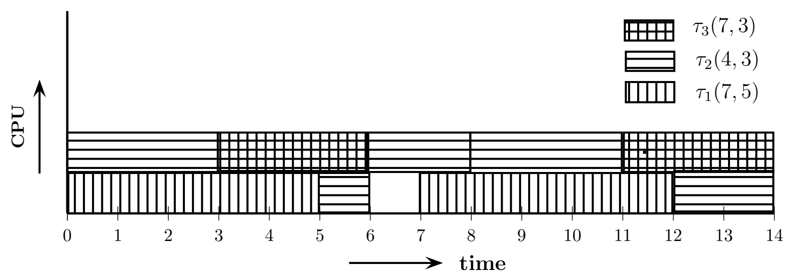


Figure 2.5: Multiprocessor Computational Task Scheduling

to scheduling of two tasks $\tau_1(7,5)$ and $\tau_2(4,3)$ in 2 CPUs, as shown in Figure 2.4a.

Now, assume that another task $\tau_3(7,3)$ is to be scheduled using the same 2 processors. A feasible schedule can be produced using Global EDF scheduler as shown in Figure 2.5. But, if we are to allocate power to an additional TCE device $D_3(7,3)$, which needs power for 3 units of time in its duty-cycle of 7 units, a similar schedule will not be feasible. This is because, as it can be observed from Figure 2.5, the restart-delay requirement of task τ_2 (analogous to TCED D_2) is violated at times $t = 5$ and $t = 12$. It may be noted here that the task τ_2 was preempted at $t = 3$ and restarted at $t = 5$, after 2 units (minutes) of time. Similarly, τ_2 was preempted at $t = 11$ and restarted just after 1 unit (minute) of time.

Table 2.2: Schedulability using gEDF and TCBM

m=3

Combinations of ACs	gEDF (without restart-Delay)	gEDF (with restart-Delay)	TCBM
2 of $AC_1(28, 9.8)$ & 2 of $AC_2(36, 19)$	Yes	No	Yes
1 of $AC_1(28, 9.8)$ & 3 of $AC_2(36, 19)$	No	No	Yes
3 of $AC_1(28, 9.8)$ & 1 of $AC_2(36, 19)$	Yes	No	Yes
All 4 of $AC_1(28, 9.8)$	Yes	Yes	Yes
All 4 of $AC_2(36, 19)$	No	No	Yes

Schedulability under Restart-Delay Constraint

In this subsection, we discuss a means to accommodate restart delay constraint using a real-time scheduling algorithm. We choose global EDF[35] as a representative scheduling algorithm, because it appears to be the most suitable for scheduling TCEDs for reasons discussed in Section 2.1.

In order to ensure restart-delay R^d in a TCE device, it is required that once powered off at time t, it will not be powered on till $t+R^d$. In general, any preemption will require a restart delay. However, for simplicity, the effect of adding R^d to the worst-case execution time (WCET) of each TCED task is studied.

We carried out feasibility analysis for various combinations of 4 ACs from a set of two types of ACs having different thermal characteristics as follows. $AC_i(P, C) = \{AC_1(28, 9.8), AC_2(36.1, 19.1)\}$, where P and C denote period and execution time respectively. The summary of the results is presented in Table 2.2, which shows that when restart delay is taken into consideration, global EDF schedulability analysis finds only one out of five combinations of AC parameters schedulable whereas all the five combinations are actually schedulable using our algorithm TCBM, discussed in Chapter 4.

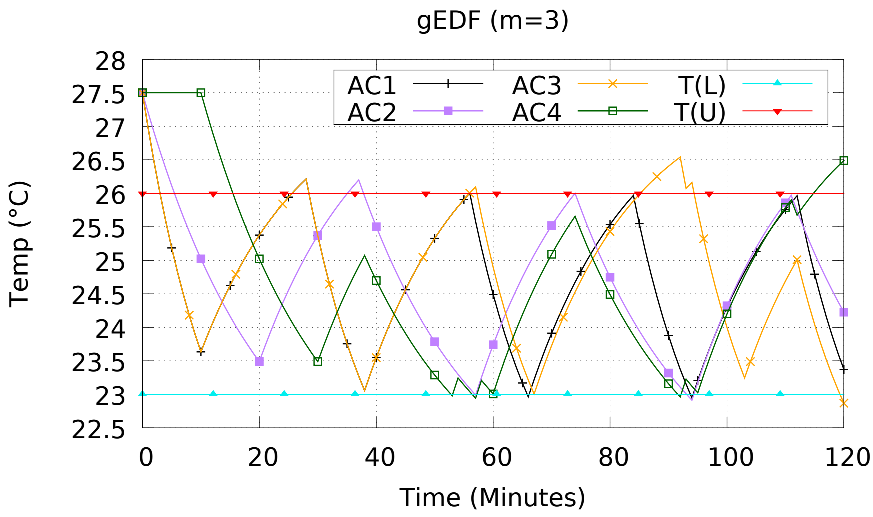


Figure 2.6: Scheduling 4 ACs with available power for 3 ACs using global EDF policy

2.3.3 Violation of Comfort Band

We take a case 4 ACs and assume that under peak demand constraint power is available only for 3 ACs at a time. This set of 4 ACs $\alpha = \{\alpha_i \mid i = 1, 2, \cdots, 4\}$ are modeled as periodic tasks according to their ON-time and OFF-time duration in their duty-cycles. The AC task set obtained by curve-fitting from experimental data of their thermal profile are as follows.

$$\alpha_1(28, 9.8), \alpha_2(36.1, 19.1), \alpha_3(28, 9.8), \alpha_4(36.1, 19.1)$$

We applied global EDF schedulability criterion[35] for scheduling the above 4 tasks on 3 processors and found them schedulable. The resulting schedule for 2 hours is shown in Figure 2.6. It can be observed from Figure 2.6 that comfort-band is violated by AC3 (α_3) at $t = 26$ minute, at $t = 85$ minute and later. Further, it can be seen from Figure 2.6 that comfort-bands of the respective zones are also violated by AC2 & AC4. It happened because, going by the scheduling policy, the global EDF scheduler did not give CPU to α_3 (AC3) as it did not have the earliest deadline at the time instants $t = 26$ and $t = 85$ minutes. The comfort-bands would not have been violated by an AC if the scheduling policy allowed preemption of some other AC whose zone temperature was below T^U, the upper limit of the comfort-band. For example, the comfort-band of the zone controlled by AC3 would not have been violated at $t = 85$ minute, if the scheduling policy allowed preemption of either AC2 or AC4, whose zone temperature were well below T^U, to make power available to AC3. Therefore, it can be concluded that even though the task set α is schedulable according to some real-time scheduling policy, comfort-band can be violated, because such scheduling policies do not consider environmental parameter feed back in making scheduling decisions.

In order to take care of comfort-band violation, we need to introduce a master controller on top of the TCED task scheduler, which will act based on the feedback of the plant state variable (temperature). Under this scheme, the scheduler will schedule n TCEDs (tasks) on m logical power sources (equivalent to processors) according to EDF policy provided plant state variable allows it. If the plant state variable associated to a particular zone goes beyond comfort-band, priority of the corresponding TCED task will be enhanced by the master controller. This is done to facilitate allocating power to TCED whose zone temperature reached comfort band limit by means of preempting some other TCED task, whose zone temperature is below the comfort band limit. Existing art suggests taking care of preemption cost by adding it up to the worst-case execution time and carrying out the schedulability analysis. But, the following issues still remain to be resolved.

- Finding means to quantify the maximum number of preemptions that can occur in a cycle due to the possible violations in the comfort-band.
- Increased TCED switching due to additional switching caused by scheduling policy itself. (e.g., unnecessary switching of AC4 during $50 - 60$ min. in Figure 2.6)
- Taking into account of restart-delay on every preemption (switching-off) of a TCE device. It can be impractical to do so as discussed in Section 2.3.

In this chapter, we established the limitations of the existing policies from real-time domain in scheduling TCEDs for the purpose of attaining desired thermal comfort in the zones controlled by them. These limitations led us to study the thermal behavior of AC (presented next in Chapter 3) for gaining further insights before presenting our solution to the problem of TCED scheduling under peak demand constraint.

Chapter 3

Thermal Characteristics of AC

In order to understand the thermal behavior of ACs, we first develop a conceptual model of an AC, validate the model with empirical observations and present the insights gained from them. In this chapter, we also present our arguments in favour of using experimentally generated characteristics of AC for the purpose of feasibility analysis and implementation of TCBM algorithm. Further, we study the effect of variations in the comfort-band on the power consumption of ACs in preparation for the development of energy-aware TCBM.

3.1 Determining the Thermal Characteristics of ACs

As portrayed in Figure 1.1, when an AC is on, i.e., the compressor is running, it cools down the room temperature; the temperature rises from the instant the AC is switched OFF because of heat loads and losses. Based on elementary principles of heat transfer [44], we develop a model, simplified by means of using overall heat transfer co-efficient in calculating heat transfer from the terminal temperatures, i.e., the temperature of the two bodies between which heat transfer takes place. It may be noted that various heat transfer co-efficients, pertaining to different heat transfer modes (conduction, convection and radiation), are combined into an overall heat transfer co-efficient for simplification of the heat transfer problem as is done in practice [45]. Using this simplified model we first derive the warming and cooling rate of an AC. Based on experimental data, we then derive i) the time taken by an AC to cool a zone from T_i to T^L and ii) the time it takes for T_i to rise up to T^U, when the AC is OFF.

3.1.1 Modeling Rate of Change in Temperature

- *Warming when AC is OFF:* When the AC is OFF and the zone temperature T_i changes, energy transfer to the zone from outside can be defined by the following equation[44].

  $$Q_1 = h_0(T_a - T_i) \tag{3.1}$$

  where, Q_1= heat transfer rate, T_a is the ambient temperature and h_0 is the overall heat transfer co-efficient of the room.

  Let Q_{hi} be the heat input rate from the sources (human body and equipments like computer) inside the zone Z_i. Therefore, the total heat energy transferred to the room can be expressed as

  $$Q = Q_{hi} + h_0(T_a - T_i) \tag{3.2}$$

  The energy transferred from the outside and from the inside heat generating sources must be stored in the room. This storage rate of energy is what effects a change in the zone temperature and can be defined by

  $$Q = \Theta_i \frac{dT_i}{dt} \tag{3.3}$$

  where Θ_i denotes the thermal capacity of the i^{th} zone Z_i.

  Since energy coming from the outside and the inside sources must be equal to the energy stored in the room, 3.2 and 3.3 can be equated. So, the rate of change of T_i can be expressed as

  $$\Theta_i \frac{dT_i}{dt} = Q_{hi} + h_0(T_a - T_i) \tag{3.4}$$

  where Θ_i denotes the thermal capacity of the zone Z_i and h_0 denotes the overall heat transfer co-efficient of the room. It follows that

  $$\frac{dT_i}{dt} = \frac{Q_{hi} + h_0 T_a}{\Theta_i} - \frac{h_0}{\Theta_i} T_i \tag{3.5}$$

  or,

  $$\frac{dT_i}{dt} = \alpha' - \beta' T_i \tag{3.6}$$

in which $\alpha' = \frac{Q_{hi}+h_0T_a}{\Theta_i}$ and $\beta' = \frac{h_0}{\Theta_i}$.

Solving Equation 3.6, we get

$$t = -\frac{1}{\beta'}ln(\alpha' - \beta'T_i) - C1$$

Since we want to maintain room temperature $\geq T^L$, we get $C1 = -\frac{1}{\beta'}ln(\alpha' - \beta'T^L)$ as at $t = 0$, $T_i = T^L$, when the AC is turned OFF.

Therefore,

$$t = \frac{1}{\beta'}ln\frac{\alpha' - \beta'T^L}{\alpha' - \beta'T_i} \tag{3.7}$$

$$\frac{\alpha' - \beta'T_i}{\alpha' - \beta'T^L} = e^{-\beta' \times t}$$

$$\frac{-\beta'T_i}{\alpha' - \beta'T^L} = -\frac{\alpha'}{\alpha' - \beta'T^L} + e^{-\beta' \times t}$$

It follows that

$$T_i = a' + b'e^{-c' \times t} \tag{3.8}$$

in which $a' = \frac{\alpha'}{\beta'}$, $b' = \frac{\beta'T^L - \alpha'}{\beta'}$ and $c' = \beta'$

- *Cooling when AC is ON:* When an AC is switched ON, it removes heat from the room. With inside heat load Q_{hi} and ambient temperature T_a remaining constant, Equation 3.4 can be modified to capture the heat removal by AC as

$$\Theta_i\frac{dT_i}{dt} = Q_{hi} - h_1(T_i - T^C) + h_0(T_a - T_i) \tag{3.9}$$

where, T^C is the temperature of the heat-transfer coil of the AC and h_1 is the overall heat transfer co-efficient of the AC. It follows that

$$\frac{dT_i}{dt} = \frac{Q_{hi} + h_1T^C + h_0T_a}{\Theta_i} - \frac{h_1 + h_0}{\Theta_i}T_i \tag{3.10}$$

or,

$$\frac{dT_i}{dt} = \alpha - \beta T_i \tag{3.11}$$

in which, $\alpha = \frac{Q_{hi}+h_1T^C+h_0T_a}{\Theta_i}$ and $\beta = \frac{h_1+h_0}{\Theta_i}$.

Solving Equation 3.11, we get

$$t = -\frac{1}{\beta} ln(\alpha - \beta T_i) - C2$$

Since we want to maintain room temperature $\leq T^U$, we get $C2 = -\frac{1}{\beta} ln(\alpha - \beta T^U)$ as at $t = 0$, $T_i = T^U$, when the AC was turned ON.

Therefore,

$$t = \frac{1}{\beta} ln \frac{\alpha - \beta T^U}{\alpha - \beta T_i} \tag{3.12}$$

Solving Equation 3.12, we get

$$T_i = a + be^{-c \times t} \tag{3.13}$$

in which, $a = \frac{\alpha}{\beta}$, $b = \frac{\beta T^U - \alpha}{\beta}$ and $c = \beta$

3.1.2 Experimentally Determining AC Thermal Characteristics

We know from [45] that i) finding characteristic constants, i.e., *thermal capacity* of the zone and *overall heat transfer co-efficient* is difficult, and ii) these constants vary widely with the changes in the ambient temperature, heat loads and losses. Therefore, it poses a challenge in on-line adaptation of thermal model of ACs, necessary for any scheduling/control mechanism to work effectively. Due to these facts, we opt for a simpler and practical approach of generating AC thermal characteristics by means of curve-fitting based on experimental data.

We measured the changing temperatures of a zone controlled by an AC using $Pt100$ RTD (Resistance Temperature Detectors) and recorded them every 10 sec. in a digital recorder (Eurotherm Chessell 5000).

From the experimental temperature data generated for a range from the ambient temperature $T_a = 27.5^0C$ to the lowest value the AC can cool the zone, we did curve-fitting and obtained the set of thermal characteristic constants $\{a, b, c\}$ and $\{a', b', c'\}$ of ACs. The thermal characteristic equations of ACs, thus obtained, are as follows:

- *Cooling Down (AC Switched ON)*: When an AC is ON, cooling of its zone is governed by the following equation.

$$T_i(t) = a + be^{-c \times t} \tag{3.14}$$

Table 3.1: Constants for AC (ON) Characteristic Equation

Ambient Temperature = 27.5^0C		
Constants	**AC1**	**AC2**
a	20.88	20.49
b	6.174	6.357
c	0.02092	0.01336

Table 3.2: Constants for AC (OFF) Characteristic Equation

Ambient temperature = 27.5^0C		
Constants	**AC1**	**AC2**
a'	26.87	27.43
b'	-6.17	-6.237
c'	0.01118	0.01141

Where, $T_i(t)$ is the temperature of the zone controlled by AC_i at time t and a, b, c are constants specific to particular ACs as shown in Table 3.1.

Solving Equation 3.14 we get,

$$t(T_i) = -\frac{1}{c} ln \frac{T_i - a}{b}$$

Therefore, the time for T_i to reach from T^U to T^L, i.e. the execution time

$$C_i = t(T^U) - t(T^L) = \frac{1}{c}(ln \frac{T^L - a}{T^U - a}) \tag{3.15}$$

Now, the cooling slope S_f^i of AC_i can be calculated from Equation 3.14 as

$$S_f^i = \frac{dT_i}{dt} = -bce^{-c \times t} \tag{3.16}$$

Rewriting, we get

$$\frac{1}{c} S_f^i = -be^{-c \times t} - a + a = a - (a + be^{-c \times t})$$

Substituting the value of T_i from Equation 3.14,

$$S^i_f(T_i) = c(a - T_i) \tag{3.17}$$

It may be noted that the value of a is equal to the lowest value of the zone temperature that can be achieved by running the AC according to the characteristic equation obtained empirically. In other words, the lower limit T^L of the comfort-band will be $\geq a$ for any subsequent analysis using Equation 3.17.

- *Warming Up (AC Switched OFF)*: When an AC is OFF, warming of its zone is governed by the following equation.

$$T_i(t) = a' + b'e^{-c' \times t} \tag{3.18}$$

Where, $T_i(t)$ is the temperature of the zone controlled by AC_i at time t and a', b', c' are constants specific to particular ACs as shown in Table 3.2.

Solving Equation 3.18, we get

$$t(T_i) = -\frac{1}{c'} ln \frac{T_i - a'}{b'}$$

Following a similar derivations as we did it for obtaining the cooling thermal characteristics for AC, we get the laxity L_i and warming slope S^i_r as follows.

$$L_i = t(T^L) - t(T^U) = \frac{1}{c'}(ln \frac{T^U - a'}{T^L - a'}) \tag{3.19}$$

$$S^i_r(T_i) = c'(a' - T_i) \tag{3.20}$$

It may be noted that the value of a' is the highest value of the temperature of the zone that can reach according to the characteristic equation obtained empirically, if the AC is not running. In other words, the upper limit T^U of the comfort-band will be $\leq a'$ for any subsequent analysis using Equation 3.20.

The following insights from experiments influenced the design of TCBM algorithm and its feasibility analysis (presented in Chapter 4).

- If T_i of a zone comes down, the average temperature across n zones (one of which is the i^{th} zone) controlled by n ACs comes down.
- Suppose heat loads and the cooling capacity of the ACs are the same in all the zones. It can be observed from Equation 3.17 and Figure 1.1 that the higher the zone temperature T_i, the faster it cools. Therefore, the AC that has the highest zone temperature will provide the fastest cooling. Further, if such an AC is not switched ON, its zone temperature will reach T^U fastest.
- When multiple ACs, whose zone temperatures are among the highest ones, are turned ON, the average temperature of the zones comes down faster.
- Let $S^i_f(T_i)$ and $S^i_r(T_i)$ denote the cooling and warming slopes of AC_i respectively at T_i. The following conditions always hold because of the exponential nature of the cooling and warming curves as can be observed from Equations 3.17 and 3.20 as well as from Figure 1.1.

$$\forall\, \delta \geq 0,\ abs(S^i_f(T_i)) \leq abs(S^i_f(T_i + \delta)) \tag{3.21}$$

$$\forall\, \delta \geq 0,\ S^i_r(T_i) \geq S^i_r(T_i + \delta) \tag{3.22}$$

It may be noted here that absolute values of S^i_f are considered, because the cooling slope is negative.

3.2 Effect of Comfort-Band Settings on AC Operation

We operated an AC in an office room on a regular working day and studied the effect of changing comfort-band $[T^U, T^L]$ on AC thermal characteristics as depicted in Figures 3.1a, 3.1b and 3.1c. The effect of comfort-band $[T^U, T^L]$ on the cooling time C_i and the period P_i of AC are shown in Tables 3.3, 3.4 and 3.5. It may be noted here that the results in Table 3.3, 3.4 and in 3.5 are based on the average of the results (C_i and P_i) obtained from 10 duty-cycles and rounded off to nearest integer.

Comfort-band (^0C)	$C_i(Min.)$	$P_i(Min.)$	C_i/P_i
25.0 – 22.0	14	28	0.5
25.5 – 22.5	12	28	0.429
26.0 – 23.0	10	29	0.345

Table 3.3: Average C and P of ACs for Comfort-bands with Equal $(T^U - T^L)$

Comfort-band (^0C)	$C_i(Min.)$	$P_i(Min.)$	C_i/P_i
25.5 – 22.0	16	34	0.471
26.0 – 22.0	17	40	0.425
26.5 – 22.0	18	46	0.391

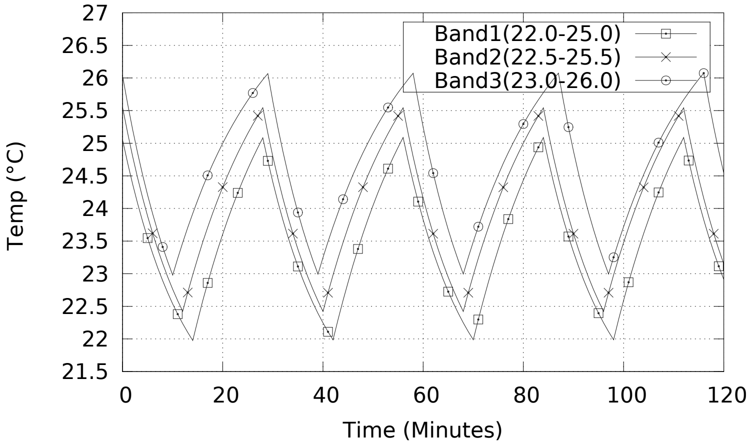
Table 3.4: Average C and P of ACs for Comfort-bands with varying T^U

Comfort-band (^0C)	$C_i(Min.)$	$P_i(Min.)$	C_i/P_i
26.0 – 23.0	10	29	0.345
26.0 – 22.5	14	34	0.412
26.0 – 22.0	18	40	0.450

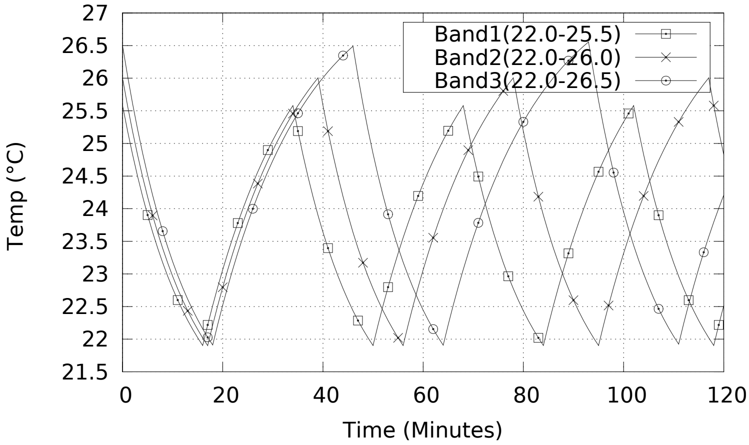
Table 3.5: Average C and P of ACs for Comfort-bands with varying T^L

The effect of three different comfort-bands on the cooling time C_i and the period P_i of AC are as follows.

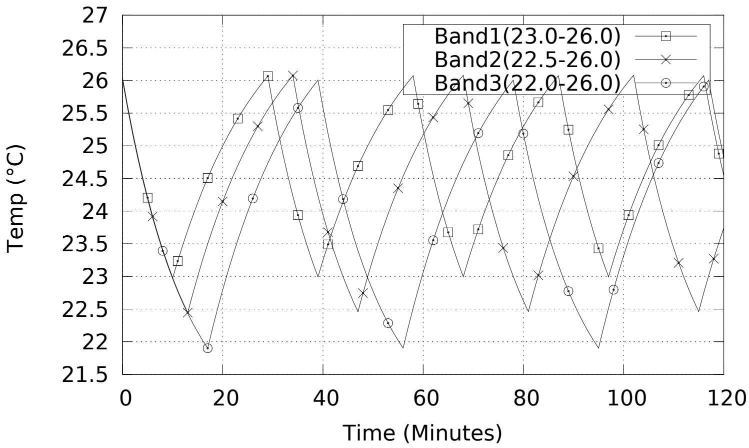
- *Comfort-Bands with equal* $(T^U - T^L)$*:* In this experiment, the position of the comfort-band is shifted along the temperature scale while keeping $(T^U - T^L)$ the same. It can be observed from the experimental data presented in Table 3.3 and from Figure 3.1(a) that the cooling time C_i as well as the *duty cycle* $(C_i + P_i)$ depend not only on the size of the comfort band but also on the values of T^U and T^L. It can also be observed from Table 3.3 that shifting of comfort-band by just



(a) Comfort-bands of equal width ($T^U - T^L$)



(b) Comfort-bands with varying T^U



(c) Comfort-bands with varying T^L

Figure 3.1: Effect of Comfort-Band on AC Operation

0.5^0C can cause a significant change in the cooling time C_i and in the utilization C_i/P_i.

These observations are in compliance with Equation 3.15. The increase in C_i can be explained from the fact that $ln\ (A-d)/ln\ (B-d) > ln\ A/ln\ B$, if $A < B$, $0 < d < A$ and $0 < d < B$. The scenario is the same with the Equation 3.15, when the comfort-band is changed from $[26.0^0C, 23.0^0C]$ to $[25.5.0^0C, 22.5^0C]$ or to $[25.0^0C, 22.0^0C]$.

- *Comfort-Bands with varying T^U:* We increased the T^U values by 0.5^0C, keeping the T^L values same, as shown in Table 3.4. I t can be observed from Table 3.4 that increase in T^U by 0.5^0C causes decrease in C_i/P_i, as expected.

- *Comfort-Bands with varying T^L:* When the values of T^L were decreased by 0.5^0C, keeping the values of T^U the same, as shown in Table 3.5, we observe that decreasing the lower limit T^L of the comfort-band, as expected, increases the value of C_i/P_i.

From Figures 3.1 (a), (b) & (c) and from Equation 3.17, it can be observed that the higher the zone temperature, the faster is the rate of cooling, because of the exponential nature of the cooling curve. Therefore, an AC will run for lesser time if T^U is shifted up as compared to the same when T^U is lower. This results in reduced power consumption.

In this chapter, we discussed the insights gained from the experiments, which influenced the design of TCBM algorithm and its feasibility analysis (presented next in Chapter 4). Besides experimental validation of the simplified model of thermal characteristics of AC, we have also shown i) how to obtain the constants a, b, c and a', b', c' experimentally, to characterize the ACs, and ii) how manipulating the comfort-band can affect power consumption of ACs. The simple technique of obtaining thermal characteristic constants of AC helps us in formulating a low cost and implementable solution for TCED scheduling (Chapter 4). The relationship between comfort-band and energy consumption is formulated in Chapter 5 and an adaptive demand-response (D-R) scheme is proposed.

Chapter 4

Maintenance of Thermal Comfort

In this chapter, we introduce TCBM scheduling and the associated feasibility analysis. We also discuss how to take care of some of the practical considerations viz., mandatory restart-delay and minimizing the number of switching while applying TCBM scheduling.

4.1 Terminologies

Some of the important and general terminologies used in this chapter are defined below. Definitions of context specific terminologies are given along with the presentation of related texts.

1. *Zone:* A zone is a thermally de-coupled space whose temperature is controlled by a TCED. A zone can be a room with a single TCED or a large room is assumed to be divided into thermally de-coupled zones whose temperatures are maintained by one TCED in each zone.

2. *Cooling slope*: It is the slope of the cooling curve of a TCED generated by plotting temperature versus time as shown in Figure 1.1. Therefore, cooling slope is the fall in zone temperature per unit time, when the TCED is ON if it is a cooling device (or the TCED is OFF if it is a heating device). We denote it as S_f or S_f^i (for i_{th} device).

3. *Warming slope*: It is the slope of the warming curve of a TCED generated by plotting temperature versus time as shown in Figure 1.1. Therefore, warming slope

is the rise in zone temperature per unit time, when the TCED is OFF if it is a cooling device (or the TCED is ON if it is a heating device). We denote it as S_r or S_r^i (for i_{th} device).

4. *Scheduling period/Scheduling decision interval*: A scheduler, when invoked, decides which task to run or suspend based on the adopted policy. In practice, scheduler is invoked periodically. We define the interval between two successive invocation of a scheduler as *scheduling period* or *scheduling decision interval* and denote it is I^S.

5. *Ambient temperature*: It is the temperature of the environment outside the envelope of room(s), which influences the temperatures of the zone(s). We denote ambient temperature as T_a.

4.2 System Model

We consider n zones in a commercial building or a home, where the temperature of each zone is maintained by one or more TCEDs. A zone can be a room with a single AC or a large room is assumed to be divided into thermally de-coupled zones whose temperatures are maintained by one AC in each zone. Peak power constraint limits the amount of energy that can be consumed at any point of time. In order not to violate the peak-demand constraint, only m of n TCEDs can run at a time. The ACs are to be scheduled such that the temperature T_i $(i = 1, 2, \cdots n)$, in individual zones lies within the comfort-band $[T^L, T^U]$. For analysis purposes, we initially assume that all the zones are thermally de-coupled. Since in practice this decoupling may not be true, later in this thesis, we remove this constraint and present our experimental results on the applicability of TCBM scheduling in thermally coupled zones. We show in Chapter 6.1 that TCBM scheduling is effective in thermally coupled zones as well.

4.3 TCBM Scheduling

The primary goal of TCBM is to maintain the comfort-band. TCBM achieves this while turning ON ACs judiciously because of the peak power constraint. Secondly, turning-ON an AC has to be done taking into account the fact that once turned-OFF, it can not be turned-ON for a minimum period of time. We refer to this as specified *restart-delay* R^d. Thirdly, the number of switchings (ON & OFF) is to be minimized because switching-ON of an induction machine (compressor in AC/refrigerator) involves high starting current leading to additional power consumption.

TCBM scheduling achieves this by allowing an AC to remain ON till its zone temperature reaches T^L or it becomes necessary to switch it OFF in the event the zone temperature of some other AC reaches T^U. An AC_i, once switched OFF, is kept OFF till T_i reaches T^U, preventing switching of ACs when their zone temperatures are within the comfort-band. In order to maintain zone temperatures within comfort-band, before switching ON an AC which has reached T^U, another AC may have to be switched-OFF. This is because, only m out n ACs can run at any point of time due to the peak power constraint. It may be noted that whenever it becomes necessary to switch OFF an AC, so that some other AC can be turned ON, it is logical to switch OFF the *coolest* available AC as defined below.

Definition 1 *Coolest AC is the one among the running ACs, whose zone temperature will take maximum time to reach* T^U*, if switched* OFF*.*

Switching OFF the coolest AC will allow it to remain OFF for a longer time before its zone temperature reaches T^U and thus make it possible to achieve smaller number of switching in a given period of time.

The TCBM Algorithm

TCBM scheduling covers both the i) *Initial cooling* phase and the ii) *Comfort-Band maintenance* phase, as described below.

- *Initial Cooling* phase: This is the phase when any zone temperature T_i is above the CB i.e., $T^U < T_i \leq T_a$ and TCBM scheduling of ACs brings down T_i of all the zones within the CB.

- *Comfort Band maintenance* phase: In this phase, the temperature of each zone is maintained within the comfort band by scheduling ACs using TCBM.

Initially, $T_i = T_a$ and an AC operates to bring down the T_i from T_a to a value that lies within the comfort-band. Specifically, the TCBM algorithm starts by switching ON $m(\leq n)$ numbers of ACs chosen arbitrarily from the set of n ACs. It may be noted here that wattages of the ACs can vary. The worst-case value of m is determined by the peak demand constraint, such that

$$\sum_{i=1}^{m} W_i \leq W^P \tag{4.1}$$

where, W_i denotes the power required by i^{th} AC and the sum is obtained from the first m of the n ACs arranged in descending order of their wattage.

Once T_i is within the comfort band, the ACs are controlled to maintain the respective T_is within the comfort band $[T^L, T^U]$. TCBM applies the following rules for scheduling ACs.

1. *Rule # 1:* Turn OFF AC_i if it is ON at time t and if
   (a) $T_i \leq T^L$ ***OR***
   (b) there is an $AC_j (i \neq j)$ with $T_j \geq T^U$ ***AND*** no. of ON-ACs $\geq m$ ***AND*** $T_i < T^U$ ***AND*** AC_i is the *coolest* one among ON-ACs.
2. *Rule # 2:* Turn ON AC_i if
   (a) $T_i \geq T^U$ ***AND***
   (b) No. of ON-ACs $< m$

Rule # $1(a)$ ensures that AC_i is switched OFF when the zone temperature T_i reaches its lower limit T^L. Running an AC below T^L not only affects the thermal comfort, but also wastes energy. But, it may be necessary to switch OFF an AC even before it's zone temperature reaches T^L, if it is observed that the zone temperature of some other AC reached T^U. This is required to provide power to the AC, whose zone temperature reached T^U, enabling it to maintain the desired thermal comfort. Rule # $1(b)$ takes care of such a situation. If the temperature of a zone reaches its upper limit T^U, Rule # 2 ensures that the corresponding AC is switched ON subject to the condition that not more than $m(\leq n)$ ACs run at a time.

The pseudo-code of the TCBM scheduling algorithm is shown in Figure 4.1

$n =$ *Total no of* ACs

$AC = \{AC_i \; : \; i = 1 \ldots n\}$

$T_i =$ *Zonal temperature corresponding to* AC_i

$m =$ *Maximum number of* ACs *that can be powered* ON *at any point of time*

$k =$ *Number of* ACs *to be switched* ON *at time* t

$ON(t) =$ *set of* ACs, *which are* ON *(running) at time* t *and* $n(ON(t)) \leq m$

$OFF(t) =$ *set of* ACs, *which are* OFF *(running in fan mode) at time* t *and* $n(OFF(t)) \geq (n-m)$

BEGIN

$t = 0$

$ON(t) = \{AC_i : i \leq m\}$ *; switch on* m ACs

$OFF(t) = \{AC_i : i > m\}$ *; keep* $(n - m)$ ACs *off.*

DO

$t = t + 1$ *; increment time*

$k = | \{AC_i \in OFF(t-1) : T_i \geq T^U\} |$ *; determine* k

$ON(t) = \{AC_i \in OFF(t-1) : T_i \geq T^U\} \cup \{AC_i \in ON(t-1) : T_i > T^L\}$ *; update the set of ACs to run at time* t

$OFF(t) = \{AC_i \in ON(t-1) : T_i \leq T^L\} \cup \{AC_i \in OFF(t-1) : T_i < T^U \cup AC_i \in \{k$ *number of coolest* AC *of* $ON(t)\}$ *; determine set of ACs to be/remain switched-*OFF *at time* t

WHILE(1)

END

Figure 4.1: Basic TCBM Algorithm

4.4 Feasibility Analysis and Practical Considerations

Peak demand constraint allows at most m out of $n(\geq m)$ ACs to run at any point of time. In this section, we discuss the feasibility of scheduling m out of n ACs that ensures a given comfort-band $[T^L, T^U]$. First, we present the basic schedulability analysis. Then we discuss how to take into account of i) the effect of discrete scheduling decision time and ii) mandatory *restart-delay* requirement in our schedulability analysis.

4.4.1 Basic Feasibility Analysis

The job of a scheduler is to allocate resource to tasks according to the adopted policy. In our context, a TCED scheduler decides which m out of n TCEDs (tasks) will be allocated power (resource) at a particular instant of time. The scheduler takes this decision, when it is invoked. In practice, scheduler is invoked periodically and the time-interval is decided judiciously so that it is i) not too short to affect task execution because of overhead due to scheduler and ii) not too large to cause unacceptable delay in start-time of the task after it is ready. In other words, scheduling decisions are taken periodically, in discrete time. Also, once an AC is switched OFF, it can not be restarted before the specified *restart-delay* R^d has elapsed. We assume here, for simplicity of exposition, that

- scheduling decision is taken continuously at every instance of time, and
- an AC can be operated (switched ON or OFF) at any time, i.e., without any restart-delay constraint.

Issues related to scheduling decisions being taken at discrete times are discussed after presentation of the basic feasibility analysis where it is assumed that there is no delay involved between two successive scheduling decision instants. How to take care of the *restart delay* constraint is discussed in Section 4.4.4.

Theorem 1 *If peak demand constraint allows m out n ACs to run at a time and ACs are scheduled by the TCBM algorithm, all the zone temperatures will eventually fall from the ambient T_a to a value T_i ($T^L \leq T_i < T^U$) and the CB $[T^L, T^U]$ will be maintained thereafter, if the following condition is satisfied.*

$$\sum_{i=1}^{m} abs(S_f^i(T_i)) > \sum_{i=1}^{n-m} S_r^i(T_i) \tag{4.2}$$

where, i) the sum on the left is obtained from the first m of the n ACs arranged in ascending order of their cooling-slopes and ii) the sum on the right is obtained from the first $(n-m)$ of the n ACs arranged in descending order of their warming-slopes.

Proof: At any point of time, change in the zone temperature depends on the cooling slope $S_f^i(T_i)$ (when the AC is ON) and the warming slope $S_r^i(T_i)$ (when the AC is OFF) of the i^{th} AC in that zone. The fall and rise in temperature at any instant of time can be quantified as $S_f^i(T_i) \times \Delta t$ and $S_r^i(T_i) \times \Delta t$ respectively, in an infinitesimally small duration of time Δt.

In order to maintain the desired comfort-band under peak demand constraint, at most m ACs can run at any point of time which will result in at least $(n-m)$ ACs remaining OFF. It may happen that comfort-band can be maintained by running $< m$ ACs, which is an optimistic case. We will consider the worst case that is, it is required to run the maximum number of ACs (permitted under peak demand constraint) for maintaining the comfort-band. So, under this worst-case scenario, the temperatures of m zones fall and that of $(n-m)$ zones rise at any point of time. It may also be noted that S_f^i and S_r^i are functions of the zone temperature (T_i). Therefore, to ensure that the average zone temperature will keep on falling, it is sufficient that the following condition is kept true for every time instance.

$$m \times min(abs(S_f^i(T_i))) \times \Delta t > (n-m) \times max(S_r^i(T_i)) \times \Delta t$$

$$m \times min(abs(S_f^i(T_i))) > (n-m) \times max(S_r^i(T_i)) \tag{4.3}$$

Note that *absolute* value of $S_f^i(T_i)$ is taken because the cooling slope is negative.

From Equations 3.22 and 3.21, it can be concluded that if Equation 4.3 is valid for some T_i, it is also valid for any zone temperature above T_i. It follows that the zone temperatures will keep on falling from some $T(> T_i)$ to T_i if Equation 4.3 is satisfied.

Also, once T_i is within the CB $[T^L, T^U]$, it will remain within the CB when ACs are scheduled according the rules of TCBM stated earlier. This is because, i) according to

TCBM rules, any number of ACs can be switched OFF, if $T_i \leq T^L$ and ii) Equation 4.3 ensures that the average zone temperature keeps on falling till any zone temperature is $\geq T_i$.

Equation 4.3 is pessimistic, because S_f^i and S_r^i can be different for different ACs. Under peak demand constraint, worst-case will arise if at any point of time, i) the set of running m ACs consists of the first m of the n ACs arranged in ascending order of their cooling slopes and ii) the set of $(n-m)$ ACs, which are off, consists of first $(n-m)$ of the n ACs arranged in descending order of their warming slopes. Considering the worst-case sets of m ACs that can be ON and $(n-m)$ ACs that can be OFF at any point of time, the proof follows. □

4.4.2 Feasibility Analysis Considering the Effect of Discrete Scheduling Decision Time

In practice, scheduling decisions (ON-OFF) are taken in discrete time. Therefore, if a zone temperature reaches T^U just after a scheduling decision is made, comfort-band can be violated before the next scheduling decision is taken. Also, switching ON of an AC may also be delayed further if more than m ACs reach T^U simultaneously. In order to avoid the possibility of comfort-band violation, an AC is considered for switching ON or OFF ahead of its temperature reaching T^U or T^L.

Let I^S denote the scheduling period. Since the set of m ACs to run is decided every I^S units of time, there can be delay, in multiples of I^S, in scheduling an AC from the time when it is ready to be scheduled (ON or OFF). So, we introduce $B^U = T^U - \Delta^U$ and $B^L = T^L + \Delta^L$, as defined below,

Definition 2 *B^U is the upper-limit of T_i only above which, the i^{th} AC is considered for switching ON. The value of B^U is calculated as $B^U = T^U - \Delta^U$, where Δ^U denotes the rise in T_i due to the maximum possible delay in switching ON the AC after it reaches B^U.*

Definition 3 *B^L is the lower-limit of T_i below which, the i^{th} AC is switched OFF unless it becomes necessary to switch ON some other AC to maintain the comfort band. The value of B^L is calculated as $B^L = T^L + \Delta^L$, where Δ^L denotes the fall of T_i due to maximum possible delay in switching OFF the AC after it reaches B^L.*

So, in order to take care of the practical case of discrete scheduling intervals, Theorem 1 can be modified as

Theorem 2 *If peak-demand constraint allows m out n ACs to run at a time, all the zone temperatures will eventually fall and reach the comfort-band [T^L, T^U], with the comfort-band maintained thereafter, if the following condition is satisfied.*

$$\sum_{i=1}^{m} abs(S_f^i(B^U)) > \sum_{i=1}^{n-m} S_r^i(B^U) \tag{4.4}$$

where, i) the sum on the left is obtained from the first m of the n ACs arranged in ascending order of their cooling-slopes at B^U, ii) the sum on the right is obtained from the first $(n-m)$ of the n ACs arranged in descending order of their warming-slopes at B^U.

Proof: Same as the proof of Theorem 1, when T_i is replaced with $B^U (< T^U)$. □

4.4.3 Calculating Δ^U and Δ^L

Now, we discuss how to derive the values of Δ^U & Δ^L and how their values are affected by the scheduling decision interval I^S.

Theorem 3 *In order to ensure that no zone temperature (T_i) of a set of TCBM schedulable ACs goes above T^U, it is necessary to consider switching OFF an AC, when T_i reaches $T^U - \Delta^U$ such that*

$$\Delta^U \geq \frac{max(c_i'(a_i' - T^U))}{1 - max(c_i')\lceil\frac{n}{m}\rceil I^S} \times \lceil\frac{n}{m}\rceil I^S \tag{4.5}$$

Proof: Let us consider the worst case scenario when all the n ACs are OFF and T_i of all the ACs reach B^U at time $t = t_0$. Peak power demand limit allows only m ACs to run at any point of time. Therefore, at time t_0, only m ACs can be switched ON. The T_i corresponding to $(n-m)$ ACs will continue to rise. Subsequently, a new set of m ACs can be selected to run only in the next scheduling point at $t = t_0 + I^S$. Therefore, there is a delay t_d involved before all the $(n-m)$ ACs (which were not running at $t = t_0$) get a chance to run. The delay t_d will be minimum, if in every subsequent interval, the m ACs selected to run are picked up from the set of $(n-m)$ ACs which remained OFF at $t = t_0$, till all the them are switched ON at least once. So, the minimum value of t_d will be

$$t_d = I^S + \lceil \frac{n-m}{m} \rceil \times I^S = \lceil \frac{n}{m} \rceil \times I^S \tag{4.6}$$

Therefore, the condition to ensure that no zone temperature will go beyond T^U within t_d, is

$$\Delta^U \geq T_i(t_0 + \lceil \frac{n}{m} \rceil I^S) - T_i(t_0) \tag{4.7}$$

Now, the worst-case rise of zone temperature during the period t_d will occur if

- we consider that the AC which remains OFF for time t_d has highest S_r^i at B^U, and
- the warming curve is linear from B^U to T^U. Note that it can be inferred from Equation 3.21 that considering the warming curve as linear here, results in an overestimation of Δ^U.

Therefore, the maximum value of the right hand side of the Equation 4.7 will be $max(S_r^i(B^U)) \times \lceil \frac{n}{m} \rceil \times I^S)$.

So, the Equation 4.7 can be re-stated as

$$\Delta^U \geq max(S_r^i(B^U)) \times \lceil \frac{n}{m} \rceil \times I^S \tag{4.8}$$

From Equation 3.20, we get the warming slope S_r^i at B^U as

$$S_r^i(B^U) = \frac{dT_i}{dt} |_{T_i = B^U} = c_i'(a_i' - B^U) \tag{4.9}$$

Substituting B^U with $T^U - \Delta^U$, [Definition 2]

$$S_r^i(B^U) = c_i'(a_i' - T^U + \Delta^U) \tag{4.10}$$

Now, substituting the value of $S_r^i(B^U)$ in Equation 4.8, we get

$$\Delta^U \geq max(c_i'(a_i' - T^U + \Delta^U)) \times \lceil \frac{n}{m} \rceil I^S$$

It can be observed from Table 3.2 that $a'_i \geq T^U$ and therefore $(a'_i - T^U)$ is positive. This is because, the constant a'_i represents the highest temperature value of the warming curve obtained by curve-fitting. Also, Δ^U is a positive number. So, we can rewrite the above equation as

$$\Delta^U \geq [max(c'_i(a'_i - T^U)) + max(c'_i)\Delta^U] \times \lceil\frac{n}{m}\rceil I^S$$

$$\Delta^U \geq \frac{max(c'_i(a'_i - T^U))}{1 - max(c'_i)\lceil\frac{n}{m}\rceil I^S} \times \lceil\frac{n}{m}\rceil I^S \tag{4.11}$$

□

Theorem 4 *In order to ensure that no zone temperature (T_i) of a set of TCBM schedulable ACs goes below T^L, it is necessary to consider switching* OFF *an AC, when T_i reaches $T^L + \Delta^L$ such that*

$$\Delta^L \geq \frac{max(c_i(T^L - a_i))}{1 - max(c_i)I^S} \times I^S \tag{4.12}$$

Proof: Peak power demand constraint does not prevent us from switching OFF any device. So, any number of ACs can be turned OFF at an instance, if the zone temperatures goes $\leq T^L$. Hence, no delay beyond I^S will be involved in switching-OFF ACs, when it is required.

let us assume that the zone temperature of AC A_i reaches T^L at $t = t_f$. Therefore, the condition to ensure that no zone temperature will go below T^L, if we allow switching OFF an AC on or before its zone temperature reaches a value $(T^L - \Delta^L)$ such that the following condition is satisfied.

$$\Delta^L \geq T_i(t_f - I^S) - T_i(t_f) \tag{4.13}$$

Now, the worst-case fall of zone temperature during the period I^S will occur if i) we consider that the AC which remains ON for time I^S has the highest S^i_f at B^L, and ii) the cooling curve is linear from B^L to T^L. Note that it can be inferred from Equation 3.22 that considering the cooling curve as linear here, is an overestimation of Δ^L.

So, Equation 4.13 can be re-stated as

$$\Delta^L \geq max(abs(S_f^i(B^L))) \times I^S \tag{4.14}$$

From Equation 3.17, we get the temperature falling slope at B^L as

$$S_f^i(B^L) = \frac{dT_i}{dt}|_{T_i=B^L} = c_i(a_i - B^L) \tag{4.15}$$

Substituting B^L with $(T^L + \Delta^L)$ [Definition 3],

$$S_f^i(B^L) = c_i(a_i - T^L - \Delta^L) \tag{4.16}$$

Substituting the value of $S_f^i(B^L)$ in 4.14, we get

$$\Delta^L \geq max(abs(c_i(a_i - T^L - \Delta^L)) \times I^S$$

$$\Delta^L \geq max(abs(c_i(T^L - a_i + \Delta^L)) \times I^S$$

It can be observed from Table 3.1 that $a_i \leq T^L$ and therefore $(T^L - a_i)$ is positive. This is because, the constant a_i represents the lowest temperature value of the cooling curve obtained by curve-fitting. Also, Δ^L is positive. So, we can rewrite the above equation as

$$\Delta^L \geq [max(c_i(T^L - a_i)) + max(c_i\Delta^L)] \times I^S$$

$$\Delta^L \geq \frac{max(c_i(T^L - a_i))}{1 - max(c_i)I^S} \times I^S \tag{4.17}$$

□

Corollary 1 *Δ^U and Δ^L increase with I^S. Further, high values of Δ^U and Δ^L reduce the effective width of the comfort-band [T^L, T^U]. This is because, an AC can be switched on if $T_i \geq (T^U - \Delta^U)$ and it will be switched off if $T_i \leq (T^L + \Delta^L)$. As a result, the number of AC switching will increase with higher Δ^U and/or Δ^L. Hence, it is desirable that the scheduling interval I^S is kept as small as feasible.*

4.4.4 Feasibility Analysis with Guaranteed Restart-Delay

A delay R^d (about 3 minutes) is mandatory for compressor-driven TCE devices before they can be restarted. Therefore, TCEDs must be scheduled under the *restart-delay* constraint. Restart-delay can be ensured if the scheduling decision interval I^S is chosen to be ≥ 3 minutes. But such a high value of I^S will lead to increased number of TCED switching (Corollary 1). So, we propose to modify one of the two rules of TCBM scheduling discussed in Section 4.3 to take care of the restart-delay constraint.

Rule # 1 allows switching-OFF an AC (under peak demand constraint) at any $T_i < B^U$, if it is required so, to turn ON an AC whose zone temperature reached T^U. So, if the value of T_i is closer to B^U, it is possible that T_i would reach B^U from T_i within a time less than the specified restart-delay R^d. It can be avoided, if switching-OFF is permitted only when $(B^U - T_i)$ is large enough so that T_i will take at least R^d time to reach B^U. Now, the worst-case will arise if we consider the warming slope of the AC as linear for all temperatures above T_i (inferred from Equation 3.21). Therefore, the worst-case time R^d to reach from T_i to B^U can be expressed as

$$R^d = \frac{B^U - T_i}{S_r^i(T_i)}$$

So, a restart-delay of R^d time will be ensured if an AC is switched off only after its zone temperature T_i reaches a *minimum* value such that

$$(B^U - T_i) = R^d \times max(S_r^i(T_i)) \tag{4.18}$$

Therefore, in order to obtain a minimum value of I^S while ensuring a restart-delay R^d, Rule # 1 stated in Section 4.3 is modified as follows.

Modified Rule # 1: Turn OFF AC_i if it is ON at time t and if

1. $(T_i \leq B^L)$ ***OR***
2. $(B^U - T_i) \geq max(S_r^i(T_i)) \times R^d$ ***AND*** there is an $AC_j (i \neq j)$ with $T_j \geq B^U$ ***AND*** no. of ON-ACs $\geq m$ ***AND*** $T_i < T^U$ ***AND*** AC_i is the *coolest* one among ON-ACs.

We carried out simulation studies to analyze the effect of *modified Rule # 1* on the maintenance of comfort-band under TCBM. We considered 5 ACs and assumed that

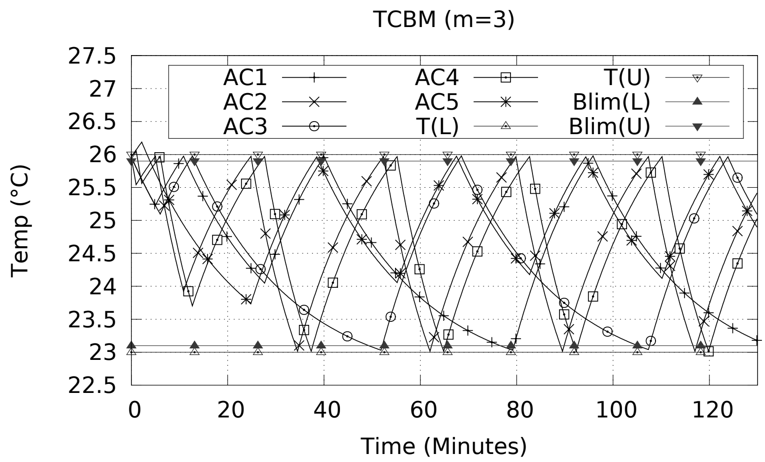


Figure 4.2: TCBM Scheduling with Modified Rule # 1

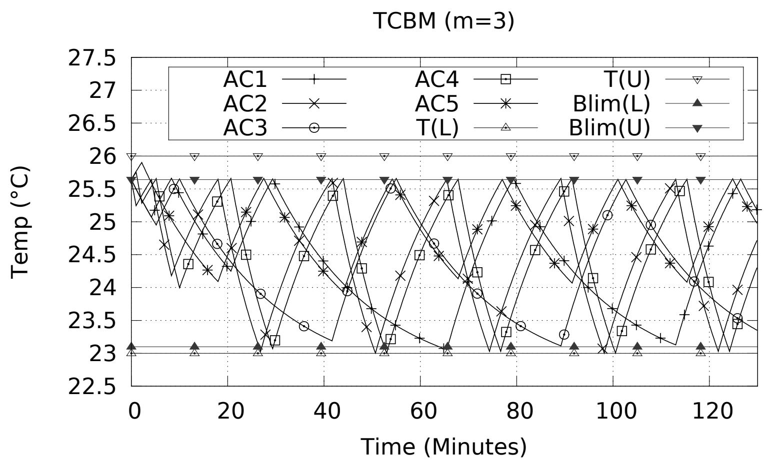


Figure 4.3: TCBM Scheduling with Guaranteed Re-start Delay

peak demand limit permits only 3 ACs to be ON at a time. The chosen comfort-band is $[26^0C, 23^0C]$ & the scheduling interval $I^S = 10$ sec. It can be observed from Figure 4.2, that when the modified Rule # 1 is applied, the T_i of some of the ACs go beyond T^U during the initial phase when all ACs are at B^U. It happened so, because no AC was allowed to be switched-OFF unless its zone temperature T_i reaches a value that satisfies Equation 4.18. Therefore, in order to avoid this undesirable situation, we need to modify the value of Δ^U.

We discussed that if an AC is switched on at B^U and it is not allowed to be switched off till its zone temperature T_i falls to a value that satisfies the Equation 4.18, the restart-delay constraint is automatically taken care of. Let t^C denote the time it takes for the zone temperature of an AC to reach the T_i from B^U, when it is ON. It follows that

$$B^U - T_i = t^C \times abs(S_f^i(T_i))$$

But, equation 4.18 is also required to be satisfied at the same T_i. Let us consider the worst case that the running AC has the slowest cooling rate so that t^C attains its highest value. Therefore, the worst-case minimum value of t^C can be calculated as

$$t^C \times abs(S_f^i(T_i)) = R^d \times S_r^i(T_i)$$

Taking into consideration all the ACs, which may have different thermal characteristics, the value of t^C will be

$$t^C = max(\frac{S_r^i(T_i)}{abs(S_f^i(T_i))}) \times R^d \tag{4.19}$$

In other words, it is required that once switched OFF, the zone temperature of no AC should reach T^U within time t^C such that it becomes necessary to switch OFF a running AC. This requirement should be valid for the pessimistic case when all the ACs are at B^U. In such a scenario, the zone temperatures of $(n - m)$ will rise above B^U and none of them can be switched OFF till a time t^C is elapsed satisfying the Equation 4.19. It can be ensured if B^U is replaced with a new value $B^{U'}$ such that the zone temperature of no AC reaches T^U from $B^{U'}$ in time t^C. Therefore, the required condition to accommodate the restart-delay is as follows.

$$T^U - B^{U'} \geq t^C \times max(S_r^i(B^{U'}))$$

Substituting the value of t^C from in-Equation 4.19, we get

$$T^U - B^{U'} \geq max(\frac{S_r^i(T_i)}{abs(S_f^i(T_i))}) \times abs(S_r^i(B^{U'})) \times R^d \tag{4.20}$$

At a higher zone temperature closer to T^U, the cooling slope S_f^i is higher than the warming slope S_r^i for any AC. Therefore, the condition above can be simplified as

$$T^U - B^{U'} \geq max(S_r^i(B^{U'})) \times R^d \tag{4.21}$$

Substituting the values of $S_r^i(B^U)$ from Equation 4.9, we get

$$T^U - B^{U'} \geq max(c'_i(a'_i - B^{U'})) \times R^d$$

Substituting the value of $B^{U'}$ according to Definition 2, we obtain the modified value of Δ^U (denoted as $\Delta^{U'}$) as follows

$$\Delta^{U'} \geq R^d \times max(c'_i(a'_i - T^U + \Delta^{U'}))$$

Now, $a'_i - T^U$ is positive because $a'_i \geq T^U$ and also $\Delta^{U'}$ is a positive number. Therefore, we can re-write the above expression as

$$\Delta^{U'} \geq R^d \times max(c'_i(a'_i - T^U)) + R^d \times max(c'_i\Delta^{U'})$$

or,

$$\Delta^{U'} \geq \frac{max(c'_i(a'_i - T^U))}{1 - max(c'_i)R^d} \times R^d \tag{4.22}$$

Modified Δ^U: While Equation 4.5 takes care of the rise in temperature due to delay in switching ON on an AC under peak demand constraint, Equation 4.22 ensures the mandatory restart-delay requirement.

Therefore, the modified minimum value of Δ^U, denoted by $\Delta^{U''}$ is as follows.

$$\Delta^{U''} = max(\Delta^U[Eq.4.5], \Delta^{U'}[Eq.4.22]) \tag{4.23}$$

It can be observed from Figure 4.3 that when the modified value $\Delta^{U''}$ (Eq. 4.23) is used for determining the new B^U, the mandatory re-start delay of R^d (3 minutes) is ensured along with the maintenance of the comfort-band.

4.5 Evaluation of TCBM through Simulation and Prototype Implementation

In this section, we report on the performance of our algorithm and compare the results with that of several candidate algorithms adapted from the real-time domain for AC scheduling. We also implemented TCBM algorithm in a prototype set-up and report on observations made from it. Simulation studies were carried out based on thermal characteristics of ACs generated by curve-fitting using the empirical data presented in Section 3.1.2. The load consisted of 5 ACs. We assume that peak power limit permits no more than 3 ACs to be ON at a time. Feasibility is checked according to Equation 4.4 for a comfort band with $T^L = 23^0C$ & $T^U = 26^0C$. Δ^U (0.24) and Δ^L (0.19) values are calculated according to the Equations 4.5 and 4.12 respectively.

4.5.1 Candidate Scheduling Algorithms

We first applied global EDF (Earliest Deadline First) scheduling [35], Least Slack First (LSF) scheduling [6], and value-based scheduling [46] [47] from the real-time domain. The periodic task model as described in Chapter 1, is used for AC tasks in this simulation with C_i as the time duration an AC needs to run to bring down T_i from T^U to T^L and L_i as the time duration it can be switched OFF, i.e., when T_i rises from T^L to T^U. The period P_i is its duty-cycle $(C_i + L_i)$. In EDF [17], the task which has the earliest absolute deadline is scheduled first. Global EDF [35] extends the EDF scheduling of tasks to uniform multi-processors, where m out of n tasks can run on m processors at any point of time. Global EDF (gEDF) scheduling appears to be a natural candidate for AC scheduling as the constraint that only m out of n ACs can run simultaneously can be straight-away mapped to scheduling n tasks on m processors. In LSF or *Least Slack-Time First (LST)* [21], the task which has the least slack (or laxity) is scheduled first, where at any time t, slack of a task having a deadline D_i is defined as $(D_i - t)$ minus the time required to complete the remaining portion of the task. In our case, slack at any time is the remaining length of time it can be OFF. Value-based scheduling [46] [47] is another promising algorithm for scheduling TCE devices, as a TCED task can be associated with a value $V_i(T_i)$, depending on the temperature T_i of the zone under its control. Specifically, we can assign a value to the AC task according to the amount of cooling it can give per unit time when it is ON and the desired comfort-band. The state-dependent attribute V_i has the highest value at $T_i = T^U$ and it becomes negative at $T_i > T^U$. V_i goes on decreasing as $(T^U - T_i)$ decreases and again attains negative value at $T_i < T^L$. We can summarize it as follows.

Table 4.1: Summary of Performance of Different Scheduling Policies

CB=comfort-band	1500 Min.	$T^U = 26^0C$	$T^L = 23^0C$	
Metric	**LSF**	**Value**	**gEDF**	**TCBM**
Time to reach CB	10	4	CB not maintained	10
No. of Switching	2197	5999	876	562
Excess Switching	1705	5507	384	70
Discomfort duration	56	14	293	33
COT (min.)	3221	4500	3242	3246
Avg. Temp. (^{0}C)	24.53	23.27	24.55	24.55

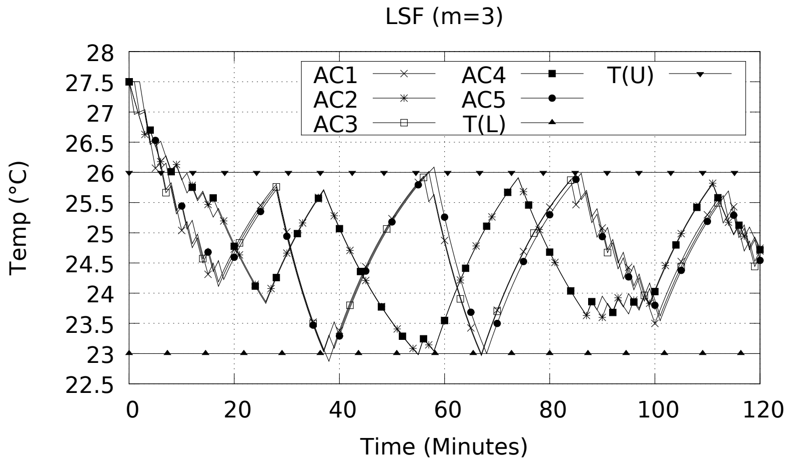
$$V_i(T_i) = \begin{cases} T^U - T_i, & \text{if } T_i > T^U \ , \\ \frac{T_i - T^L}{T^U - T^L}, & \text{if } T_i \leq T^U \end{cases} \tag{4.24}$$

4.5.2 Relative Performance of the Algorithms

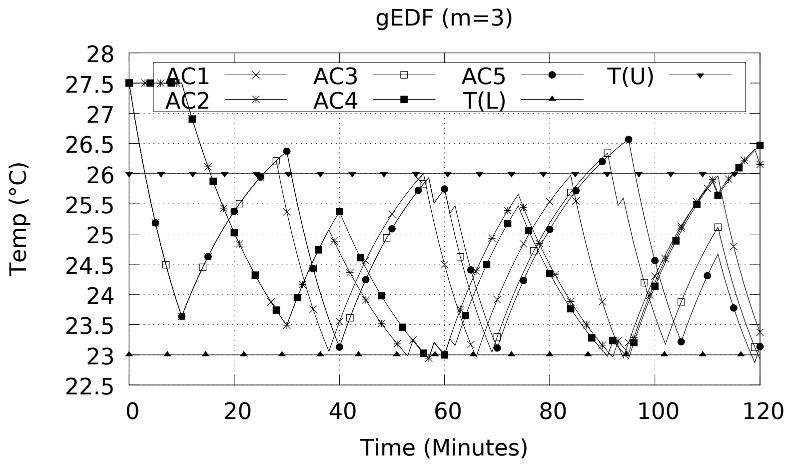
Figures 4.4a, 4.4b, 4.4c and 4.5 show the simulation results of LSF, global EDF, Value-based and TCBM scheduling respectively, considering initial room temperature $T_r = 27.5^0C$. The observations are summarized in Table 4.1 and in Figure 4.6. It is important to note that

LSF, Value-based and TCBM scheduling take $\leq$ 10 minutes, which can be considered to be a reasonable amount of time, to bring down the room temperatures within $[26^0C, 23^0C]$ from the initial temperature of 27.5^0C and maintain it thereafter. In contrast, global EDF takes 31 minutes. Global EDF does not always maintain the room temperature in the comfort-band, which is obviously unacceptable. Even under LSF scheduling, T_i goes beyond T^U on some occasions.

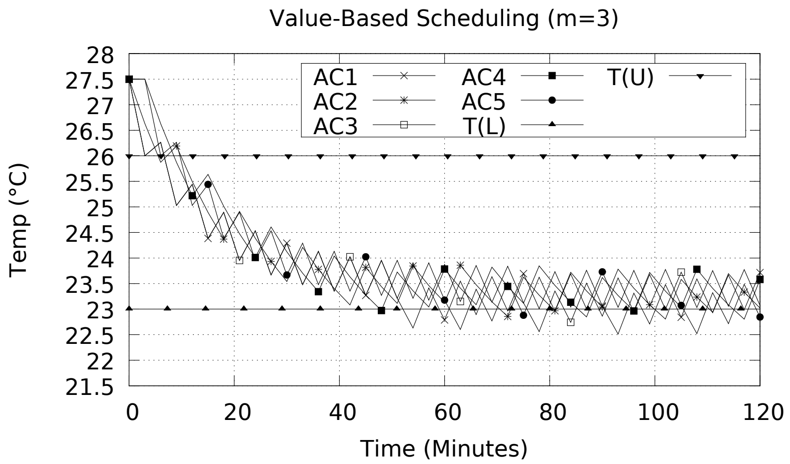
It can also be observed from Figure 4.4a that all ACs are switched OFF at different points of time causing higher T_i, because LSF policy keeps a load OFF irrespective of T_i, if it has consumed power (i.e., remains ON) for C_i amount of time within its period P_i. Similarly, in case of gEDF scheduling, in Figure 4.4b, loads are switched OFF because



(a) LSF Scheduling of ACs



(b) gEDF Scheduling of ACs



(c) Value-Based Scheduling of ACs

Figure 4.4: AC Scheduling Under Various Candidate Scheduling Policies

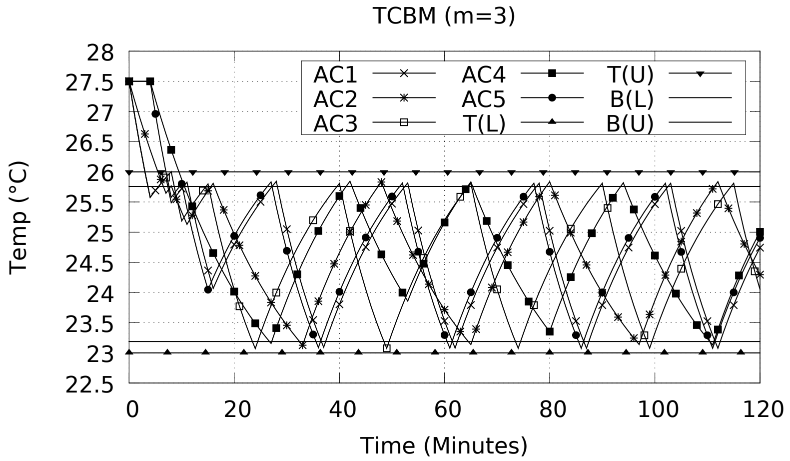


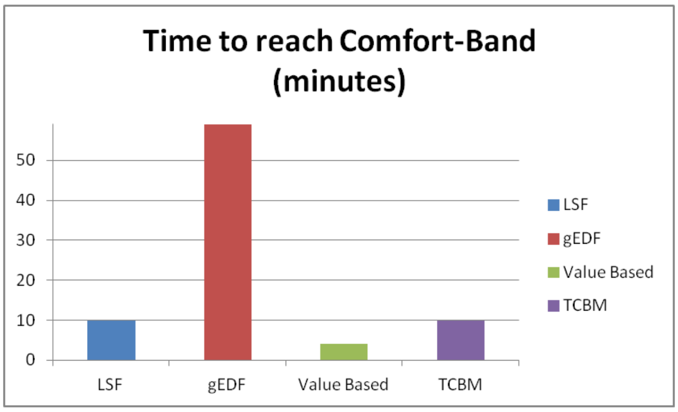
Figure 4.5: TCBM Scheduling of ACs

they consumed power for C_i amount of time within their period P_i, without taking into consideration the value of T_i. This also explains the long durations of discomfort shown in Table 4.1 under LSF and gEDF scheduling.

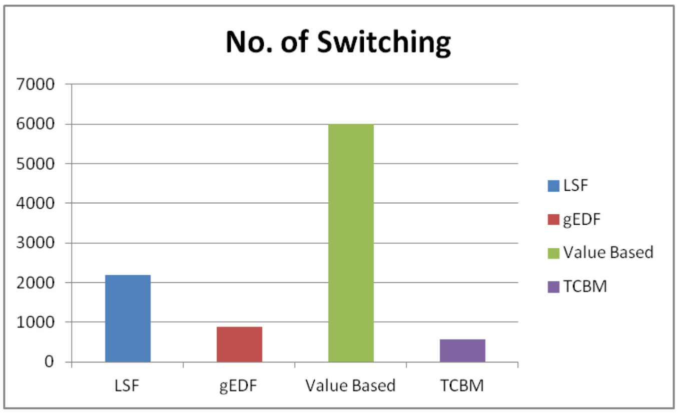
In case of TCBM, it can be observed in Figures 4.5 that m ACs are always ON, as long as they are required to maintain the comfort-bands. During the initial phase, when the zone temperature is high (27.5^0C), T_i of some ACs increases only because it is not possible to run more than m ACs at a time.

The number of ON/OFF switching of ACs in LSF and Value-based scheduling is very high, 400% and 1050% more respectively, compared to our TCBM scheduling. Switching in global EDF scheduling is 150% higher compared to TCBM scheduling. We calculated the expected number of switchings of 5 ACs in 1500 min. of simulation considering 2 (ON & OFF) switchings per period when run only under thermostatic control. The number of excess switchings above the minimum value of 492 is shown in Table 4.1 and it can be observed that the no. of excess switchings under TCBM is only 70 as against 5507, 1705 & 384 under value-based, LSF and gEDF respectively.

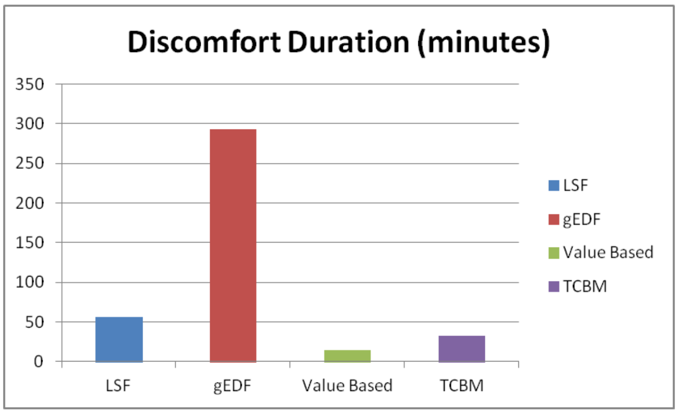
In case of value based scheduling, This can be observed from Figure 4.4c and Table 4.1 that the number of AC switching is extremely high (5999 for 5 ACs). It can be explained from the fact that as an AC is switched ON, its corresponding room temperature decreases, which in turn deceases the value of supplying power to it. In the subsequent scheduling period(s), the same AC is likely to be switched OFF because of its reduced



(a) Time to Reach Comfort-Band



(b) Number of Excess Switching



(c) Discomfort Duration

Figure 4.6: Comparison Chart: Performance Evaluation

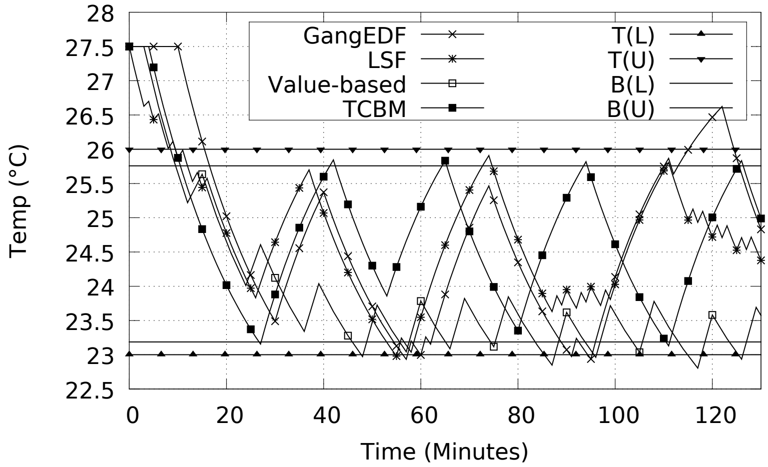


Figure 4.7: Effect of Different Scheduling Policies on an AC

value and hence later its value will rise again. Therefore, such cyclical rise and fall of values causes excessive switching.

We also calculated cumulative ON-time (COT) of the 5 ACs during the 1500 minutes of simulation and derived the average temperatures of the zones as shown in Table 4.1. It can be concluded from Table 4.1 that for a particular comfort-band, the consumption of energy (expressed in terms of COT) does not vary much with adoption of different scheduling policies, except for Value-Based. Such an outcome is expected because, in order to maintain a particular average temperature of a zone, the AC needs to run for the same amount of time irrespective of what scheduling policy is adopted. This explains the almost same amount of energy consumption under TCBM, gEDF and LSF, because the average temperatures maintained by them are nearly the same. But, in case value-based scheduling, the energy consumption is higher because, the average temperature maintained is much lower.

In Figure 4.7, we focus on a single AC. It highlights the superior performance of our TCBM algorithm with respect to different performance metrics like number of AC switching, maintenance of comfort band and time to reach comfort-band.

In summary, none of the candidate scheduling algorithms from the real-time domain namely, LSF, global EDF and Value-based scheduling, is suitable for TCED scheduling because they suffer from the following disadvantages:

- Maintaining room temperature within comfort zone $[T^L, T^U]$ is not guaranteed in

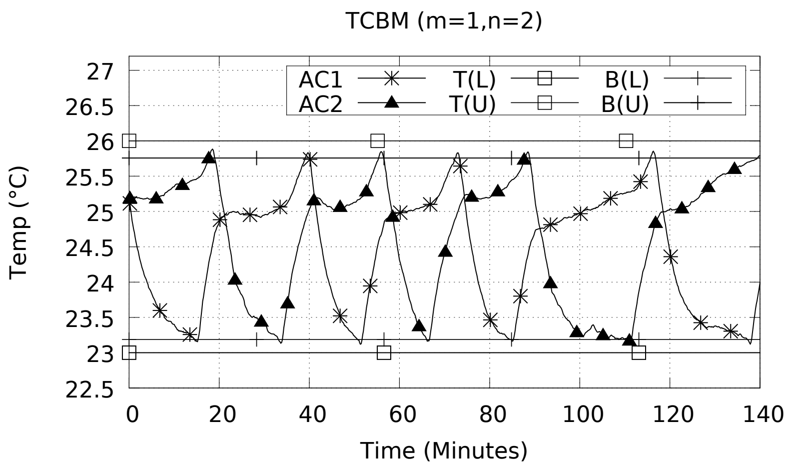


Figure 4.8: Effect of TCBM Scheduling on 2 ACs

LSF and gEDF scheduling, as the basic criterion for these algorithms is to provide resource for C_i units of time within every period P_i, irrespective of *when* this C_i time is allocated. This lacuna can cause the controlled environmental parameter to go beyond its limit even though the task gets resource (power in case of TCED) for C_i unit of time within every P_i, as explained in Chapter 1.

- Excessive and undesirable switching of ACs since LSF, gEDF and Value-based policies decide to switch ON/OFF ACs irrespective of whether room T_i is within the comfort zone $[T^L, T^U]$.

Summary of the performance comparison is presented in bar chart form in Figure 4.6.

4.5.3 Prototype Experimental Studies

We implemented TCBM in prototype systems and present the results of our experiments in this section. First, we show how TCBM helps in reducing peak demand without compromising the desired comfort in a small system with 2 homogeneous ACs. Then we present the results of our experiment with a larger system consisting of 6 ACs of different makes and capacities.

The results of real-life behavior of 2 ACs in a room using TCBM algorithm, after both ACs reach the comfort-band, are shown in Figure 4.8.

It may be noted here that, when an AC is switched ON, its compressor and fan run

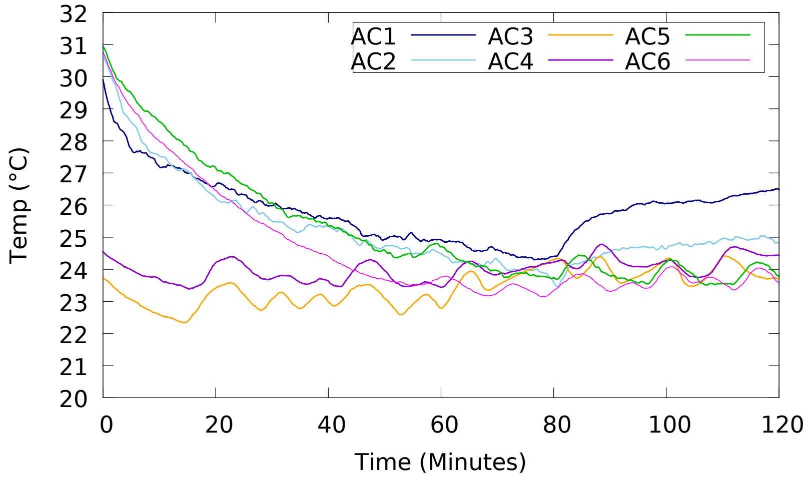


Figure 4.9: ACs under Thermostat Control (10 am - 12 noon)

and when it reaches the lower value of its set point, the AC is switched to fan-mode. Fan mode is the operating mode when compressor is OFF, but fan is running. It may be noted here that power requirement in the fan-mode is very low [1] as compared to the same when AC is in cooling-mode (compressor & fan both running). Hence, for simplicity of explanation, we ignore the energy consumed in fan-mode. Feasibility analysis according to Equation 4.4 indicates that comfort-band of $[23^0C, 26^0C]$ can be maintained with peak power permitting only one AC to be ON at a time. Figure 4.8 demonstrates that both ACs function alternatively, while maintaining the comfort-band. The values of Δ^U and Δ^L obtained using the methods discussed in Section 4.5 and 4.12 are 0.24^0C and 0.18^0C respectively. It can be observed from Figure 4.8 that whenever an AC is switched ON, it can affect the temperature of the other zone marginally. For example, at time t=40, when AC1 is switched ON while the AC2 was OFF, the temperature of the zone corresponding to AC2 falls by about 0.2^0C and then goes up again. This is because our assumption that the zones controlled by the two ACs are thermally de-coupled may not hold true in reality, because they are in the same room. How to consider such dependencies is discussed in Chapter 6.

Now, we compare peak demand observed with ACs left to their own thermostat control against the same when ACs are put to centralized control under TCBM.

Figures 4.9 and 4.10 show the operation of 6 ACs in three different rooms when they

[1] $8 - 10\%$ of the total AC load

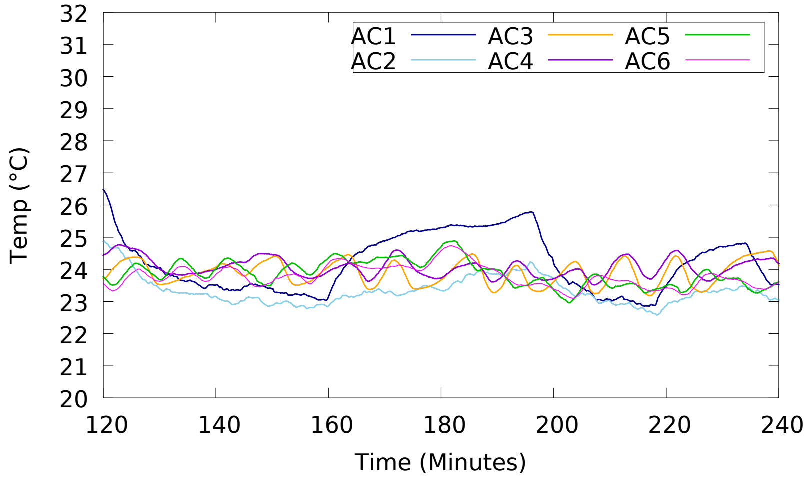


Figure 4.10: ACs under Thermostat Control (12 noon - 2 pm)

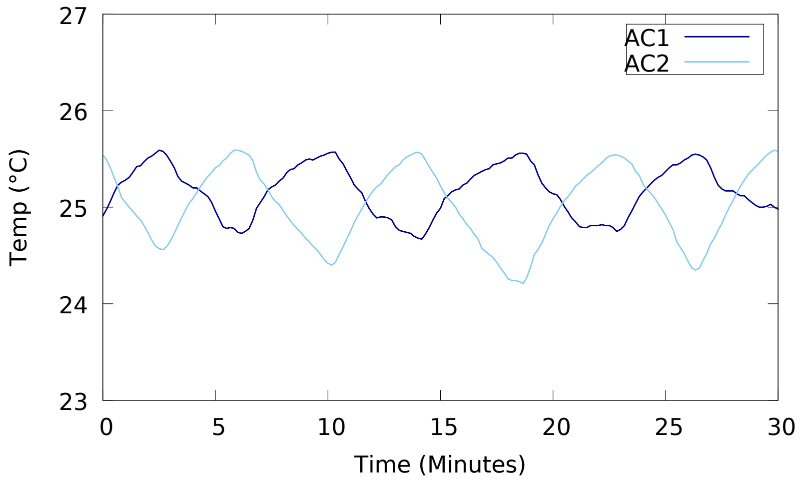


Figure 4.11: ACs under TCBM control in room R1

were left to run under individual built-in thermostat control. Each room is fitted with 2 ACs. Two *Carrier* make ACs (AC_1 & AC_2) in room R_1 are old window ACs with no star rating. In room R_2 the two ACs (AC_3 & AC_4) are of *Voltas* make split-ACs with 3-star rating and the ACs (AC_5 & AC_6) in room R_3 also split-ACs, but they are *Panasonic* make and have 4-star rating. During the experiment the occupants were allowed to change the temperature set points of the ACs, as they desired. The ambient temperature was 31^0C and usual change in occupancy were also observed.

It can be observed from Figures 4.9 and 4.10 that more than 50% of the time all the 6 ACs ran during their operating period of 4 hours demanding peak power requirement of

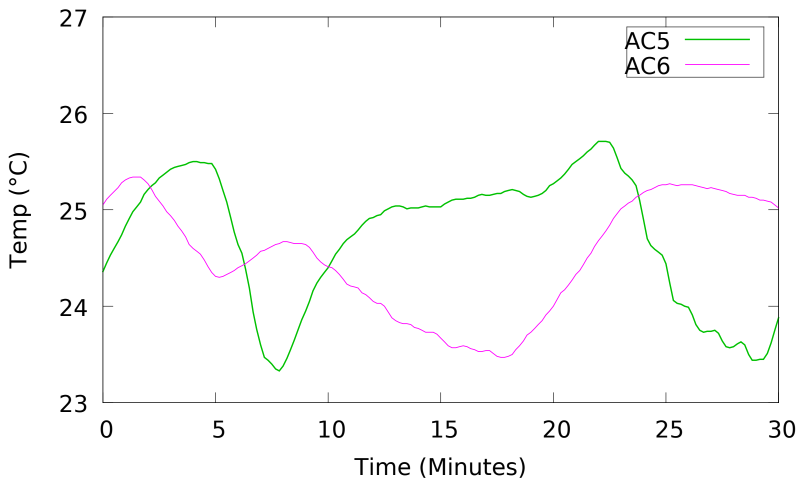


Figure 4.12: ACs under TCBM control in room R3

6 ACs. We find that it is feasible to reduce the peak demand up to 50% by coordinated scheduling of ACs in individual rooms. For example, it can be observed from Figures 4.11 and 4.12 that under TCBM control temperatures of rooms R_1 and R_3 can be maintained within CB$[23.5^0C, 25.5^0C]$ by running 1 out of 2 ACs in each of them.

4.5.4 Power Partitioning and Reduction in Peak Demand at Grid Level

The results of experimental studies discussed in Section 4.5.3 demonstrate that coordinated scheduling of multiple ACs by individual TCBM controllers in large rooms can reduce peak demand by 50%. This can be extended to a centralized controller coordinating operations of the ACs in multiple rooms of a building. Further, the building level controllers can coordinate with the controller at institution (e.g., academic institute, commercial cluster and housing complex) level for reduction in peak consumption. The idea is that if peak demand power is reduced and maintained within limits by consumers with granularity level of buildings in every institution in a particular area, then the overall peak demand in that area will be reduced, which in turn will have an impact on the grid level peak demand.

Let us assume that peak demand power contract between the distribution company and n institutions are $W_1, W_2 \cdots W_n$ respectively in a particular area. If each institution

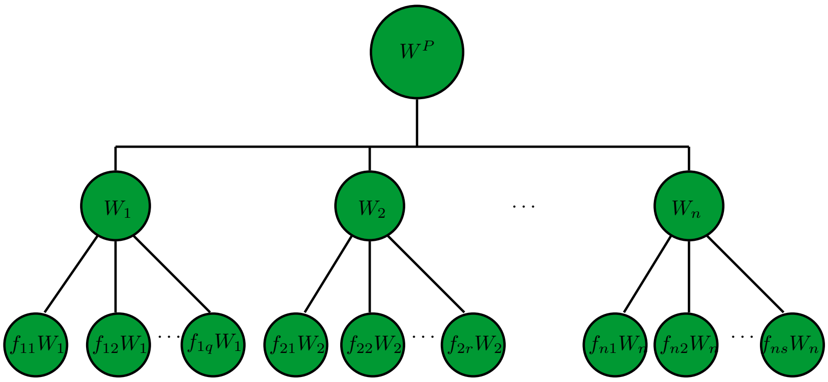


Figure 4.13: Power Partitioning to meet Peak Demand Limit

keeps their peak demand within the contract limits, the distribution company only needs to cater to a maximum peak demand W^P, such that

$$W^P = \sum_{i=1}^{n} W_i \tag{4.25}$$

Where, W_i denotes the peak power demand of the i^{th} institution.

Each institution can further divide/partition the available power to logical power sources, which are fractions f_{ij} of W_i equivalent to the peak demands of j^{th} building of the i^{th} organization, as shown in Figure 4.13.

We propose a building peak power management system in line with brownout scheme in [48], which will partition power according to peak demand registered by each building. It is assumed here that in order to keep the peak power demand within a limit, each building is allocated a specific share of power by the overall power management system of an organization/institution. The idea behind partitioning power as a resource is that if individual buildings maintain their own peak-demand within limit, the peak demand of the institution will not be exceeded. While global scheduler monitors the power consumption in each building, schedulers in individual buildings coordinate allocation of power to the loads consistent with its agreed quota of peak power. Power scheduler in each building implements its own policy so that its total power consumption does not exceed the specified limit at any point of time.

The following scheme of power partitioning for maintaining peak demand is proposed.

- Global power scheduler monitors power consumption by each building. If any building exceeds its registered power demand limit, warning signal is sent to the building

Table 4.2: AC loads in KReSIT Building, IIT Bombay

	Window AC	**Split AC**	**AHU**	**VRF System**
Load	70.4 KW	128 KW	25 KW	73 KW
Total AC Load	296.4 KW			

power scheduler for reducing peak demand.

- If warning is not honored, the global power scheduler cuts off supply to the errant building, except for the emergency loads. It is assumed here that each building will have their emergency loads identified and arrangements to feed power to these loads through a separate breaker in such a situation.

4.6 Estimated Peak Shaving in a Building

Here, we present the estimated reduction in peak demand of the KReSIT building in IIT Bombay, using TCBM. The building has 296.4 KW of load due to ACs, which is about 65% of the connected electrical load of 455.7 KW.

It can be observed from Table 4.2 that the highest share (67%) of these AC loads (198.4 KW out of 296.4 KW) in KReSIT are due to Window and Split type of ACs. TCBM technique can be applied to all these ACs in order to reduce peak demand. As discussed in Section 4.5.3, up to 50% of peak demand can be reduced if these ACs are put under TCBM control. Let us take into account of the peak consumption of 260 KW during June 2015. Theoretically, it is possible that all the ACs were running during the period when peak consumption of 260 KW was recorded in June. Therefore, 65% of this peak consumption could be due to AC loads. Considering 43% ($0.65 \times 0.67 \times 100$) of this peak consumption due to split and window ACs, it is possible to reduce the peak consumption by ~110 KW in one academic building (KReSIT) of IIT Bombay. It requires a systematic survey of TCED loads in commercial, educational and public utility buildings in a particular area in order to arrive at a figure for actual reduction in peak demand from the grid. But, the above estimation clearly indicates the potential of TCBM in reducing peak demand from grid, using the technique proposed in Section 4.5.4.

4.7 Variable Frequency Drive AC System and TCBM

Variable Frequency Drive (VFD) air-conditioning (AC) system use VFD to control the compressor and/or the fans in AC. A VFD AC, popularly known as inverter-type AC, controls the compressor speed depending on heat load and the cooling requirement. For example, when temperature inside the room is nearly equal to the ambient and a VFD AC is switched on, it drives its compressor and fan at full speed in order to attain the desired temperature faster. Once the set temperature is attained, it drives the compressor at a lower speed (depending on heat load and losses) only for maintaining it. A VFD does not switch ON/OFF the compressor like a bang-bang controller and saves energy by avoiding losses due to switching a compressor from ON to OFF, which involves in-rush current.

However, so far as peak demand is concerned, VFD ACs can also cause rise in peak demand during the initial phase of its operation. This can happen, for example, in an academic building, when the classes start and all the ACs are switched on, practically at the same time. Staggering the operation of VFD ACs during their initial phase can reduce peak demand. Also, introducing comfort band $[T^L, T^U]$ in operating multiple VFD ACs can facilitate peak reduction. This can be achieved by setting the temperatures of m out of $n(> m)$ zones at T^U and setting the temperatures of $(n - m)$ zones at T^L. At any point of time, the compressors of the ACs corresponding to m zones will run at lower speed as compared to AC compressors belonging to $(n - m)$ zones, because they will be maintaining temperatures at $T^U(> T^L)$. Since lower speed demands lesser power, introducing comfort band in controlling VFD ACs will result in peak reduction while maintaining the zone temperatures within $[T^L, T^U]$. A suitable fairness algorithm may be utilized in selecting m ACs, which will run at lower speed (maintaining zone temperatures at the upper limit T^U of the comfort band) over a period of time. We are carrying out further studies on VFD as well as Variable Refrigerant Flow (VRF) ACs, so that TCBM technique of reducing peak demand can be applied to these type of ACs also.

It may be noted here that VFD ACs are very costly and the recovery period of the initial investment from energy saving is long. In our assessment, the traditional ACs ON/OFF are not going to be replaced soon. This is true, especially in developing countries like India, where even very low efficiency (2-star and 3-star) traditional ACs have a sizable market share due to their low cost.

In this chapter, we presented TCBM algorithm and the feasibility analysis of scheduling TCEDs under peak demand constraint. We have shown, along with simulation results, how TCBM is a practically implementable solution that takes care of mandatory restart delay along with minimum switching of the TCEDs. Evaluation carried out in Section 4.5 established superior performance of TCBM algorithm over the candidate algorithms from real-time domain. Supported by prototype implementation, we also proposed a building power management system along with a scheme of power partitioning so that the aggregated peak demand of buildings from grid is reduced. We carry this work further to deal with varying environmental parameters, time-of-day (TOD) charges and varying peak demand limit that can affect the energy-efficiency of TCE devices as discussed next in Chapter 5.

Chapter 5

Energy Consumption and Adaptive Demand-Response Control

In this chapter we discuss how energy consumption varies with changes in comfort-band. We also discuss how adjustment in comfort-band can be utilized for energy-efficiency and dynamic demand-response (D-R) control under peak power demand constraint.

The energy consumption of an AC not only depends on how much change in zone temperature it brings, but also on the values of the initial temperature T_1 and the final temperature T_2. Let t_1 represent the time when AC was started and the zone temperature was T_1. Let t_2 represent the time when AC stopped cooling after bringing down the zone temperature to T_2 from T_1. Due to exponential nature of the cooling curve, the ON-time $(t_2 - t_1)$ of an AC can vary even it causes the same amount of variation in temperature $(T_1 - T_2)$. For example, it can be observed from Figure 1.1 that the time required for the AC to bring down the temperature 24^0C to 23^0C is much less compared to the time required for bringing down the temperature from 23^0C to 22^0C. In other words, even if the comfort-band width $(T_1 - T_2)$ is kept same, the energy consumption by AC can vary for different values of T_1 and T_2. Therefore, adjustment in the comfort-band can help reducing energy consumption.

We develop a theoretical basis and discuss how dynamic adjustment of the comfort-band can be utilized to

- adapt to the time varying peak power demand limit,

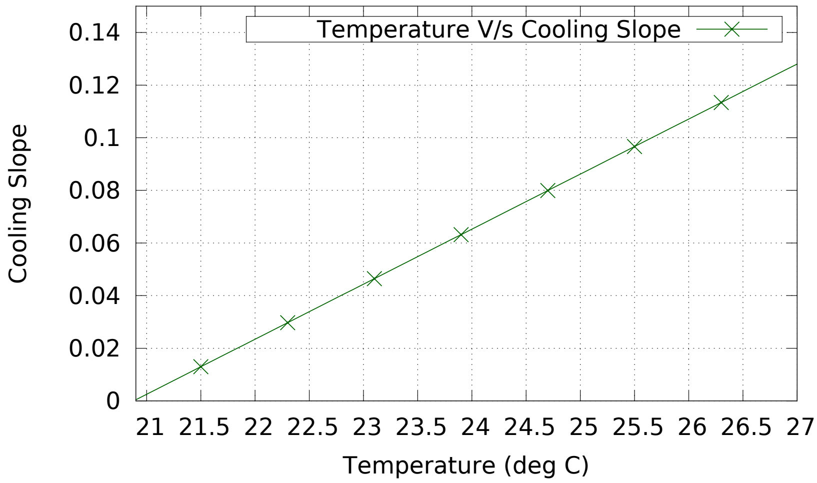


Figure 5.1: Cooling Slope Varies with Zone Temperature

- minimize energy consumption, and
- handle the effect of varying ambient temperature.

5.1 Cooling Slope, Zone Temperature and Energy Consumption

The cooling slope S_f of an AC represents the drop in temperature T per unit time. From Equation 3.17, we get the cooling slope at any temperature T as

$$S_f = c(a - T) \tag{5.1}$$

where, a and c are the characteristic constants of the cooling curve of the AC.

It can be observed from Equation 5.1, that the slope (S_f) of the cooling curve depends on the zone temperature and S_f reduces with the fall in zone temperature. This is validated by the experimental results shown in Figure 5.1.

Again, from Equation 3.16, we get

$$\frac{S_f}{-bc} = e^{-c \times t}$$

$$c \times t = ln \frac{S_f}{-bc}$$

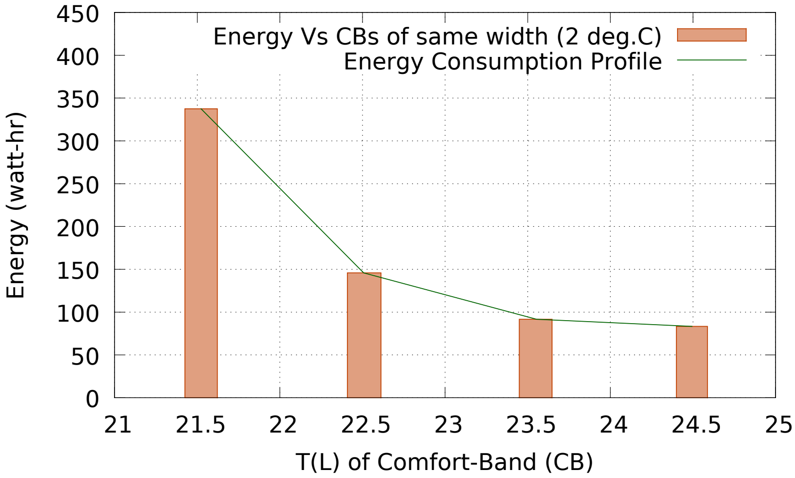


Figure 5.2: Energy Consumption with Variation in CB

$$t = -\frac{1}{c} ln \frac{S_f}{-bc} \tag{5.2}$$

When an AC runs for a time interval $[t_1, t_2]$, the energy consumption E can be expressed as

$$E = \int_{t_1}^{t_2} W dt = W[t_2 - t_1]$$

Where, W is the wattage of an AC.

Substituting t from Equation 5.2, we get

$$E = W \times \frac{1}{c}[ln \frac{S_f(t_1)}{-bc} - ln \frac{S_f(t_2)}{-bc}]$$

$$E = \frac{W}{c} ln \frac{S_f(t_1)}{S_f(t_2)} \tag{5.3}$$

Assume that at t_1 (when the AC is switched ON), the zone temperature is T^U and at t_2 (when the AC is switched OFF), the zone temperature is T^L.

The Equation 5.3 can be re-written as

$$E = \frac{W}{c} ln \frac{S_f(T^U)}{S_f(T^L)} \tag{5.4}$$

Now, from Equation 5.4, it can be concluded that as the ratio of the cooling slopes between the T^U and T^L, increases, the energy consumption increases exponentially even if the width $(T^U - T^L)$ of the comfort-band remains same.

We also calculated the energy consumption for various comfort-bands. For this purpose, we considered the experimentally obtained thermal characteristics of an AC shown in Figure 1.1. We assume that the power rating of the AC is 1.5 KW. The mathematically calculated energy consumption data for cooling down the zone from T^U to T^L for different comfort-bands of equal width $[(T^U - T^L) = 2^0C]$ are shown in Figure 5.2. From Figure 5.2, it can be observed that if the comfort-band is shifted up just by 1^0C from $[21.5^0C, 23.5^0C]$ to $[22.5^0C, 24.5^0C]$, the energy consumption can be reduced significantly.

5.2 Prototype Implementation to Quantify Energy Savings

The result of a real-world implementation that demonstrates the energy-saving by shifting of comfort-band is presented in this subsection.

We applied TCBM algorithm on 2 ACs installed in a room and experimented for two different comfort-bands. We assume that peak power constraint allows only 1 AC to run at a time. TCBM analysis applied on the experimentally obtained thermal characteristics of the ACs shows that it is feasible to run 1 out of 2 ACs at a time in order to maintain the comfort-bands.

We started with a CB of $[24^0C, 22^0C]$ and then shifted it to $[24.5^0C, 22.5^0C]$ i.e., shifted up by 0.5^0C. We assume that a small change in temperature (0.5^0C) will not affect the thermal comfort of the occupants. The experiment was carried out for 1 hour in both the cases.

Figures 5.3 and 5.4 show the operation of ACs under TCBM control for CB $[24^0C, 22^0C]$ and CB $[24.5^0C, 22.5^0C]$ respectively. The cumulative on-times (COT) of the ACs in both the cases are also shown. It can be observed from Figures 5.3 and 5.4 that COTs of the ACs have been reduced by 11 minutes by means of shifting the CB only by 0.5^0C.

Since energy-consumption is directly related to the cumulative ON-time of the ACs,

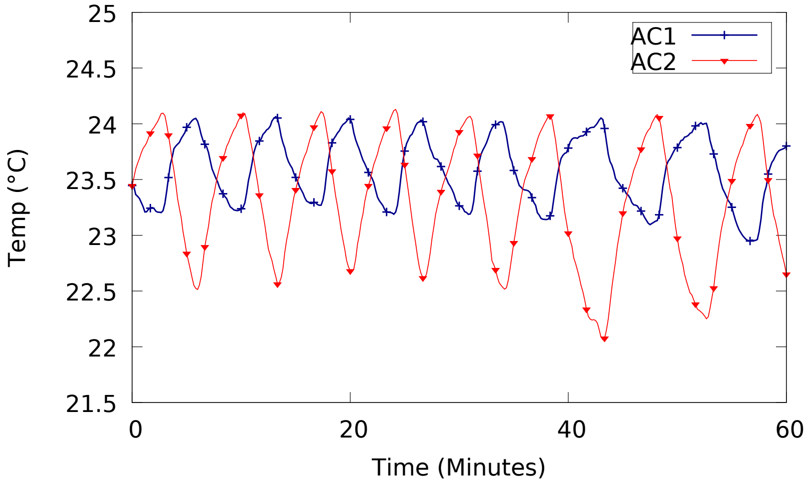


Figure 5.3: COT= 60 min. with CB 24^0C - 22^0C

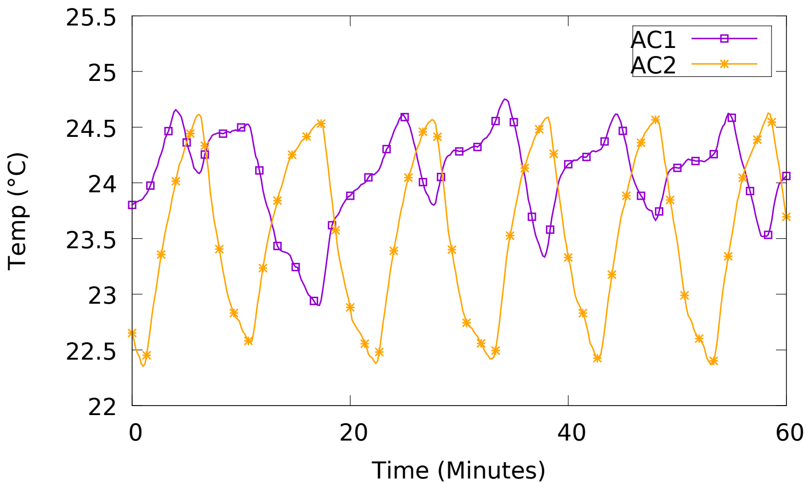


Figure 5.4: COT= 49 min. with CB 24.5^0C - 22.5^0C

the results in Figures 5.3 and 5.4 show about 18% saving in energy in a small 2 AC system in one hour. The energy consumption of an 1.5 ton AC is about 1.8 KW. Therefore, if we assume that the room is occupied 10 hours/day on an average, the energy-savings in a small 2 AC system comes out to be

$$\frac{11}{60} \times 10 \times 30 \times 1.8 = 99 \text{ units (KWh) of energy every month.}$$

5.3 Adaptive Demand-Response Control

Electricity bills for commercial sites typically contain energy charges and demand charges. Today, TOD (time-of-day) and peak-demand electricity charge [49][16] are applicable to bulk consumers, which include commercial buildings and academic institutions. It is likely that small residential consumers will come under TOD and peak demand tariffs in the near future. Also, peak demand charge may not be the same throughout the day. So, in order to reduce electricity bill, consumers need to adapt to the *i*) time varying peak power demand limit and/or *ii*) need for limiting energy consumption demand during some period of the day due to TOD charges.

Further, energy consumption of TCEDs are affected by the change in the ambient temperature. This is because, it changes the thermal characteristics (represented by the characteristic constant discussed in Section 3.1) of the TCEDs due to changes in heat transfer rate. Also, the experimental results in Section 5.2 show that even a small shift in the CB by 0.5^0C can cause a significant change in energy consumption. Therefore, we attempt to formulate an adaptive technique for controlling TCE devices both under time varying peak power limit and variations in the ambient temperature.

Changes in thermal characteristics result in changes in the cooling slope S_f^i and the warming slope S_r^i. Changes in peak demand affect the value of m, the maximum number of TCEDs that can run at a time [Equation 4.1]. So, the schedulability of TCEDs gets affected in both these cases [Equation 4.2].

5.3.1 Adapting Energy Consumption with TOD Charges

We have already discussed in Section 5.1 on how energy consumption can vary with variations in the comfort-band. Therefore, electricity bill can be reduced by adjusting comfort-band according to the TOD charges. For example, comfort-band can be shifted up slightly, say by 0.5^0C during 9 am to 12 noon, when TOD charge is higher.

5.3.2 Handling Varying Ambient Temperature

Here we assume that the peak demand limit is constant, but ambient temperature varies with time.

Table 5.1: Schedulability with varying ambient (5 ACs)

		Ambient 27^0C			*Ambient* 32^0C		
Comfort-band (^0C)	m	$\sum S_f$	$\sum S_r$	**feasibility** ($\sum S_f \geq \sum S_r$)	$\sum S_f$	$\sum S_r$	**feasibility** ($\sum S_f \geq \sum S_r$)
$23-25$	2	0.149	0.140	Yes	0.35	0.53	No
$24-26$	2	0.218	0.098	Yes	0.46	0.35	Yes

We recorded the temperature data of ACs on two different days when the ambient temperatures were 27^0C and 32^0C respectively. The thermal profile of an AC is characterized by its cooling-slope S_f and the warming slope S_r. Table 5.1 shows the effect of changed thermal characteristics of ACs on schedulability. Note that the schedulability data for 5 ACs presented in Table 5.1 are generated by the feasibility criterion stated in Equation 4.2. It can be observed from Table 5.1 that by running $m(=2)$ out of $n(=5)$ ACs at a time, it is possible to maintain a CB $[23^0C, 25^0C]$, when the ambient temperature is 27^0C. It is not so, when the ambient temperature is 32^0C. But, as it can be observed from Table 5.1, we have the following option.

- Adjust the comfort-band to CB $[24^0C, 26^0C]$ so that the peak demand limit of available power for 2 ACs is not violated.

We propose the following scheme to adapt to the changes in ambient temperature.

- *Scheme I:* Generate AC characteristics (constants) at various ambient temperature values (assuming change in heat loads to be negligible) obtained by off-line curve-fitting, store them in TCBM controller and use the same for adaptive control.

- *Scheme II:* Carry out on-line curve-fitting based on the room temperature data obtained in the immediate past say, last 15 minutes. We assume that there will be no major variation in ambient temperature within 15 minutes. Use the data for feasibility analysis and apply adaptive control accordingly. This scheme is capable of handling changes in heat loads also.

Table 5.2: Schedulability by shifting comfort-band (5 ACs)

Comfort-band (^0C)	m	$\sum S_f$	$\sum S_r$	**feasibility** ($\sum S_f \geq \sum S_r$)
$23-25$	3	0.72	0.34	Yes
$23-25$	2	0.35	0.53	No
$24-26$	2	0.46	0.35	Yes

5.3.3 Varying Peak Limit and Shifting of Comfort-Band

The following example demonstrates the effect of shifting of CB on the TCBM feasibility under constant ambient temperature. Suppose, peak demand constraint allows power for 3 ACs at a time and we have 5 ACs to control using TCBM algorithm. We consider that out of 5 ACs, two ACs have the same thermal characteristics as that of AC1 and three ACs have the same characteristics as that of AC2. The constants of their characteristic equations are as shown in Table 3.1 and 3.2. The data related to feasibility of these 5 ACs under TCBM are generated using Equations 3.17 & 3.20 are shown in Table 5.2. It can be observed from Table 5.2, that it is feasible to maintain a comfort-band of $[23^0C - 25^0C]$ by running 3 ACs at a time. But, the same comfort-band can not be maintained if peak demand constraint allows powering-ON of at most 2 ACs at a time. Now, let's shift the comfort band from $[23^0C, 25^0C]$ to $[24^0C, 26^0C]$. It can be observed from Table 5.2 that in this case, comfort-band can be maintained by running 2 out of 5 ACs at a time. Therefore, we conclude that under varying peak demand limit, comfort-band $[T^L, T^U]$ can be suitably shifted to meet the peak demand constraint.

5.3.4 Adaptive Demand-Response Policy

The above discussion highlights the implications of shifting or relaxation of the comfort-band on adaptive demand-response in dynamic energy pricing/availability scenarios. We propose the following D-R (demand-response) policy.

1. The comfort-band can be adjusted dynamically and the user informed about it upon

- Changes in the externally-imposed peak demand constraint,
- Changes in the ambient temperature, and
- Changeover to the time-of-day (TOD) slots with different charges imposed by the distribution company.

2. If a user insists on staying with a pre-set comfort-band, he/she can be warned about the implications of violating the peak power consumption limit or consuming more during higher TOD-charge slot ahead of time.

5.4 TCBM as Anytime Algorithm

Anytime algorithms are algorithms whose quality of results vary with computation-time. The quality of results gradually improves with the increase in allotted computation time. The concept of imprecise computation was introduced in [50] and the authors applied it to real-time systems. They showed that in order to meet the computational deadline, the imprecise computation techniques offers scheduling flexibility with a compromise on quality of the result.

Given a peak demand, TCBM can compute schedulability and come out with a YES/NO answer for maintaining the desired comfort-band $[T^L, T^U]$. Alternatively, it can compute what comfort-band can be maintained under the given peak demand limit. Therefore, we observe that under peak demand constraint, TCBM can be utilized as an anytime algorithm. If TCBM schedulability analysis finds that the desired comfort-band can not be maintained, it can offer a maintainable but slightly inferior thermal comfort-band than what is most desirable by the consumer. We assume that consumer may accept a slightly inferior comfort-band, as there is a financial incentive involved if power consumption is maintained within peak limit due to acceptance of inferior comfort.

Imprecise Computation and Inferior Comfort

We draw an analogy between imprecise computation and variation in desired thermal comfort level, which we term as *inferior comfort*, as shown in Table 5.3.

Table 5.3: Analogy between Anytime Algorithm and TCBM Algorithm

	Computational Output	**Constraint**
Anytime Algorithm	Imprecise	Deadline
TCBM Algorithm	Inferior comfort level	Peak Demand Limit

Table 5.4: 7-point ASHRE thermal scale

Vote	**Thermal Comfort Level**
+3	Hot
+2	Warm
+1	Slightly Warm
+0	Neutral
−1	Slightly Cold
−2	Cool
−3	Cold

Let us consider a system of n ACs maintaining temperature of n zones. Given a peak demand constraint that allows only $m(\leq n)$ ACs to run at a time, TCBM schedulability analysis can tell us if a desired thermal comfort-band $[T^L, T^U]$ that can be maintained or not. Iteratively, by increasing T^L and T^U say, by 0.5^0C in each step, TCBM can also compute the comfort-band that can be maintained under the given peak limit.

Individual thermal comfort preference can be expressed in terms of 7-point PMV scale defined by ASHRE in [41] as shown in Table 5.4. Whereas the desired thermal comfort is defined as 0, we assume that a consumer may be ready to accept a thermal comfort level of +1 or −1, for example. It may be noted that +1 and −1 represent the PMV values corresponding to *slightly warm* and *slightly cold* state respectively.

We propose a inferior-comfort algorithm by TCBM, which facilitates users' participation in D-R control. The pseudo-code of the inferior comfort algorithm is given in Figure 5.5.

In this chapter we formulated the relationship between energy consumption and comfort. We showed how a small shift of 0.5^0C in the comfort band can cause significant change in energy consumption. Utilizing these facts, we proposed an adaptive demand-response control technique under changes in the ambient conditions and dynamic variation in peak demand limit.

$n =$ Total no of ACs and $m =$Maximum number of ACs that can run at a time

PMV $= 0$

$T^S = 24$*; Default Temperature Set Point (^0C)*

Comfort-Band (CB) $[T^L, T^U] = [T^S - 1, T^S + 1]$*; Default Comfort-Band*

```
BEGIN
t = 0,    t_1 = 0
DO
read t, PMV and calculate m from given peak demand constraint W^P
IF ((t - t_1) <= 10) minutes CONTINUE; ELSE t = t_1; END IF
IF (PMV > 0)    THEN
    T^L = T^L - 0.5 and T^U = T^U - 0.5
    run TCBM feasibility analysis for m and CB[T^L, T^U]
    IF feasible, CONTINUE;
    ELSE
        notify Consumer
        IF customer agrees to accept slightly less (inferior) comfort THEN
            T^L = T^L + 0.5 and T^U = T^U + 0.5;
        END IF
    END IF
ELSE IF (PMV < 0)    THEN
T^L = T^L + 0.5;  T^U = T^U + 0.5;
END IF
WHILE(1)
END
```

Figure 5.5: TCBM Inferior Comfort Algorithm

Chapter 6

Thermally Coupled Zones, Heating Loads and Multiple Comfort Bands

The main assumption in feasibility analysis of scheduling TCEDs described in Section 4.3 is that the zones controlled by individual TCEDs are thermally de-coupled. But, it has been observed that many a large rooms/laboratories are fitted with multiple ACs for maintaining the desired temperature in the rooms. In such cases, the cooling of individual zones is affected by the operating conditions of the neighboring ACs.

In this chapter, we present the results of our experiments carried out to evaluate how the TCBM feasibility analysis is effected by the operating conditions of the neighboring ACs. We also discuss the applicability of TCBM in coordinated scheduling of TCE heating loads and the devices with different comfort-bands (e.g., ACs and refrigerators).

6.1 Effect of Coupled Zones on TCED Characteristics

As stated in Theorem 1, the feasibility of scheduling depends on the cooling slopes S_f^i and the warming slopes S_r^i of the TCEDs involved [Equation 4.2]. Now, the cooling slope S_f^i and the warming slope S_r^i of an AC are affected by the operating condition of the neighboring AC(s).

Therefore, we carried out experiments to find out the effect of neighboring ACs on

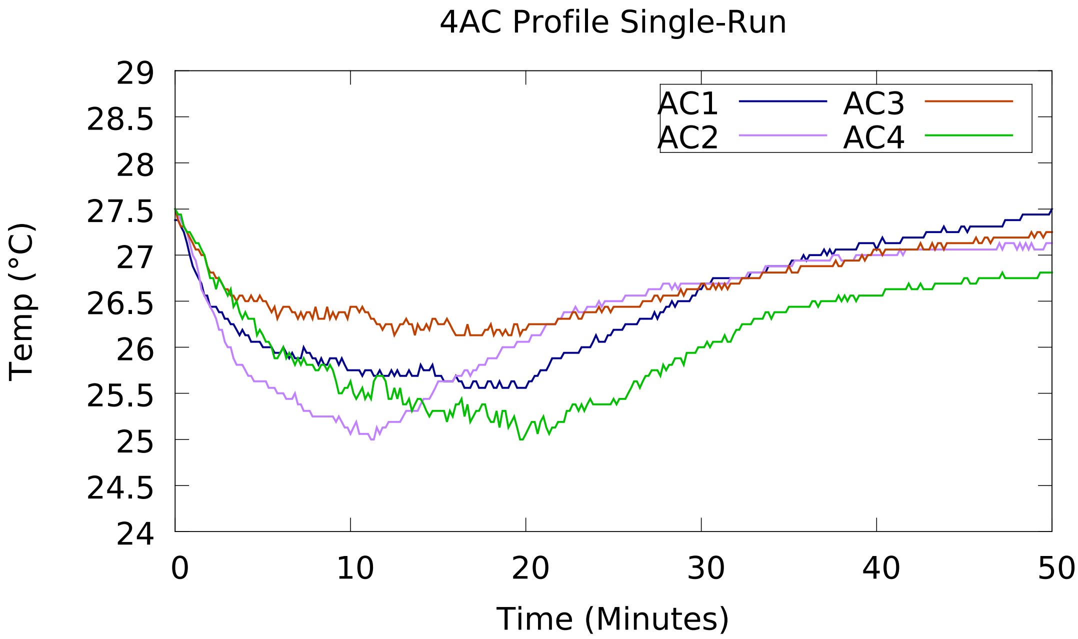


Figure 6.1: AC thermal characteristics with neighboring AC off

the TCBM feasibility analysis. The experiments were carried out with two rooms, each fitted with 2 ACs, where AC1 & AC2 are in room R1 and AC3 & AC4 are in room R2.

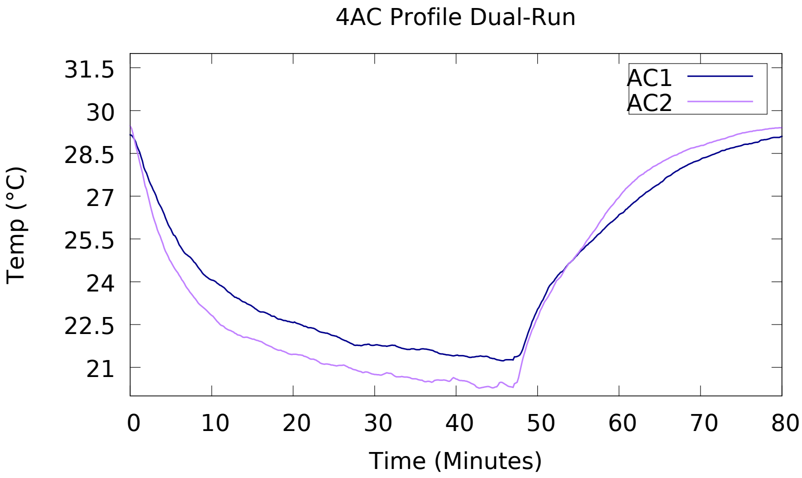
6.1.1 Thermal Characteristics Without Considering the Effect of Neighboring AC

In this experiment, we generated the thermal characteristics of each AC while keeping it's neighboring AC off. Thus, the influence of the neighboring AC is eliminated. But, thermal coupling with air-volume in the neighboring zone does affect cooling of the zone where AC is running.

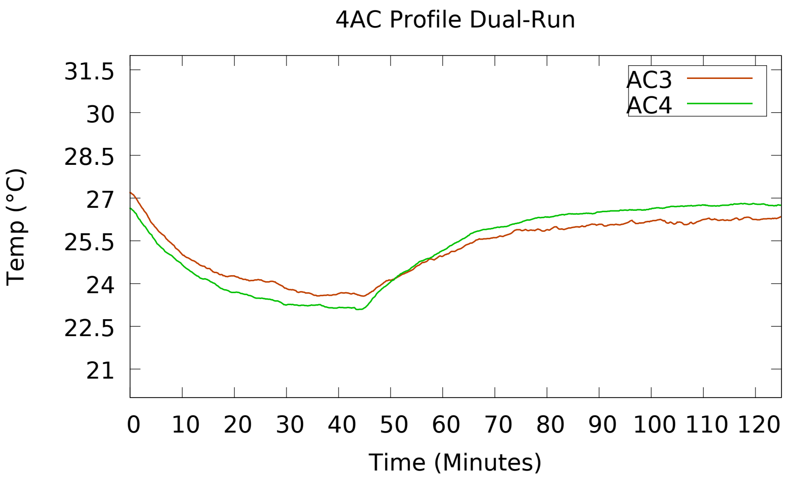
Figure 6.1 shows the thermal characteristics of AC1 to AC4 generated by running only 1 AC in a room at a time.

6.1.2 Thermal Characteristics Considering the Effect of Neighboring AC

In this experiment, we generated the thermal characteristics of the ACs by operating both the ACs in the rooms simultaneously.



(a) AC1 and AC2 with simultaneous operation



(b) AC3 and AC4 with simultaneous operation

Figure 6.2: Thermal Characteristics with Simultaneous Operation of all ACs in a Zone

Figures 6.2a and 6.2b show the thermal characteristics of AC1 & AC2 of room R1 and AC3 & AC4 of room R2 respectively.

The following observations are made from the above experiments.

- Figure 6.1 shows that when thermal characteristics are generated by running one AC at a time, in a room fitted with two ACs, it is able to bring down the temperature of its zone only to a value of about 25^0C. This minimum zone temperature achieved thus is high, because of the thermal coupling with the neighboring zone. Due to thermal coupling, the AC of a zone not only cools the air of its own zone, but also a fraction of the air-volume of its neighboring zone. It may be noted here that a particular AC can not bring down the temperature of a zone below a value represented by the thermal characteristic constant a [Equation 3.17 and Table 3.1], which in turn depends on the heat loads and losses. Therefore, the resulting thermal characteristics (obtained by running one AC at a time in a coupled zone) do not reflect the effective cooling capabilities of the 2 ACs, when they run in a coordinated manner.

- In contrast, it can be observed from Figures 6.2a and 6.2b that when both the ACs in a room are operated simultaneously, they bring down the room temperature to 23^0C in room R1 and to 21^0C in room R2.

6.2 Implementation of TCBM in Thermally-Coupled Zones

We applied TCBM feasibility analysis according to Equation 4.4. It is found that if the thermal characteristics as shown in Figure 6.1 are used, it is not feasible to maintain a CB of $[26^0C, 23^0C]$ by running 2 out of 4 ACs at a time. But, the same is feasible if the thermal characteristics according to the Figures 6.2a and 6.2b are used for checking feasibility.

We implemented TCBM scheduling for coordinated control of the 4 ACs in two rooms, each one fitted with 2 ACs. We assumed that peak power limit allows only 2 ACs to run at a time. The result is shown in Figure 6.3. The effect of neighboring AC is considerable in a thermally coupled zone. For example, it can be observed from Figure 6.3 that the pattern of the temperature profiles of the zones corresponding to AC3 and AC4 follow each other. During the period from 60 to 120 minutes, the AC3 remains OFF, yet the temperature of its zone varies from about 23.5^0C to 25^0C due to the varying operating state (ON/OFF) of the neighboring AC4. Alternatively, during the period from 165 to 240 minutes, though the AC4 remains OFF, its zone temperature gets affected by the ON/OFF state of AC3. But, it can be observed from Figure 6.3 that even though the zones are not thermally de-coupled, the TCBM algorithm maintains the room temperature within

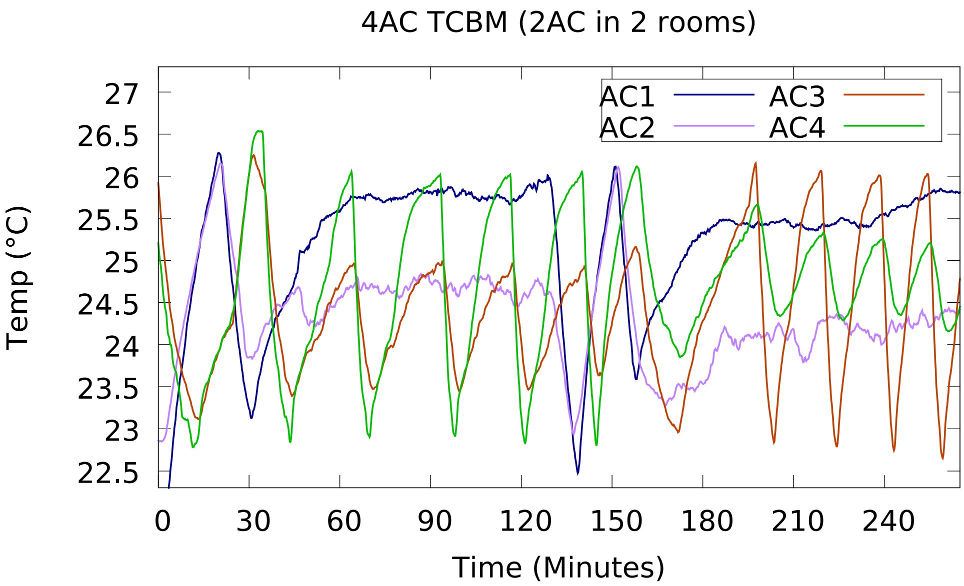


Figure 6.3: TCBM scheduling in thermally-coupled zones

the feasible band of $[23^0C, 26^0C]$.

Therefore, we conclude that TCBM feasibility analysis is applicable to thermally coupled zones also. But, it may be noted that in case of thermally coupled zones, the characteristics of the ACs are to be obtained by running all the ACs in a coupled zone simultaneously for reasons discussed in the beginning of this section.

6.3 Effect on Equipment Operation in a Thermally-Coupled Zone

Another phenomenon, which can be observed from Figure 6.3 is that when AC4 is running, AC3 remains OFF for a long time. This is because, the zone temperature of AC3 does not go beyond the comfort-band due to the cooling effect of the neighboring AC4. It may be noted that in this experiment, at about $t = 150$ minutes, we deliberately switched AC4 OFF and switched ON AC3. Figure 6.3 shows that thereafter AC3 keeps on running while AC4 remains OFF.

This experiment shows that in a thermally coupled zone, it is possible that some AC(s) will keep on running and some other AC(s) will remain idle for a very long time. Such a situation may affect the life of the continuously running AC(s). Therefore, we suggest a corrective measure of limiting the continuous running-time of an AC to a pre-determined value. A running AC may be deliberately switched OFF if it runs continuously for a long time say, ≥ 1 hour, even if its zone temperature remains within the CB.

Such a corrective measure can be considered as an external disturbance to the coordinated scheduling of TCEDs. But, as already discussed, even with external disturbances (manual intervention here as shown in Figure 6.3), TCBM meets its design objective of maintaining the comfort bands of the zones. It also demonstrates the robustness of the TCBM algorithm.

6.4 Feasibility of TCE Heating Loads

A TCE heating load (e.g., room-heater) functions exactly in the opposite manner compared to a TCED cooling load like an AC. A heater must be switched ON whenever the zonal temperature T_i goes below $T^L(> T_a)$. A heater must be switched OFF, if $T_i \geq T^U$. We assume that each zone is heated by a single heater. Therefore, for feasibility analysis of running m out of n TCE heaters under peak demand constraint, we apply arguments complimentary to what is used for TCE cooling load like AC. We denote TCE heater as *heater* in the rest of the chapter.

Theorem 5 *If peak-demand constraint allows m out n heaters to run at a time and the heaters are scheduled under TCBM algorithm, all the zonal temperatures will eventually rise from the ambient T_a to a value T_i ($T^L \leq T_i < T^U$) and the CB $[T^U, T^L]$ will be maintained thereafter, if the following condition is satisfied.*

$$\sum_{i=1}^{m} S_r^i(T_i) > \sum_{i=1}^{n-m} abs(S_f^i(T_i)) \tag{6.1}$$

where, i) the sum on the left is obtained from the first m of the n heaters arranged in ascending order of their heating-slopes and ii) the sum on the right is obtained from the first $(n-m)$ of the n heaters arranged in descending order of their cooling-slopes.

Proof: Peak demand constraint allows at most m heaters to remain ON. The remaining $(n-m)$ heaters will be kept OFF. Let $S_r^i(T_i)$ denote the slope of the temperature-rising

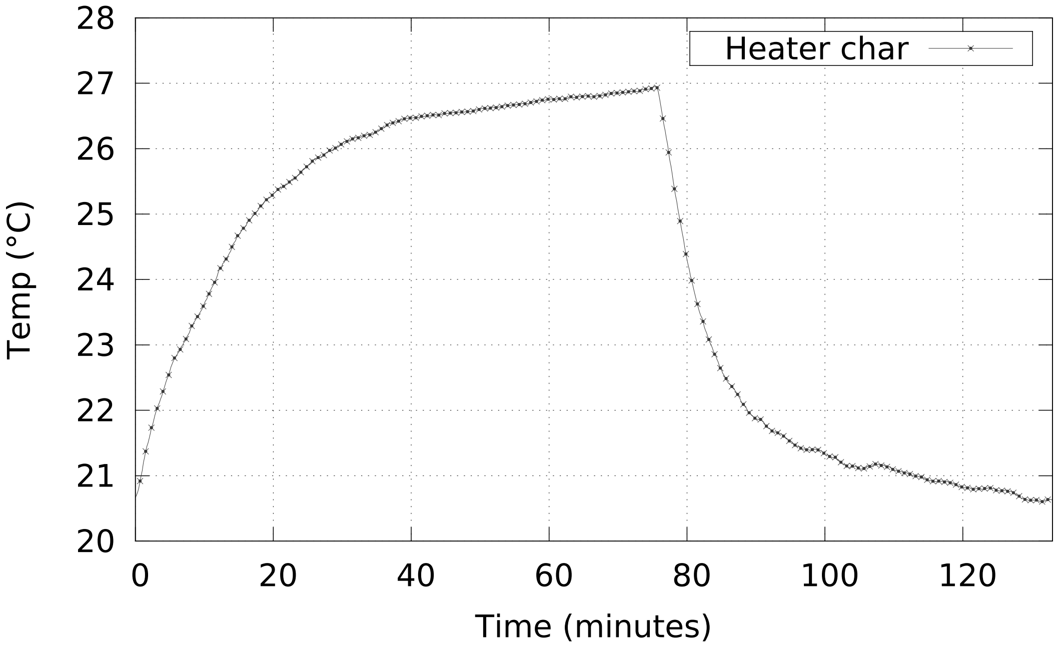


Figure 6.4: Thermal characteristics of a heater

curve of zone Z_i at temperature T_i, when the corresponding heater H_i is ON, which we also refer to as the heating-slope of H_i. Let $S_f^i(T_i)$ denote the slope of the temperature-falling curve of zone Z_i at T_i when the heater H_i is OFF, which we also refer to as the cooling-slope of H_i.

At any point of time, the heating and cooling of a zone depend on the heating slope S_r^i and the cooling slope S_f^i of H_i respectively. The rise and fall in temperature at any instant of time can be quantified as $S_r^i(T_i) \times \Delta t$ and $S_f^i(T_i) \times \Delta t$ respectively, where Δt is infinitesimally small duration of time.

Under peak demand constraint, at any point of time, at least m heaters will be ON and at most $(n-m)$ heaters will remain OFF when required. So, at any point of time, the temperatures of m zones will rise and that of $(n-m)$ zones will fall. It may also be noted that S_f^i and S_r^i are functions of the zonal temperature (T_i).

At any instant of time, the minimum cumulative rise in zonal temperature will be

$$\sum_{i=1}^{m} S_r^i(T_i) \times \Delta t$$

if the sum is obtained from the first m heaters arranged in ascending order of their heating-slopes.

Again, the maximum cumulative fall in zonal temperature at any instant of time will be

$$\sum_{i=1}^{n-m} abs(S_f^i(T_i)) \times \Delta t$$

when the sum is obtained from the first $(n-m)$ heaters arranged in descending order of their cooling-slopes.

It can be observed from Figure 6.4 that Equations 3.21 and 3.22 are also valid for exponential nature of the heating and cooling curves of a heater. Therefore, the average zonal temperature will keep on rising from any temperature $T(< T_i)$ to T_i, if the following condition is satisfied.

$$\sum_{i=1}^{m} S_r^i(T_i) \times \Delta t > \sum_{i=1}^{n-m} abs(S_f^i(T_i)) \times \Delta t \tag{6.2}$$

It follows that eventually all the zones will attain the temperature T_i and it will be maintained thereafter, if Equation 6.2 is satisfied. Eliminating Δt from both sides of the equation, the proof follows. □

6.5 Applying TCBM to Devices with Different Comfort Bands

The comfort-band of ACs/room-heaters and refrigerators are different. Also, we discussed in Section 5.3 that with varying peak demand or changed ambient temperature, consumers can participate in demand-response control by shifting comfort-band. Further, ambient temperatures for AC/heater and refrigerator are different. Therefore, we find that it is necessary to consider the feasibility of running m out of n appliances separately for equipments with different comfort-bands. In this section, we discuss the feasibility of scheduling TCEDs having different comfort-bands, under peak demand constraint.

The feasibility of TCE cooling loads (ACs & refrigerators) and that of TCE heating loads (heaters) are derived from the original feasibility conditions of Equation 4.4. and 6.1 respectively. We consider the worst case, when all the TCEDs of each group (having same comfort-band) reach their respective B^Us at the same time. Let us assume that there are n_1 ACs, n_2 refrigerators and n_3 heaters. Let us consider the case when under peak-demand constraint of P (watts), only m_1 AC(s), m_2 refrigerator(s) and m_3 heater(s) can be powered-ON at a time. We can derive individual feasibility conditions of ACs, refrigerators and heaters separately. Now, if the feasibility conditions of individual group of ACs, heaters and refrigerators are satisfied, the comfort-band of all these devices will be maintained if the following condition is also satisfied.

$$\sum_{i=1}^{m_1} W_A^i + \sum_{i=1}^{m_2} W_R^i + \sum_{i=1}^{m_3} W_H^i \leq W^P \tag{6.3}$$

where, W_A^i, W_R^i and W_H^i denote the wattage of individual ACs, refrigerators and heaters respectively and W^P is the peak demand limit. Further, in order to take care of the worst-case, the $\sum_{i=1}^{m_1} W_A^i$ is taken from the first m_1 ACs arranged in descending order of their wattages, $\sum_{i=1}^{m_2} W_R^i$ is taken from the first m_2 refrigerators arranged in descending order of their wattages and $\sum_{i=1}^{m_1} W_H^i$ is taken from the first m_3 heaters arranged in descending order of their wattages.

Chapter 7

Conclusion and Future Work

In this thesis, we have shown that modeling of TCEDs (which have cyclic execution profile) as real-time tasks has its own detractors: the execution time and duty-cycle of a TCED are dynamic and therefore application of traditional scheduling policies in coordinated control of TCED has its own limitations. We critically analyzed similarities and the differences between a periodic real-time task and the cyclic operation of a TCED. We formulated the analogy between allocating power (resource) to a TCE device and allocating CPU (resource) to a computational task and mapped the problem of scheduling TCED under peak demand constraint to multiprocessor task scheduling problem. Though, the one-to-one mapping of allocating power to m out of n TCEDs at a time with scheduling n tasks on m processors tempted us to apply the existing technique from real-time domain for scheduling TCEDs, we found its limitations in doing so. We established that besides maintenance of comfort band, the practical requirements of minimum switching and accommodation of restart delay pose serious challenge to the existing scheduling policies.

Based on our empirical study of the functioning of ACs, we developed a conceptual model of power consumption and maintenance of thermal comfort. From the insights gained from this study, a basic feasibility analysis technique was proposed for maintaining thermal comfort under peak power demand constraint. The feasibility analysis is then extended to consider the practical aspect of ensuring mandatory restart delay to make coordinated scheduling of TCE devices implementable in real-world applications. Driven by the goal of maintaining the comfort-band with minimal number of switching of power between appliances, we presented the TCBM approach for selecting the subset of appliances to power at a given point in time.

Our performance study demonstrates the superior performance characteristics of our algorithm compared to algorithms adapted from the literature. It showed that existing scheduling algorithms for timely task execution are not suitable for scheduling TCE devices because, either i) they do not prevent undesirable switching (preemption) of the devices even when the temperature of the environment under their control is within the associated comfort-band or ii) they do not guarantee maintenance of comfort-band. In contrast, our TCBM algorithm offers a minimum of 500% less excess-switching as compared to the candidate algorithms. Furthermore, unlike TCBM, none of the existing techniques takes care of the restart delay constraint.

Further, we developed a technique to calculate the energy requirement of a TCED for maintaining different comfort-bands. We formulated the correlation between energy consumption and the comfort band and shown how the consumption varies exponentially with ratio of colling slopes $S_f(T^U)/S_f(T^L)$ taken at the end limits of the comfort band $[T^L, T^U]$. Our simulation as well as experimental results show that it is possible to reduce energy-consumption due to TCEDs by shifting/adjusting of comfort-band without noticeable effect (variation of 0.5^0C only) in the thermal comfort level. We showed how this insight can be utilized for adaptive demand-response control of TCE devices under time varying peak power demand constraint. We demonstrated that if the desired comfort band can not be achieved under a given peak demand constraint, TCBM can act like an anytime algorithm offering a inferior but acceptable level of comfort. We also proposed a *inferior comfort* algorithm that facilitates users' participation in D-R under dynamically varying peak demand limit and changes in ambient temperature.

Initially we assumed that zones controlled by TCE devices are thermally de-coupled and TCBM algorithm was formulated based on this assumption. Since in practice de-coupling of zones in a large room having multiple TCEDs may not be feasible, we carried out empirical studies on the applicability of TCBM in such a scenario. Our experimental results established the validity of TCBM feasibility analysis even for thermally coupled zones. Additionally, we also analyzed the combined scheduling of different categories of TCE loads having different comfort bands.

Implementation of TCBM, so far, was kept limited to nearby rooms using a centralized controller and its applicability was demonstrated for both thermally coupled and decoupled zones. A large-scale experiment involving large number of rooms/zones is worth considering. Carrying out studies on variable frequency drive (VFD) as well as Variable Refrigerant Flow (VRF) ACs and applicability of TCBM technique of peak reduction for these type of ACs is part of our future work.

Participation of consumers in demand-response (D-R) control is an important aspect of smart grid. Facilitating consumers' participation in the D-R control and integrating it with TCBM is part of our ongoing work. Home appliances other than TCE devices like washing machine and dishwasher also consume significant amount of power. Taking this work further to include these appliances and offering a complete smart home appliance control solution is also worth considering as a future work.

Chapter 8

Appendix

A brief description of the prototype implementation and experiment set-ups used in this work along with a few selected photographs is presented here.

Initially, we developed an experimental set-up and prototype implementation of TCBM scheduling of ACs using manual control, which we refer to as Set-up 1. Subsequently, we developed set-up 2, which is a Raspberry-Pi based automatic controller that implements TCBM algorithm along with remote control of the ACs.

8.1 Prerequisites

For the prototype systems, we obtained the following information before applying TCBM in scheduling the ACs.

Number of TCEDs: n

Number of TCEDs that can run at a time due to peak demand constraint: m, which can be derived from Equation 4.1 of the thesis given the knowledge of individual wattages (W_i) of the TCEDs are known

Desired comfort band: $[T^L, T^U]$

The cooling and warming slopes of the thermal profile of the TCEDs: S_f^i and S_r^i

Figure 8.1: Eurotherm Chessell Chartless Recorder

Experimental Set-up

We have taken a system of two regular office rooms each room fitted with two numbers of window ACs. The zone temperatures were measured using Resistance Temperature Detector Pt 100 and all these temperatures were recorded for the generation of thermal profile of the ACs and control. We utilized the alarm generation facility of the Eurotherm Chessell chartless recorder (Figure 8.1) to general alarm for taking on-off control action manually. The time-lag between the generation of alarm and the manual control action was ≤ 30 seconds.

The brief description of set-up 1 is described in Section 8.1 below.

Set-up 1

- Manual Control of Window ACs.
- Two rooms with $n = 2$ ACs in each room.
- Temperature Sensor: Pt 100
- Data Recording: Eurotherm Chessell Chartless Recorder, Model 5100V

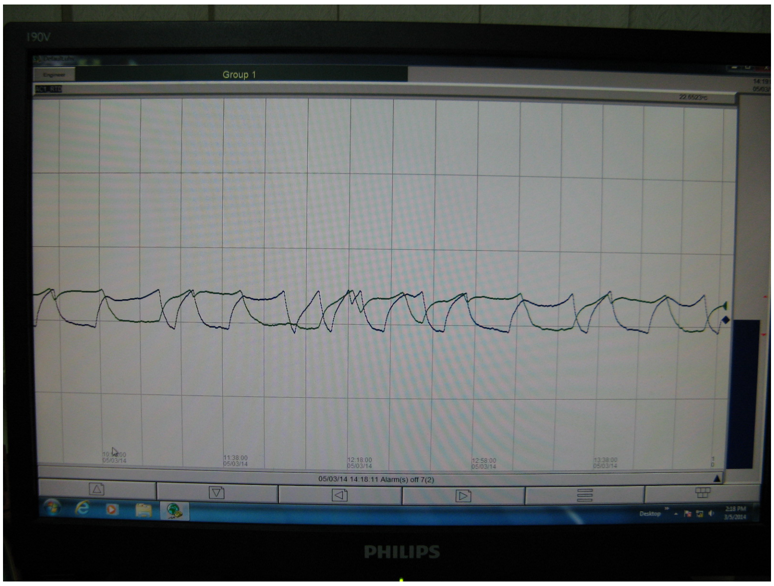


Figure 8.2: Temperature Record: TCBM Control of 2 ACs

- Assumption: Peak demand limit allows only one AC ($m = 1$) to run at a any point of time.

- Feasibility: Feasibility analysis (Equation 4.4) indicates that comfort-band of $[23^0C, 26^0C]$ can be maintained with peak power permitting only one AC to be ON at a time.

- Control Logic: Manual on generation of audio alarm when zone temperature T_i crosses comfort-band $[T^L(23^0C), T^U(26^0C)]$ limit.
  - Switch-off[1] AC, if $T_i \leq T^L$
  - Switch-on AC, if $T_i \geq T^U$

TCBM Control of 2 ACs

The photograph of Coordinated scheduling of 2 ACs in a room, which depicts peak demand reduction of 50% is shown in Figure 8.2. It also shows the effect of thermally coupled zones on the temperature maintenance.

[1] Switching-off implies putting the AC into fan-mode only

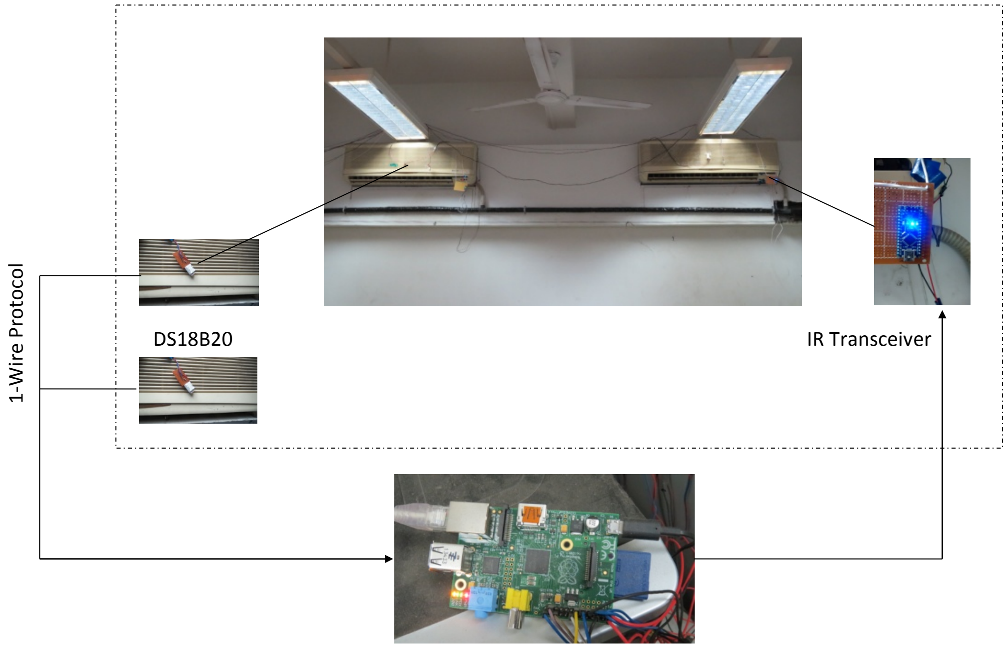


Figure 8.3: Test Setup: TCBM Scheduling using Raspberry Pi

Set-up 2

In order to automate the process of coordinated scheduling of TCEDs, we developed another set-up, which uses semiconductor sensors with in-build digital network capability. It also reduces the wiring complexity of bringing all the cables from each temperature sensors to one recording instrument. We use a Raspberry-Pi [51] board to collect all the temperature data digitally using 1-wire protocol network supported by the DS18B20 digital temperature sensors. Further, Infra-Red (IR) remote command data for AC control is decoded and the AC remote controller is replaced by dedicated IR transceiver to facilitate individual AC control.

In this scheme the Raspberry-Pi based controller generates the thermal characteristics of the ACs on line based on the temperature data using curve-fitting. It checks for schedulability of m out of n ACs under peak demand constraint. If schedulable, it schedules the AC operations and sends commands to individual ACs via IR transceivers. The schematic of the TCBM test setup 2 is shown in Figure 8.3. A brief description of

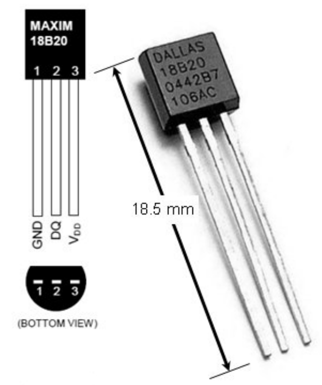


Figure 8.4: DS18B20 Temperature Sensor

the main components used in the test setup is given below.

DS18B20 Temperature Sensors

DS18B20[52] is a programmable temperature sensor from Maxim (shown in fig:8.4). It uses 1-wire protocol[53]. Each DS18B20 sensor has a unique 64-bit ID programmed in it. It can give temperature data with 9 to 12 bit precision. Since it is a 1-wire protocol device, many such sensors can be connected on a single wire. The specifications of DS18B20 is given below.

- Requires an input voltage of 3.0-5.5V.
- It has an accuracy of $\pm 0.5\,°C$ accuracy from $-10\,°C$ to $+85\,°C$.
- It has an temperature range from $-55\,°C$ to $+125\,°C$.

One Wire Protocol

1-Wire is a bus system designed by Dallas Semiconductor Corp. for device communications[53]. It is a simple serial signalling protocol combining data, clock and power into a single connection and ground return. This significantly reduces the interface complexity. It has longer range than I^2C protocol. In one wire protocol, a single master is connected to one or more slaves. These slaves are connected on a single line. Each of these slaves have a unique ID(64 bit) which is factory programmed. It supports communication speeds upto 15.4kbps in standard mode and 125kbps on overdrive mode. The entire communication is initiated and controlled by the master. Slave devices have a capacitor which powers them. These capacitors store power when the line is active or high.

Placement of Sensor

Placement of temperature sensor plays an important role in maintaining thermal comfort in a building. Ideally, temperature in all the areas closer to each occupant in the building should be monitored and maintained. But, it requires large number of sensors and wiring. In our experiments, we placed sensors at the air suction point of window AC units (indoor unit in case of split AC). This is because a sensor placed at the suction measures temperature of the air that is being sucked in for cooling and thus provides a better representation of the zone temperature.

Raspberry Pi

Raspberry Pi is a credit-card sized computer which can carry out many functions that a conventional development board such as Arduino board cannot do. It offers almost all the functionalities that a normal computer can have.

The operating system Raspbian (A version Debian distribution of Linux customized for Raspberry-Pi) is installed on Raspberry Pi for this set-up.

Bibliography

[1] H. Farhangi, "The path of the smart grid," *Power and Energy Magazine, IEEE*, vol. 8, no. 1, pp. 18–28, January 2010.

[2] Y. Agarwal, B. Balaji, S. Dutta, R. K. Gupta, and T. Weng, "Duty-cycling buildings aggressively: The next frontier," in *in HVAC Control. In IPSN*, 2011.

[3] M. Maasoumy and A. L. Sangiovanni-Vincentelli, "Total and peak energy consumption minimization of building HVAC systems using model predictive control," *IEEE Design & Test of Computers*, vol. 29, no. 4, pp. 26–35, 2012.

[4] K. Nakayama, C. Zhao, L. Bic, M. Dillencourt, and J. Brouwer, "Distributed real-time power flow control with renewable integration," in *Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on*, Oct 2013, pp. 516–521.

[5] M. Ortega-Vazquez and D. Kirschen, "Assessing the impact of wind power generation on operating costs," *Smart Grid, IEEE Transactions on*, vol. 1, no. 3, pp. 295–301, Dec 2010.

[6] S. K. Barker, A. K. Mishra, D. E. Irwin, P. J. Shenoy, and J. R. Albrecht, "SmartCap: Flattening peak electricity demand in smart homes," in *Proceedings of the 2012 IEEE International Conference on Pervasive Computing and Communications*, March 2012, pp. 67–75.

[7] P. Srikantha, C. Rosenberg, and S. Keshav, "An analysis of peak demand reductions due to elasticity of domestic appliances," in *Proceedings of the 3rd International Conference on Future Energy Systems: Where Energy, Computing and Communication Meet*, ser. e-Energy '12, 2012.

[8] A. Bar-Noy, M. P. Johnson, and O. Liu, "Peak shaving through resource buffering," in *Approximation and Online Algorithms,6th International Workshop, WAOA 2008*, September 2008, pp. 147–159.

[9] S. Keshav and C. Rosenberg, "How internet concepts and technologies can help green and smarten the electrical grid," in *Proceedings of the 1st ACM SIGCOMM Workshop on Green Networking 2010, New Delhi, India, August 30, 2010*, 2010, pp. 35–40.

[10] L. Prez-Lombard, J. Ortiz, and C. Pout, "A review on building energy consumption information," *Energy and Buildings*, vol. 40, no. 3, pp. 394–398, 2008.

[11] C. E. A. (CEA), "National electricity plan-generation," Central Electricity Authority (CEA), Govt. of India, Tech. Rep. Vol. 1, 2012.

[12] G. Ghatikar, G. Venkata, and C. Basu, "Expanding buildings-to-grid (B2G) objectives in india," Lawrence Berkeley National Laboratory and University of California Berkeley, Tech. Rep., July 2013.

[13] H. Saele and O. Grande, "Demand response from household customers: Experiences from a pilot study in Norway," *Smart Grid, IEEE Transactions on*, vol. 2, no. 1, pp. 102–109, March 2011.

[14] TRF, *Understanding PECOs General Service Tariff.* Philadelphia, PA 19106-1591: (available at www.trfund.com), 2007.

[15] C. E. Authority, *National Electricity Plan.* Govt. of India, Ministry of Power, 2012.

[16] Maharashtra State Electricity Distribution Company, India, "HT bill format," http://www.mahadiscom.in/, 2014, [Accessed 15-August-2014].

[17] C. L. Liu and J. W. Layland, "Scheduling algorithms for multiprogramming in a hard-real-time environment," *J. ACM*, vol. 20, no. 1, pp. 46–61, 1973.

[18] M. L. D. Vedova, M. Ruggieri, and T. Facchinetti, "On real-time physical systems," in *18th International Conference on Real-Time and Network Systems RTNS, 2010*, November 2010, pp. 41–49.

[19] M. L. D. Vedova, E. D. Palma, and T. Facchinetti, “Electric loads as real-time tasks: An application of real-time physical systems,” in *Proceedings of the 7th International Wireless Communications and Mobile Computing Conference, IWCMC 2011*, July 2011, pp. 1117–1123.

[20] A. Subramanian, M. Garcia, A. Dominguez-Garcia, D. Callaway, K. Poolla, and P. Varaiya, “Real-time scheduling of deferrable electric loads,” in *American Control Conference (ACC), 2012*. IEEE, 2012, pp. 3643–3650.

[21] J. W. S. Liu, *Real-Time Systems*. Pearson Education, 2000.

[22] A. Afram and F. Janabi-Sharifi, “Theory and applications of HVAC control systems a review of model predictive control (MPC),” *Building and Environment*, vol. 72, no. 0, pp. 343 – 355, 2014.

[23] T. G. Hovgaard, S. Boyd, L. F. Larsen, and J. B. Jørgensen, “Nonconvex model predictive control for commercial refrigeration,” *International Journal of Control*, pp. 1–18, 2012.

[24] O. Frauke, P. b. Alessandra, C. N. Jonesc, G. Dimitrios, G. Markus, S. Vanessa, L. Beat, and M. Manfred, “Use of model predictive control and weather forecasts for energy efficient building climate control,” *Energy and Buildings*, vol. 45, p. 1527, November 2012.

[25] M. Avci, M. Erkoc, A. Rahmani, and S. Asfour, “Model predictive HVAC load control in buildings using real-time electricity pricing,” *Energy and Buildings*, vol. 60, no. 0, pp. 199 – 209, 2013.

[26] E. F. Camacho and C. Bordons Alba, *Model Predictive Control*. Springer, Berlin, 1999.

[27] P. X. Gao and S. Keshav, “SPOT: A smart personalized office thermal control system,” in *Proceedings of the Fourth International Conference on Future Energy Systems*, ser. e-Energy ’13, 2013, pp. 237–246.

[28] T. Nghiem, M. Behl, R. Mangharam, and G. J. Pappas, "Green scheduling of control systems for peak demand reduction," in *Proceedings of the 50th IEEE Conference on Decision and Control and European Control Conference, CDC-ECC 2011*, December 2011.

[29] Y. Ma, F. Borrelli, B. Hencey, B. Coffey, S. C. Bengea, and P. Haves, "Model predictive control for the operation of building cooling systems," *IEEE Trans. Contr. Sys. Techn.*, vol. 20, no. 3, pp. 796–803, 2012.

[30] K. Deng, P. Barooah, P. Mehta, and S. Meyn, "Building thermal model reduction via aggregation of states," in *American Control Conference (ACC), 2010*, June 2010, pp. 5118–5123.

[31] C. Chen, J. Wang, Y. Heo, and S. Kishore, "MPC-based appliance scheduling for residential building energy management controller," *Smart Grid, IEEE Transactions on*, vol. 4, no. 3, pp. 1401–1410, Sept 2013.

[32] G. Xiong, C. Chen, S. Kishore, and A. Yener, "Smart (in-home) power scheduling for demand response on the smart grid," in *IEEE Innovative Smart Grid Technologies (ISGT)*, January 2011, p. 17.

[33] S. Lee, "On-line multiprocessor scheduling algorithms for real-time tasks," in *Proceedings of the IEEE Region 10s Ninth Annual International Conference. Theme: Frontiers of Computer Technology TENCON94*, 1994, p. 607611.

[34] R. I. Davis and A. Burns, "A survey of hard real-time scheduling for multiprocessor systems," *ACM Computing Surveys*, vol. 43, no. 4, pp. 35:1–35:44, Oct. 2011.

[35] S. Baruah, "Techniques for multiprocessor global schedulability analysis," in *Proceedings of the 28th IEEE International Real-Time Systems Symposium, RTSS '07*, 2007, pp. 119–128.

[36] S. Kato and Y. Ishikawa, "Gang EDF scheduling of parallel task systems," in *Proceedings of the 2009 30th IEEE Real-Time Systems Symposium*. IEEE Computer Society, 2009, pp. 459–468.

[37] B. Balaji, H. Teraoka, R. Gupta, and Y. Agarwal, "ZonePAC: Zonal power estimation and control via HVAC metering and occupant feedback," in *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*, ser. BuildSys'13, 2013.

[38] J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, and K. Whitehouse, "The Smart Thermostat: Using occupancy sensors to save energy in homes," in *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '10. ACM, 2010, pp. 211–224.

[39] Y.-W. Chen, X. Chen, and N. Maxemchuk, "The fair allocation of power to air conditioners on a smart grid," *Smart Grid, IEEE Transactions on*, vol. 3, no. 4, pp. 2188–2195, Dec 2012.

[40] P. O. Fanger, *Thermal comfort: Analysis and applications in environmental engineering.* Copenhagen, Denmark: Danish Technical Press, 1970.

[41] A. S. 55-1992, *Thermal Environmental Conditions for Human Occupancy.* Atlanta, GA: American Society of Heating, Ventillation, Refrigerating and Air-Conditioning Engineers (ASHRAE), 1992.

[42] V. L. Erickson and A. E. Cerpa, "Thermovote: Participatory sensing for efficient building HVAC conditioning," in *Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, ser. BuildSys '12. New York, NY, USA: ACM, 2012, pp. 9–16.

[43] T. Facchinetti, E. Bini, and M. Bertogna, "Reducing the peak power through real-time scheduling techniques in Cyber-Physical Energy Systems," in *Proceedings of the 1st International Workshop on Energy Aware Design and Analysis of Cyber Physical Systems (WEA-CPS)*, April 2010.

[44] F. P. Incropera and D. P. DeWitt, *Introduction to Heat Transfer, Sixth Edition.* John Wiley and Sons, 2011.

[45] ASHRAE, *Fundamentals of HVAC Systems.* Atlanta, GA: ASHRAE Handbook, 2001.

[46] C. D. Locke, "Best-effort decision making for real-time scheduling," Ph.D. dissertation, Carnegie-Mellon University, Computer Science Department, 1986.

[47] A. Burns, D. Prasad, A. Bondavalli, F. D. Giandomenico, K. Ramamritham, J. A. Stankovic, and L. Strigini, "The meaning and role of value in scheduling flexible real-time systems," *Journal of Systems Architecture*, vol. 46, no. 4, pp. 305–325, 2000.

[48] S. Kelkar, N. Kothari, and K. Ramamritham, "Brownout energy distribution scheme for mitigating rolling blackouts," in *Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems*, ser. e-Energy '15. New York, NY, USA: ACM, 2015, pp. 193–194. [Online]. Available: http://doi.acm.org/10.1145/2768510.2770937

[49] Tata Power, "Tata power tariff," https://cp.tatapower.com/, 2014, [Accessed 15-August-2014].

[50] J. W. S. Liu and S. Wei-Kuan, "Algorithms for scheduling imprecise computations with timing constraints to minimize maximum error," *IEEE Transaction on Computers*, vol. 44, no. 3, pp. 466–471, March 1995.

[51] "Raspberry-Pi," http://www.raspberrypi.org/, 2014, [Accessed 10-September-2014].

[52] "DS18B20 programmable resolution 1-wire digital thermometer," http://datasheets.maximintegrated.com/en/ds/DS18B20.pdf, 2014, [Accessed 10-September-2014].

[53] "Maxim 1-wire tutorial," www.maximintegrated.com/en/products/1-wire/flash/overview/, 2014, [Accessed 10-September-2014].