Abstract

One of the most prominent applications of smart technology for energy saving is in buildings, in particular, for optimizing heating, ventilation, and air-conditioning (HVAC) systems. Traditional HVAC systems rely on wired temperature regulators and thermostats installed at fixed locations, which are both inconvenient for deployment and ineffective to cope with dynamic changes in the thermal behavior of buildings. New generation of wireless sensors are increasingly becoming popular due to their convenience and versatility for sophisticated monitoring and control of smart buildings. However, there also emerge new challenges on how to effectively harness the potential of wireless sensors. First, wireless sensors are often powered by batteries, which makes it a paramount concern to make them energy efficient. The second challenge is to ensure that the wireless sensors can work in uncertain environments with minimal human supervision. Therefore, in this work, we study a fundamental problem of optimizing the trade-off between the battery lifetime and the effectiveness of HVAC remote control in the presence of uncertain fluctuations in room temperature. We provide an effective offline algorithm for deciding the optimal control decisions of wireless sensors, and a 2-competitive online algorithm that is shown to attain performance close to offline optimal through extensive simulation studies. We also evaluate the performance of our algorithm in a real-world air-conditioning system and show that we can balance the trade-off between thermal comfort and energy consumption of wireless sensors by choosing appropriate control strategy and the way we make use of wireless sensors. The implication of this work is to shed light on the fundamental trade-off optimization in wireless sensor controlling HVAC systems.

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Muhammad Aftab

Masdar City, June 30, 2013.

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CHAPTER 1

Introduction

1.1 Introduction

Buildings are among the largest consumers of energy, topping 40% of total energy usage in many countries [12]. A significant portion of energy use in buildings is attributed to the heating, ventilation, and air-conditioning (HVAC) systems, which may account for up to 50% of the total energy consumption [8]. Therefore, improving energy efficiency of buildings, in particular, optimizing HVAC system is critically important and will have a significant impact in reducing the overall energy consumption.

Usually, the air-conditioning systems need to maintain room temperature within a certain desirable range to create a comfortable situation. It is often unnecessary to maintain the indoor temperature at a rigid fixed value. To detect the variations of temperature, traditional air-conditioning systems rely on wired temperature regulators and thermostats installed at fixed locations to characterize all zones within a building. These classical controllers, though still popular because of their lower initial cost, are expensive in the long run because they operate at very low energy efficiency. They are both inconvenient for deployment and ineffective to cope with dynamic changes in the thermal behavior of buildings. In particular, the temperature distribution is not spatially uniform across a thermal space; individual rooms throughout a house may have different thermal characteristics and respond differently to the thermal conditioning system. Control decisions based on a single sensor may unnecessarily regulate the thermal environment and therefore consume excess energy. Moreover, having sensors installed at fixed and limited locations cannot react to the rapidly varying room conditions due to transient and non-stationary human behavior.

New generation of wireless sensors enable low-cost spatially distributed environmental sensing which is revolutionizing the design of HVAC systems. A wireless sensor node consists of a microprocessor, radio module, memory, power source, and one or more sensors. Individual nodes communicate together by routing packets from node to node to create a communication network. A network of wireless sensors can be deployed throughout a building, providing a more accurate description of environmental conditions compared to a conventional single-sensor thermostat, thus presenting new opportunities for advanced thermal control. Wireless sensors, being not limited by wired installation, can be deployed strategically close to the fluctuating thermal sources in an ad-hoc fashion (e.g., near to doors, windows, computers, and where people usually sit etc.). They can be integrated into both existing and new buildings without making major structural changes. With wireless sensors, demand responsive air-conditioning control can be developed that dynamically adjusts the room temperature according to intelligent monitoring and tracking of human behavior and room conditions. Also, multiple temperature signals from multiple sensors can be taken into account to deal with the non-uniform spatial distribution of temperature across the room. Furthermore, wireless sensors can be integrated with home security and infotainment systems, where networks between home appliances, sensors and wireless media enable more sophisticated smart home control systems.

Despite the promising potential, wireless sensors pose several challenges:

1. **Battery Lifetime**: Wireless sensors are often battery-powered and typically have to operate for prolonged periods of time. Therefore, one of the primary goals is to maximize the battery lifetime of sensors. According to a survey of several commercial wireless sensors (see Appendix D), the communication operations consume the most energy. Thus, an effective way to extend battery lifetime is to reduce the communication frequency, thereby inducing limited communication among wireless sensors.

2. **Control Effectiveness**: Wireless sensors are also distributed autonomous computing devices. They can be programmed to intelligently optimize their energy consumption with respect to the effectiveness of their control operations. Intuitively, energy consumption is inversely proportional to the effectiveness (i.e., sleeping all the time can effectively reduce energy consumption, but is ineffective to satisfy the control requirement). The ability to balance the energy consumption and effectiveness is critical to the usefulness of these wireless sensors, particularly for smart home applications.

3. **Uncertain Deployment**: Wireless sensors are supposed to be deployed in an ad hoc fashion, without a-priori measurement or calibration. It is critical to ensure that wireless sensors operate robustly and reliably in the presence of uncertainty of new environments. They should be able to rapidly cope with dynamic displacements with minimal human supervision. An important question is to investigate the fundamental ability of wireless sensors to

control room temperature without assuming any a-priori or stochastic knowledge of the temperature fluctuations caused by various uncertainties like external weather, energy source availability, metabolism of people's bodies, and the speed of air in the heating zone etc. These are activities that occur without being planned and change the structure of the problem.

1.2 Thesis Statement – Objectives

The main purpose of this research is to study a fundamental problem of optimizing the trade-off between the lifetime of the wireless sensors and the effectiveness of HVAC remote control in the presence of uncertain (even adversarial) fluctuations in room temperature. The novelty of our work lies in the fact that unlike most intelligent HVAC control techniques (as summarized in chapter 3), our approach is to solve the optimization problem in an online manner without stochastic modeling or machine learning methods. The work involves development of a theoretical framework for air-conditioning control, which will be accompanied by real-world implementations for testing and verifying various aspects of the research as well as performance of the system.

1.3 Research Contribution

The key contributions of this work are summarized as follows.

1. We formulate a new online optimization problem of balancing the trade-off between communication frequency of wireless sensor and the effectiveness of HVAC remote control. Our goal is to simultaneously maintain thermal comfort and maximize the battery lifetime of the wireless sensor. In other words, we aim to maximize the sensor energy efficiency through reduced

frequency of actuation while meeting the required control performance. To the best of our knowledge, this specific problem has not been studied before.

2. We present an effective offline algorithm, which is based on dynamic programming, for determining the optimal control decisions by wireless sensors when all future temperature fluctuations are known in advance. The offline algorithm is useful to benchmark the online algorithm we propose.

3. We devise an online algorithm that optimizes the control decisions without the knowledge about future temperature fluctuations. We prove that our online algorithm is 2-competitive against offline optimal algorithm.

4. We evaluate the performance of our algorithm through simulations and show that our online algorithm can attain performance close to the offline optimal solution.

5. We implement our algorithm in a real-world air-conditioning system and empirically evaluate its performance under different scenarios.

6. The preliminary results were published in [1]

1.4 Thesis Organization

The rest of the thesis is organized as follows. In chapter 2, we present the background of online algorithmic approach, competitive analysis, and a related problem known as dynamic TCP acknowledgement problem and its comparison to our problem. In chapter 3, we provide a review of related work. It summaries various thermostat based, sensor network based, and common intelligent HVAC control strategies. We present the models and formulations of ambient room temperature and wireless sensor network control in chapter 4. In chapter 5, we present the offline and online algorithms which are based on our proposed models. The chapter also provides a competitive analysis of the algorithms. In chapter 6, we evaluate the performance of our algorithms through extensive simulations run in Matlab/Simulink. In chapter 7, we present the empirical results obtained from implementing our control algorithms in a real-world air-conditioning system. Finally, we summarize the thesis and discuss future extensions in chapter 8.

CHAPTER 2

Background

In this chapter, we present background information about online algorithms and a well-known online problem known as dynamic TCP acknowledgment problem which is closely related to our problem.

2.1 Online algorithms

Online algorithms have received considerable attention in the literature for their fundamental principles and practical applications. In an online problem, a sequence of input is revealed gradually over time. The algorithm needs to make certain decisions and generate output instantaneously over time, based on only the part of the input that has been seen so far, without knowing the rest of the input to be revealed in the future. There are many practical problems studied in the online algorithmic setting that require real-time and instantaneous decisions, such as real-time resource allocation in operating systems, data structuring, robotics or communication networks [2, 10]. The performance of online algorithms is evaluated using competitive analysis. The *competitive ratio* of an online algorithm is defined as the worst-case ratio between the cost of the solution obtained by the online algorithm versus that of an offline optimal solution obtained by knowing the all input sequence in advance [27].

Online algorithms have several practical implications. First, they do not require a-priori or stochastic knowledge of the input sequence, which makes them robust in any uncertain (even adversarial) environments. Second, online algorithms often use simple decision-making mechanisms, without being hampered by inaccurate or slow convergent machine learning techniques. Third, online algorithms can give a fundamental characterization without further assumptions of the problems, which is useful to benchmark other sophisticated and more complicated decision-making mechanisms. In this thesis, we adopt the online algorithmic approach to study the fundamental problem of optimizing the trade-off between the battery lifetime and the effectiveness of HVAC remote control in the presence of uncertain fluctuations in room temperature.

2.2 Dynamic TCP acknowledgment

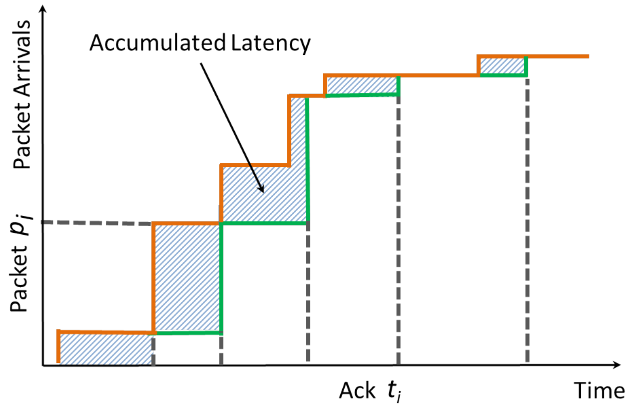
A well-known example involving online algorithms is the dynamic TCP acknowledgment problem described as follows. A stream of packets arrives at a destination. The packets must be acknowledged in order to notify the sender that the transmission was successful. However, it is possible to simultaneously acknowledge multiple packets using a single acknowledgments packet. The delayed acknowledgment mechanism reduces the frequency of the acknowledgments, but it might also add excessive latency to the TCP connection and interfere with the TCP's congestion control mechanisms [13]. The problem is to find an optimal trade-off between the total number of acknowledgments sent and the latency cost introduced due to delaying acknowledgments. More specifically, Dooly et al. [7] formulated this trade-off as the dynamic TCP acknowledgement problem as follows.

In the dynamic TCP acknowledgement problem, a sequence of n packets $\sigma = (p_1, p_2, ..., p_n)$ arrive at a certain destination. An algorithm divides the received sequence σ into m subsequences $\sigma_1, \sigma_2, ..., \sigma_m$, where a single acknowledgment is sent at the end of each subsequence. All the packets contained in $\sigma_j (1 \leq j \leq m)$ are acknowledged together by the j-th acknowledgement at time t_j. The objective is to choose an optimal acknowledgment time sequence that minimizes the weighted sum of the cost for transmitting acknowledgements and the cost of the latency of delayed acknowledgements. The decision of transmitting an acknowledgment time is decided in an online fashion without knowing the future packet arrivals.

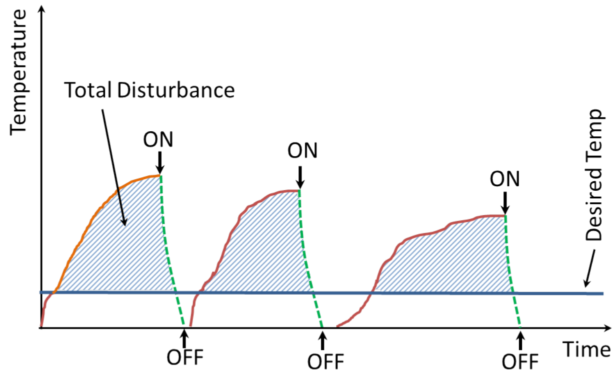
2.3 Comparison to our problem

Our problem is somewhat similar to the dynamic TCP acknowledgment problem. In TCP, random arrivals of packets are received, such that the receiver makes online decisions when to transmit acknowledgments considering the weighted total cost of number of acknowledgment and latency. In our problem, random fluctuations of temperature and external thermal sources are perceived by the wireless sensor, and the wireless sensor makes online decisions when to transmit control commands to remote air-conditioning system considering the weighted total cost of transmissions and effectiveness (defined by the disturbance of temperature compared to a desirable temperature). A pictorial comparison between the two problems is provided in Fig. 2.1.

Despite the similarity, our results are not direct applications of the dynamic TCP acknowledgment problem. In particular, the dynamic TCP acknowledgment



(a) Dynamic TCP acknowledgment



(b) Wireless sensor controlling AC system

Figure 2.1: A pictorial comparison between dynamic TCP acknowledgment and wireless sensor controlling AC system.

problem assumes latency as a linearly increasing function of time, whereas in our problem the total disturbance of temperature changes non-linearly with time. This requires a non-trivial extension of the original TCP acknowledgment problem to the new context of air-conditioning control. Furthermore, we present extensive simulation and empirical studies that are specific to the air-conditioning control setting for corroborating the usefulness of our online algorithms for this new problem.

CHAPTER 3

Literature Review

Over the years, a number of HVAC control methods have been proposed and developed for deployment. These methods vary from simple techniques like manipulation of setpoint [1] temperatures, to more sophisticated techniques such as fuzzy logic, neural networks, genetic algorithms etc. In this chapter, we first summarize a few works that are relatively simple extensions of the traditional HVAC control techniques, then we discuss several state-of-the-art intelligent control techniques employed in HVAC systems. We also present a brief survey of the recent works on HVAC control based on sensor networks. We conclude the chapter by discussing a paper that is somewhat related to our work in that it also aims to optimize the wireless sensors cost while maintaining the control performance within acceptable range.

[1] A setpoint is the temperature at which the air-conditioner aims to keep the internal air temperature of a building.

3.1 Extensions of traditional techniques

Traditional techniques like thermostat control and manipulation of setpoint temperatures constitute an area of opportunity to reduce energy consumption. In [15], the authors proposed a relatively simple way of controlling the HVAC systems in which the setpoint temperature of the regulator and thermostat is manipulated. They developed an adaptive module of classical regulator to control the peak consumption and provide thermal comfort. Their regulator is based on varying temperature setpoint of the air-conditioning in response to maximum permissible power. Similar approach has been used in [16], where an optimal control scheme for compressor on/off cycling operations has been proposed. Their control scheme minimizes a cost function that involves power consumption and the compressor on-off cycling frequency. They tested their system on an air-conditioning and refrigeration system model through simulations. However, they haven't provided clear data about the performance of their system.

Programmable thermostats are also used to control an HVAC system by scheduling different setpoint temperatures based on time of day and user's preferences. In [11], the authors present the concept of a self-programming thermostat that automatically creates an optimal schedule based on the occupancy patterns in a building. Their system monitors occupancy statistics using motion sensors in rooms and magnetic reed switches on doors. These statistics are then fed to optimization algorithms implemented in the programmable thermostat. Their self-programming thermostat allows the user to define the desired balance between energy and comfort. According to the authors, their experiments provides a strong support for their hypothesis that substantial HVAC waste can be reduced by monitoring the occupants of homes and automatically optimizing HVAC operation schedules. However, recent studies have shown energy savings from programmable thermostats may be less than expected [26].

Traditional controllers prove to be of high cost as they have low efficiency and high maintenance. Therefore, they are replaced by advanced controllers (described in the next section) which produce improved thermal comfort and use less energy.

3.2 Intelligent HVAC control

Recently, many studies have explored the use of intelligent methods to control HVAC systems [20, 21]. This category of controllers includes Neural Network based [2], Genetic Algorithms [3] based, Fuzzy Logic [4] based Controllers, and other evolutionary techniques.

These methods are popular due to their attractive features like human knowledge and reasoning as well as advanced optimization methods. Neural networks are useful when the system models are not analytically known fully. Fuzzy logic control is another popular controlling choice. It is robust to changes in environments as it is based on the operational experience of human expert. The main advantage of fuzzy logic controllers as compared to conventional control approaches resides in the fact that no mathematical modeling is required for the design of the controller. Genetic algorithms are attractive for optimization purposes without involving the mathematical theory. Both neural networks and fuzzy logic control methods can be combined with genetic algorithms for further optimization.

In [17], the design of an intelligent comfort control system by using human learning strategy for an HVAC system was proposed. Based on a standard thermal comfort model, a human learning strategy was designed to tune the user's comfort zone by learning the specific user's comfort preference using a neural network

[2] Neural networks are mathematical representations of biological neurons that relate input and output through a massively connected and parallel distributed network.

[3] Genetic algorithms are optimization techniques based on biological evolution theory involving crossover and mutation and survival of the fittest.

[4] Fuzzy logic is a methodology to represent human knowledge and reasoning in the form of membership functions and rules to make useful inference actions for the modeling and control of uncertain physical systems.

controller. The integration of comfort zone with the human learning strategy was applied for thermal comfort control. The authors in [31] proposed a multi-objective particle swarm optimization algorithm, embedded in a controller. The algorithm was used to determine the amount of energy dispatched to HVAC equipment based on utilizing swarm intelligence technique.

A method based on fuzzy logic controller dedicated to the control of HVAC systems has been proposed in [3]. They obtained the initial knowledge base required by fuzzy logic controller from human experts and control engineering knowledge which they subsequently tuned by a genetic algorithm. In [24], a hierarchical structure for the control of an HVAC system using the Model Predictive Control (MPC) algorithms and fuzzy control algorithms has been proposed. The main task of the proposed hierarchical control system is to provide thermal comfort and minimize energy consumption. Their technique showed a good comparison between two conflicted objectives: thermal comfort and energy consumption. The authors of [4] used model-predictive control technique to learn and compensate for the amount of heat due to occupants and equipment. They used statistical methods together with a mathematical model of thermal dynamics of the room to estimate heating loads due to inhabitants and equipment and control the air-conditioner accordingly.

Majority of the existing intelligent HVAC control techniques rely on stochastic knowledge about the input which makes them less robust in uncertain environments. For example, neural network, although useful in cases where there is no mathematical model, suffers from the enormous time taken for off-line training.

3.3 Sensor network based HVAC control

HVAC control based on sensor networks has also been studied to some extent. In [14], an air-conditioning control system for a dynamical situation in wide public spaces has been proposed. They tracked people movement through multiple large scale scanners. Also, networked temperature sensors were deployed in the target space for temperature monitoring. The obtained temperature distribution was integrated with the results of people tracking in real-time to direct HVAC to locations with high population density and insufficient temperature. The authors in [23] describe a system for a heating control which is based on wireless sensor network. They use a real-time control method that allows peak consumption to be reduced while maintaining thermal comfort. If total power demand does not exceed permissible power, the control system operates like a traditional temperature control in order to ensure thermal comfort. If peak consumption exceeds permissible power, the control system switches to the adaptive mode. This mode is based on a variable setpoint value of temperature to limit the consumption peak. The experiment results show that their thermal control system enables to reduce peak load while maintaining thermal comfort. In [30], a ZigBee-based wireless controller is proposed for control of split air-conditioning units. The controller needs to be connected to the temperature sensor of an air-conditioner. The primary function of the controller is to affect the on/off functions of the air-conditioner unit according to the readings from the wireless temperature sensors. Wireless temperature sensors were placed at primary cooling demand zones which were the focus of control of temperature. They reported that less cooling would be needed when only the primary cooling zones are targeted to reach comfort conditions.

In [28], the authors presented the conceptual design of an adaptive multi zone HVAC control system that utilized WSN for predicting the occupancy pattern of people in a building. Their control strategy involved turning off the air-conditioner in unoccupied zones and manipulating the setpoint temperature. A multi-sensor non-learning control strategy has been proposed in [25]. This paper evaluates the energy and comfort performance of three multi-sensor control strategies that use wireless temperature and humidity sensors and that can be applied to existing on/off central HVAC system. The multi-sensor control strategies adjust the temperature set point of a thermostat to (i) control the average of all room temperatures using temperature threshold logic, (ii) minimize aggregate discomfort of all rooms, or (iii) maximize the number of rooms within a comfort zone. The strategies were evaluated in a real occupied house and were found to outperform single-sensor control strategies. In [18], the authors replace a single temperature sensor used to control a set of rooms with a sensor network that provides one sensor per room. However, there is still just one controller and one HVAC unit for the set of rooms. The focus of their work is on how to make use of the additional information available from a network of sensors, and an evaluation of how different methods of using the information affect energy performance and thermal comfort. They investigated simple, ad hoc methods (e.g. taking average of all sensors) as well as developed an optimization method that balances energy consumption with thermal comfort. They compared the performance of the single-sensor strategy with the ad hoc strategies and optimized strategies using simulations and reported that most of the multi-sensor control strategies do better than the single-sensor strategy on the basis of both energy performance and comfort. However, they haven't applied their strategies on real-world air-conditioning systems. The authors in [9] deployed an wireless camera sensor network in a building to determine the occupancy (i.e. number of people in the building) thereby enabling to control the HVAC systems in an adaptive manner based on occupancy. They reported that knowing the occupancy and usage patterns will result in significantly higher energy savings compared to strategies assuming fixed occupancy and usage patterns. However, they used camera sensors which raise privacy and resource usage issues.

In [19], the authors proposed somewhat similar approach to our work. They introduced a methodology that optimizes the sensor network cost while maintaining the control performance within an acceptable range. They applied their methodology to a distributed control of building lighting systems. They empirically compared the developed system for building lighting control with a baseline control method and reported significant reduction in energy use and saving in the network cost while maintaining the user comfort.

In summary, a number of different control methods have been developed and incorporated into commercial, industrial and residential buildings. However, most existing techniques and systems have significant limitations e.g. inability to deal with non-uniform spatial distribution of temperature, non-stationary and transient heat sources, and different response by thermal zones to thermal conditioning system etc. Accordingly, there is a need to design, implement, and validate new techniques with the aim to reduce existing limitations.

CHAPTER 4

Model and Formulation

The goal of our study is to optimize the trade-off between the wireless sensor battery lifetime and the effectiveness of ambient room temperature control in the presence of uncertain fluctuations. In this chapter, we present the models of ambient room temperature and wireless sensor control as well as the assumptions we make in order to improve the tractability of our models. It should be noted that a complete table of notations with explanations is provided in Appendix E.

4.1 Assumptions of ambient room temperature

The thermal behavior of buildings is a complex system. The mathematical models in the literature typically involve several empirical constants, non-linear functions and uncertain factors such as heat flow and material properties [22]. Moreover, external factors, such as weather condition (e.g., temperature, humidity), soil temperature, radiation effects and other sources of energy (e.g., human activities, lighting and equipment), also play a critical role in determining the thermal behavior of buildings [22].

Tractable mathematical models of building thermal behavior are particularly useful for the design of intelligent controls and regulations of HVAC systems. Therefore, assumptions are often imposed to improve the tractability of the thermal models of buildings.

In this work, we employ a simple yet commonly used thermal model for a single room. This model considers several major factors, such as the outdoor environment, the thermal characteristics of the room, and the air-conditioning system. We mostly consider the setting of cooling, where the air-conditioning system is required to make continual adjustment to the room temperature for maintaining a (lower) desirable temperature level. We remark that our results can be applied to the setting of heating with minor modifications.

First, we list several common assumptions of the ambient room temperature in the literature [29] for improving the tractability:

- The air in the room is assumed to be fully mixed.
- The temperature distribution is assumed to be uniform and the dynamics can be expressed using a lump capacity model.
- The room behaves ideally, such that the effect of each wall is uniformly equivalent.
- The density of the air is constant and is not affected by the changes in temperature and humidity.

4.2 Dynamic model of ambient room temperature

Based on the above assumptions, a simple dynamic model of ambient room temperature can be formulated as follows. We consider the setting of continuous time, and model the ambient room temperature at time t by a function $T(t)$, which depends on several major factors:

1. The *initial ambient room temperature* T_0 at time $t = 0$.

2. The *influence of outdoor temperature* $T_{\text{od}}(t)$, which is a function of time affected by time-of-day and weather. A simple example is a sinusoidal function depending on the time-of-day. We assume that the variation of $T_{\text{od}}(t)$ is relatively slow, as compared to the effect of air-conditioning system. Hence, we simply write $T_{\text{od}}(t)$ as a constant T_{od}.

3. The *external thermal sources* entering into the room, for example, due to human body heat or human activities (e.g., computers). We model the arrivals of thermal sources by a function $W(t)$, such that there is a level of thermal intensity $W(t)$ (measured by degree Celsius) arriving at time t.

4. The *heat absorptivity and insulation properties* of the materials in a room (e.g., walls). Heat can be retained in a room for a longer period of time in a well-insulated room with sufficiently absorptive materials.

5. The *air-conditioning system output*. This is the control variable we seek to optimize in order to maintain the ambient room temperature within a desirable range.

4.2.1 Without external thermal sources

Throughout this paper, we rely on a widely-used model of dynamic ambient room temperature [6]. First, we assume that there is no external thermal sources entering into the room (i.e., $W(t) = 0$ for all t). In particular, we denote the ambient room temperature without external thermal sources as $\tilde{T}(t)$. Given the initial ambient room temperature T_0 and outdoor temperature T_{od}, the dynamic behavior of $\tilde{T}(t)$ can be described by the following differential equations

$$\frac{\mathrm{d}\tilde{T}(t)}{\mathrm{d}t} = \frac{1}{\mathsf{c}\cdot M_{\text{air}}} \cdot \left(\frac{\mathrm{d}Q_{\text{in}}(t)}{\mathrm{d}t} - \frac{\mathrm{d}Q_{\text{ac}}(t)}{\mathrm{d}t} \right) \tag{4.1}$$

$$\frac{\mathrm{d}Q_{\text{in}}(t)}{\mathrm{d}t} = \frac{T_{\text{od}} - \tilde{T}(t)}{R_{\text{eq}}} \tag{4.2}$$

$$\frac{\mathrm{d}Q_{\text{ac}}(t)}{\mathrm{d}t} = \frac{\mathsf{c}\cdot M_{\text{ac}} \cdot (\tilde{T}(t) - T_{\text{ac}})}{E_{\text{ac}}} \tag{4.3}$$

Where T_{ac} is the temperature output by the air-conditioning system, $Q_{\text{in}}(t)$ is the net heat transfer from outdoor, $Q_{\text{ac}}(t)$ is the net heat chilled by the air-conditioning system, M_{air}, M_{ac}, E_{ac}, c, R_{eq} are constants that model the heat absorptivity and insulation properties in the room (see Appendix E for full explanations). By substitution, one can solve the differential equations by the following lemma.

Lemma 1. *In the above model, the solution to Eqns. (4.1)-(4.3) is given by*

$$\tilde{T}(t) = \frac{\mathsf{C}_1}{\mathsf{C}_2} - \left(\frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(0) \right) \cdot e^{-\mathsf{C}_2 \cdot t} \tag{4.4}$$

Where

$$\mathsf{C}_1 = \frac{\mathsf{c}\cdot T_{\text{ac}} \cdot M_{\text{ac}} \cdot R_{\text{eq}} + E_{\text{ac}} \cdot T_{\text{od}}}{\mathsf{c}\cdot M_{\text{air}} \cdot R_{\text{eq}} + E_{\text{ac}}} \tag{4.5}$$

$$\mathsf{C}_2 = \frac{E_{\text{ac}} + \mathsf{c}\cdot M_{\text{ac}} \cdot R_{\text{eq}}}{\mathsf{c}\cdot E_{\text{ac}} \cdot M_{\text{air}} \cdot R_{\text{eq}}} \tag{4.6}$$

We provide the proof in Appendix B.

4.2.2 With external thermal sources

Next, we consider the setting with external thermal sources. We consider $W(t)$ as a sequence of *impulsive thermal sources*, such that

$$W(t) = \sum_{i=1}^{m} w_i \cdot \delta(t - t_i) \tag{4.7}$$

Where $\delta(t)$ is Dirac delta function, and w_i is the level of thermal intensity entering into the room at time t.

Impulsive thermal sources are a reasonable assumption for modeling short-lived thermal sources (e.g., temporarily opening a door). Further, any arbitrary $W(t)$ can be approximated by a sequence of appropriately placed impulsive thermal sources by taking $w_i = W(t_i)$ (see Fig. 4.1 for an illustration). Note that, in this paper, we do not assume any a-priori knowledge of the stochastic property of $W(t)$. We denote $\mathbf{a} \triangleq ((w_i, t_i) : i = 1, \ldots, m)$ for a sequence of arrivals of impulsive ther-

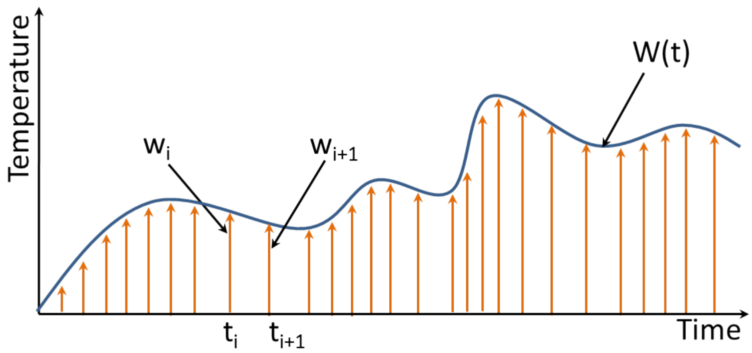


Figure 4.1: An illustration of using impulsive heat sources to approximate arbitrary $W(t)$.

mal sources, where m is the total number of arrivals. Given $\mathbf{a}$, the ambient room temperature at time t can be obtained recursively as follows. For $i \in \{1, \ldots, m\}$, we note that there is no external thermal source during interval $t_{i-1} < t < t_i$. We denote the ambient room temperature during interval $t_{i-1} \leq t < t_i$ by $\tilde{T}_i(t)$. Thus, following by Lemma 1, we obtain

$$\tilde{T}_i(t) = \frac{\mathsf{C}_1}{\mathsf{C}_2} - \left(\frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}_{i-1}(t_{i-1}) - w_{i-1}\right) \cdot e^{-\mathsf{C}_2 \cdot (t - t_{i-1})} \tag{4.8}$$

Where $\tilde{T}_{i-1}(t_{i-1}) + w_{i-1}$ is the initial temperature at t_{i-1}.

For completeness, we let $t_0 = 0$, $w_0 = 0$ and $\tilde{T}_0(t_0) = T_0$. Hence, we obtain the ambient room temperature for given external thermal sources $\mathbf{a}$ and initial ambient room temperature T_0 as

$$T(t; \mathbf{a}, T_0) = \tilde{T}_i(t), \text{ if } t_{i-1} \leq t < t_i \tag{4.9}$$

4.3 Model of wireless sensor control

To model wireless sensor control, we consider a wireless sensor deployed in the target zone for sensing the ambient temperature. The wireless sensor issues control commands to a remote air-conditioning system when the locally sensed ambient temperature exceeds a certain desirable temperature range. There are several issues considered in our sensor model.

a) Trade-off: Since wireless sensors are energy constrained and often powered by batteries, the wireless sensor is required to optimize the battery lifetime without affecting the thermal comfort. Although various operations are performed in wireless sensors (e.g., computations and sensing), the wireless communication operations typically consume most of the energy in a wireless sensor (see Appendix D). Hence, it is crucial to reduce the number of wireless communication operations for extending the battery lifetime.

There are two prominent conflicting factors that a wireless sensor needs to optimize:

1. The *update frequency* of control commands to remote air-conditioning sys-

tem in the presence of random fluctuating thermal sources, which characterizes the effectiveness of ambient room temperature control.

2. The *communication operations* for transmitting the control commands, which critically governs the wireless sensor battery lifetime.

Note that increasing of the number of communication operations will reduce the battery lifetime. This naturally gives rise to an online decision problem, where the wireless sensor decides the update frequency in an online manner without a-prior information of random fluctuating arrivals of thermal sources.

b) Air-conditioning operations: Let $T_{\rm des}^{\max}$ be the maximally desirable temperature (e.g., 25 degree Celsius), and $T_{\rm des}^{\min}$ be the minimally desirable temperature (e.g., 21 degree Celsius). The desirable ambient room temperature is aimed to be retained within $[T_{\rm des}^{\min}, T_{\rm des}^{\max}]$.

A simple setting of control command by wireless sensor is the "ON/OFF" or hysteresis control, such that when the ambient room temperature is sufficiently higher than $T_{\rm des}^{\max}$, an ON command is communicated to air-conditioning system, whereas when the sensed ambient room temperature is sufficiently lower than $T_{\rm des}^{\min}$, an OFF command is communicated to air-conditioning system[1]. This induces an ON/OFF cycle of air-conditioning operations (see Fig. 4.2 for an illustration), which is one of the most commonly used control strategy in today's air-conditioning systems [16].

Furthermore, for the sake of tractability, we assume that an OFF command is automatically issued when the ambient room temperature drops below $T_{\rm des}^{\min}$, and the cooling process is rather efficient, i.e. cooling can be achieved in a relatively short time. However, we may allow the ambient room temperature to exceed $T_{\rm des}^{\max}$ temporarily. Hence, our study is simplified to only optimize the ON command de-

[1] In our ambient room temperature model, the air-conditioning system can be disabled by letting $M_{\rm ac} = 0$

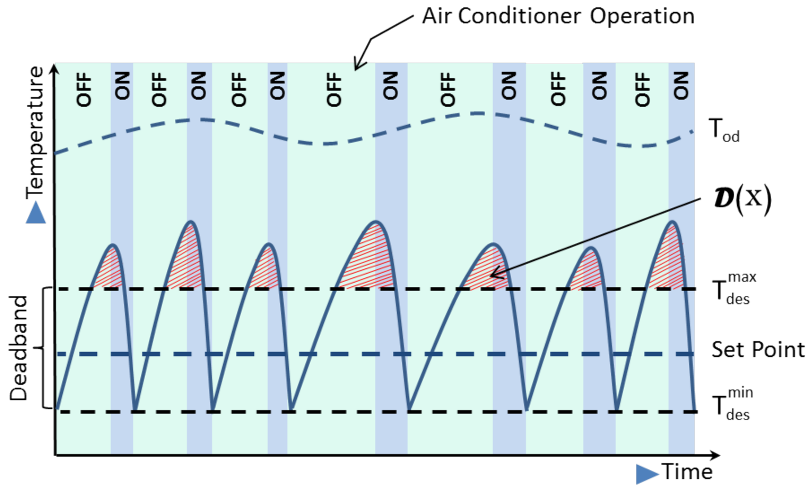


Figure 4.2: An illustration of the ON/OFF cycle of air-conditioning.

cisions in order to balance the trade-off between the wireless sensor battery lifetime and the effectiveness of ambient room temperature control, without considering the OFF commands.

We consider a finite time horizon for any $t \in [0,B]$. We define the *decision variables* as $\mathbf{x} = (x_k \in [0,B])_{k=1}^{K}$, where each x_k is the time that the k-th ON command is issued by the wireless sensor, while K is the total number of ON commands which the wireless sensor needs to optimize without affecting the thermal comfort.

c) Disturbance of temperature: We characterize the thermal comfort by a metric defined as the total disturbance of ambient temperature exceeding the desirable temperature range.

For given time τ, we let $\mathbf{a}_\tau$ be the sub-sequence, such that

$$\Big((w_i, t_i - \tau), (w_{i+1}, t_{i+1} - \tau), (w_{i+2}, t_{i+2} - \tau), \ldots\Big) \tag{4.10}$$

Where t_i is defined such that $t_{i-1} < \tau \le t_i$. Namely, $\mathbf{a}_\tau$ is a truncated sequence of $\mathbf{a}$ starting at τ.

We define $T_\tau(t)$ to be the temperature function $T(t; \mathbf{a}, T_0)$ starting at time τ with initial temperature $T_0 = T_{\text{des}}^{\min}$ and sequence of thermal sources $\mathbf{a}_\tau$. That is, for any $t \geq \tau$,

$$T_\tau(t) \triangleq T\left(t-\tau; \mathbf{a}_\tau, T_{\text{des}}^{\min}\right) \tag{4.11}$$

Hence, the total *disturbance* given decision variables $\mathbf{x}$ is defined by (also shown in Fig. 4.2)

$$\mathscr{D}(\mathbf{x}) \triangleq \sum_{k=1}^{K} \int_{t=x_k}^{x_{k+1}} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t \tag{4.12}$$

Where $[x]^+ = \max(x, 0)$ and $T_{\text{des}}^{\max}$ is the maximal desirable temperature threshold.

Definition 1. *Formally, we define the decision problem for wireless sensor controlling air-conditioning (WSAC) as follows:* **WSAC problem***:*

$$\min_{\mathbf{x}} \text{Cost}(\mathbf{x}) \triangleq \min_{\mathbf{x}} \eta \cdot K + (1-\eta) \cdot \mathscr{D}(\mathbf{x}) \tag{4.13}$$

Where $\eta \in [0,1]$ is a weight assigned to balance the update frequency and the thermal comfort.

In the offline decision setting, $\mathbf{x}$ is decided given a-priori information of $\mathbf{a}$ and T_{od} without any restriction; whereas in the online decision setting, we require $\mathbf{x}$ to be decided such that x_k only considers the thermal sources before time x_k: $\{(w_i, t_i) \mid t_i \leq x_k\}$.

Let $\mathbf{x}^*$ be the offline optimal solution to WSAC problem, while $\mathbf{x}_{\mathscr{A}}$ is the output solution given by an online algorithm $\mathscr{A}$. We define the competitive ratio as

$$\mathsf{CR}(\mathscr{A}) \triangleq \max_{\mathbf{a}, T_{\text{od}}} \frac{\text{Cost}(\mathbf{x}_{\mathscr{A}})}{\text{Cost}(\mathbf{x}^*)} \tag{4.14}$$

In our problem, we seek to find an optimal online algorithm $\mathscr{A}$ to solve WSAC problem with the minimal $\mathsf{CR}(\mathscr{A})$.

CHAPTER 5

Results

In this chapter, we present an offline algorithm as well as an online algorithm to solve WSAC problem. We also provide an example to illustrate the working of both algorithms. We conclude by proving the online algorithm to be 2-competitive.

5.1 Offline algorithm

While the rest of the thesis considers online algorithm, we first devise an effective offline algorithm to solve WSAC problem based on dynamic programming. The ramifications are that (1) the offline algorithm will enable us to compute the competitive ratio under diverse simulation settings; (2) the offline algorithm is useful in the setting with predictable **a**. For example, based on the past history and statistics of **a**, one can effectively solve WSAC problem by offline algorithm.

In the offline decision setting, we assume that all future temperature fluctuations are given in advance. We present our offline algorithm ($\mathscr{A}_{\text{OFL}}$) in Algorithm 1 that gives an optimal solution to WSAC problem. The basic idea of $\mathscr{A}_{\text{OFL}}$ is based on dynamic programming, which relies on solving a sub-problem to decide when the previous ON command should be transmitted, assuming all the previous ON commands can be decided optimally. Recall that t_i is the arrival time of the i-th

Algorithm 1 Optimal Offline Algorithm $\mathscr{A}_{\text{OFL}}$, Input(a)

$\text{Cost}_{\min}[0] \leftarrow 0$
$\text{Cost}[1,1] \leftarrow 1\cdot\eta + (1-\eta)\cdot\left[\int_{t=0}^{t_1}[T_{t_0}(t) - T_{\text{des}}^{\max}]^+ \text{d}t\right]$
$\text{Cost}_{\min}[1] \leftarrow \text{Cost}[1,1]$, $\text{idx}[1] \leftarrow 1$
for $i \in [2,m]$ **do**
  for $j \in [1,i]$ **do**
    $\text{Cost}[i,j] \leftarrow 1\cdot\eta + (1-\eta)\cdot\left[\int_{t=t_{i-j}}^{t_i}[T_{t_{i-j}}(t) - T_{\text{des}}^{\max}]^+ \text{d}t\right] + \text{Cost}_{\min}[i-j]$
    if $\text{Cost}[i,j] < \text{Cost}_{\min}[i]$ **then**
      $\text{Cost}_{\min}[i] \leftarrow \text{Cost}[i,j]$
      $\text{idx}[i] \leftarrow j$
    end if
  end for
end for
$y_1 \leftarrow t_m$, $k' \leftarrow 1$, $r \leftarrow m$ ▷ *backtrack to find* $\mathbf{x}^*$
while $r > 1$ **do**
  $r \leftarrow r - \text{idx}[r]$, $k' \leftarrow k' + 1$
  $y_{k'} \leftarrow t_r$
end while
$K \leftarrow k'$
Output $(x_k = y_{K-k+1})_{k=1}^{K}$

external thermal source in sequence **a**. Let $\text{Cost}[i,j]$ be the minimum cost when the last ON command is transmitted at time t_i and the second to last ON command is transmitted at time t_{i-j}, over all possible $\mathbf{x}$ with fixed $x_K = t_i$ and $x_{K-1} = t_{i-j}$. Also, let $\text{Cost}_{\min}[i]$ be the minimum cost when the last ON command is transmitted at time t_i. We note that $\text{Cost}[i,j]$ and $\text{Cost}_{\min}[i]$ can be computed recursively in Algorithm 1. Once $\text{Cost}_{\min}[m]$ is found, the optimal decision $\mathbf{x}^*$ can be determined by backtracking. To enable backtracking, we maintain indices $\text{idx}[i]$ to record j when $\text{Cost}_{\min}[i] \leftarrow \text{Cost}[i,j]$.

Theorem 1. *$\mathscr{A}_{\text{OFL}}$ in Algorithm 1 outputs an optimal solution to WSAC problem*

Proof. The proof can be achieved in two steps.

(i) WSAC problem exhibits the optimal sub-structure property;

(ii) $\mathscr{A}_{\text{OFL}}$ explores all sub-problems and thus gives an optimal solution.

To prove (**i**), we consider a subsequence of thermal sources

$$\Big((w_1,t_1),(w_2,t_2),...,(w_i,t_i),\Big) \tag{5.1}$$

Where the last ON command is transmitted at time $x_k = t_i$. Let us assume that we know that (perhaps told by an oracle) the second to last ON command is transmitted after the $(i-j)$-th arrival of thermal sources (i.e., $x_{k-1} = t_{i-j}$) is optimal, then we only need to optimize the subsequence $\Big((w_1,t_1),(w_2,t_2),...,(w_{i-j},t_{i-j})\Big)$ in order to obtain the full optimal solution. Thus, the problem exhibits the optimal sub-structure property.

To prove (**ii**), we need to examine the execution of $\mathscr{A}_{\text{OFL}}$. We note that there are two FOR-loops. For each iteration of the outer loop (i.e., upon arrival of each new thermal source), the inner loop is executed from start to i (i.e., all subsequences in $\Big((w_1,t_1),(w_2,t_2),...,(w_i,t_i),\Big)$ are traversed). This process is repeated for each new thermal source until we reach the end of the sequence. By doing so, $\mathscr{A}_{\text{OFL}}$ is able to explore all subsequences and, therefore, all sub-problems. □

5.2 Online algorithm

In this section, we present a deterministic online algorithm that optimizes the trade-off between the frequency of ON commands and the thermal comfort. Our online algorithm achieves so by balancing the cost of transmitting the ON command immediately with the cost of delaying the ON command. We assume that a wireless temperature sensor continuously tracks the change of temperature. Without the arrival of external thermal sources, the change in ambient temperature occurs smoothly as given by the differential equations Eqns. (4.1)-(4.3). However, when there is an arrival of external thermal source, the wireless sensor will be able to detect a sudden spike (because we assume impulsive thermal sources) in temperature, and hence, infer the arrival time of thermal source. Recall that the j-th thermal source arrives at t_j. Let

$$\sigma_k \triangleq \{i \in \{1, ..., m\} \mid x_{k-1} < t_i \leq x_k\} \tag{5.2}$$

Namely, σ_k is the set of thermal sources arrived between the $(k-1)$-th and the k-th ON commands. Upon each new arrival of thermal source, our online algorithm sets a timer such that the total cost (i.e., sum of transmission and disturbance costs) for σ_k if an ON command is transmitted immediately is equal to the disturbance cost for σ_k if an ON command is transmitted after waiting for some time τ. To be specific, suppose the last ON command is transmitted at time x_k. We decide the transmission time of the next ON command (x_{k+1}). The cost incurred if an ON command is transmitted immediately (i.e., at time t_j) is given by:

$$\eta + (1-\eta) \cdot \int_{t=x_k}^{t_j} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t \tag{5.3}$$

On the other hand, the total cost if an ON command is transmitted after waiting for time τ (i.e., at $t_j + \tau$) is given by

$$(1-\eta) \cdot \left[\int_{t=x_k}^{t_j} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t + \int_{t=t_j}^{t_j+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t \right] \tag{5.4}$$

Equating Eqn. (5.3) and (5.4), we obtain τ as a solution to the following equation.

$$\frac{\eta}{(1-\eta)} = \int_{t=t_j}^{t_j+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t \tag{5.5}$$

However, if there is an arrival of a new thermal source (at t_{j+1}) before timer expires, then we have to reset the timer and obtain a new τ as follows:

$$\frac{\eta}{(1-\eta)} = \int_{t=t_j}^{t_{j+1}+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^{+} \mathrm{d}t \tag{5.6}$$

Thus, upon each new arrival, we increment the upper integration limit in Eqn. (5.6) and get a new τ. The complete algorithm is presented in Algorithm 2 ($\mathscr{A}_{\text{ONL}}$).

Algorithm 2 OnlineAlgorithm $\mathscr{A}_{\text{ONL}}$, Input(t_{now})

Global variables: τ, timer
Initialization: $\tau \leftarrow 0$, timer $\leftarrow 0$

if $t_{\text{now}} >$ timer **then** ▷ *upon the beginning or after each OFF command*
  Find τ such that

$$\frac{\eta}{(1-\eta)} = \int_{t=t_{\text{now}}}^{t_{\text{now}}+\tau} [T_{\text{x}_\text{k}}(t) - T_{\text{des}}^{\max}]^{+} \mathrm{d}t$$

  timer $\leftarrow t_{\text{now}} + \tau$
end if
if $t_{\text{now}} =$ timer **then** ▷ *timer has expired*
  Transmit an ON command
else if $t_{\text{now}} <$ timer **then** ▷ *timer has not expired yet*
  if j-th new thermal source is detected at t_{now} **then**
    Let t_j be the time after the last ON command
    Find τ such that ▷ *decrease the timer due to new thermal source*

$$\frac{\eta}{(1-\eta)} = \int_{t=t_j}^{t_{\text{now}}+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^{+} \mathrm{d}t$$

    timer $\leftarrow t_{\text{now}} + \tau$
  else
    Do not transmit ▷ *wait for timer expiry*
  end if
end if
if Room Temperature $\leq T_{\text{des}}^{\min}$ **then**
  Transmit an OFF command
end if

Selecting the timer in such a manner will make $\mathscr{A}_{\text{ONL}}$ behave as follows. Upon the arrival of a each new temperature command, the algorithm sets a timer such that the expiry of timer will indicate that the comfort level threshold has reached and an ON command will be transmitted to the air-conditioning system. If an additional thermal source arrives before the timer expires, then a new smaller timer is set because the comfort level threshold will reach sooner due to the additional thermal source. In any case, whenever the timer expires, an ON command is transmitted and the current outstanding sequence is ended.

5.3 Example

We provide an example to illustrate the operations of offline optimal and online algorithms. In the example, the outdoor temperature is assumed to follow sinusoidal pattern. The input temperature sampled by the wireless sensor as a result of thermal sources entering the room at random intervals are given by Table. 5.1. For convenience of illustration, we restrict the example to 10 input samples (i.e., $m = 10$). The maximally desirable temperature $T_{\text{des}}^{\max}$ is 24 degree Celsius.

Table 5.1: Arrivals of impulsive thermal sources

t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
4	12	15	21	26	30	34	35	40	43
w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
24	23	24	25	23	29	24	27	25	28

For the arrivals shown in Table. 5.1, we execute $\mathscr{A}_{OFL}$. Table. 5.2 lists the entries $\text{Cost}[i, j]$, where the minimum costs (i.e.,$\text{Cost}_{\min}[i]$) are highlighted in yellow.

After obtaining $\text{Cost}_{\min}[m]$, we use backtracking to determine the optimal decision variables $\mathbf{x}^*$ as

$$\mathbf{x}^* = (t_1, t_3, t_4, t_6, t_8, t_{10})$$

Where each t_i is the time to transmit an ON command.

For the same arrivals, the online algorithm online algorithm $\mathscr{A}_{\text{ONL}}$ gives the

Table 5.2: $\text{Cost}_{\min}[i]$ and $\text{Cost}[i,j]$ for offline optimal algorithm

i, j	1	2	3	4	5	6	7	8	9	10
1	1.4									
2	4.1	4.5								
3	7.4	7.1	7.9							
4	11.5	12.0	12.6	14.4						
5	17.1	17.2	18.5	20.0	22.5					
6	23.9	23.8	24.6	26.6	28.7	31.8				
7	31.0	31.1	31.8	33.2	35.9	38.6	42.3			
8	37.4	36.6	36.7	37.4	38.8	41.5	44.2	47.9		
9	44.8	46.3	47.2	49.1	51.4	54.4	58.6	62.7	67.8	
10	54.0	53.2	54.6	55.5	57.4	59.7	62.7	66.9	71.0	76.1

following solution

$$\mathbf{x}_{\text{ONL}} = (t_6, t_{10})$$

The decisions made by both algorithms are illustrated in Fig. 5.1.

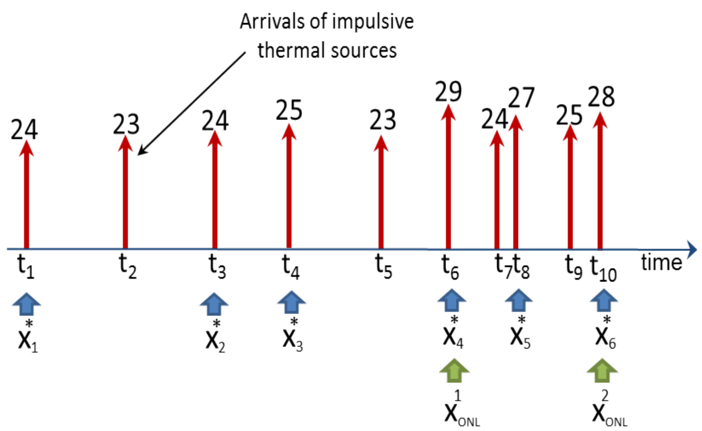


Figure 5.1: An illustration of the decisions by the offline optimal and online algorithms

Finally, the costs of both algorithms and the competitive ratio are computed as:

$$\text{Cost}(\mathbf{x}^*) = 53 \qquad \text{Cost}(\mathbf{x}_{\text{ONL}}) = 63 \qquad \text{CR}(\mathscr{A}_{\text{ONL}}) = 1.19$$

5.4 Competitive analysis

Let $\mathbf{x}^*$ be the offline optimal solution, while $\mathbf{x}_{\text{ONL}}$ is the output solution given by online algorithm $\mathscr{A}_{\text{ONL}}$. We define the competitive ratio as

$$\mathsf{CR}(\mathscr{A}_{\text{ONL}}) \triangleq \max_{\mathbf{a},T_{\text{od}}} \frac{\text{Cost}(\mathbf{x}_{\text{ONL}})}{\text{Cost}(\mathbf{x}^*)} \tag{5.7}$$

We show that the competitive ratio i.e., $\mathsf{CR}(\mathscr{A}_{\text{ONL}}) \leq 2$.

Theorem 2. $\text{Cost}(\mathbf{x}_{\text{ONL}}) \leq 2 \cdot \text{Cost}(\mathbf{x}^*)$

Proof. Assume that $\mathscr{A}_{\text{ONL}}$ sends a total of m ON commands for certain external thermal source arrivals, thus partitioning the sequence into m subsequences, where each subsequence ends with an ON command being transmitted to the air-conditioning system. The total cost by $\mathscr{A}_{\text{ONL}}$ for the input $\mathbf{a}$ is the sum of the cost for transmitting m ON commands and the extra latency cost for each subsequence, which can be calculated as follows.

First, as shown previously, $\mathscr{A}_{\text{ONL}}$ sets τ, such that

$$\frac{\eta}{(1-\eta)} = \int_{t=t_j}^{t_j+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t \tag{5.8}$$

Note that $\int_{t=t_j}^{t_j+\tau} [T_{x_k}(t) - T_{\text{des}}^{\max}]^+ \mathrm{d}t$ is a strictly increasing function in τ. Hence, the solution τ always exists and is uniquely defined. Also, it can be seen from Eqn. (5.8) that the timer is set in a manner that equalizes the total thermal disturbance of the subsequence to $\eta/(1-\eta)$. Thus, the disturbance cost for each subsequence is $\frac{\eta}{(1-\eta)} \cdot (1-\eta) = \eta$. The total cost incurred by $\mathscr{A}_{\text{ONL}}$, therefore, is

$$\begin{aligned} \text{Cost}(\mathbf{x}_{\text{ONL}}) &= \text{cost of } m \text{ ON commands} \\ &\quad + \text{disturbance cost for } m \text{ subsequences} \\ &= m\eta + m\eta = 2m\eta \end{aligned} \tag{5.9}$$

To calculate $\text{Cost}(\mathbf{x}^*)$, let m^* be the number of ON commands transmitted to the air-conditioning system in an optimal solution. When $m \leq m^*$, it immediately follows that $\text{Cost}(\mathbf{x}^*) \geq m^*\eta \geq m\eta$. Thus $\text{Cost}(\mathbf{x}_{\text{ONL}})/\text{Cost}(\mathbf{x}^*) \leq 2$.

We now consider the case when $m > m^*$. Since the m^* optimal ON commands are distributed over the m subsequences partitioned by $\mathscr{A}_{\text{ONL}}$. Thus, at least $m - m^*$ subsequences in online algorithm partition have no ON command at their end from the corresponding optimal solution. We claim that for each such a sequence, the disturbance cost is at least η in $\mathscr{A}_{\text{ONL}}$, because $\mathscr{A}_{\text{ONL}}$ decides ON command in such a way that the disturbance cost is equal to weighted cost of ON command (i.e., η). It is straightforward to see that disturbance cost of such a subsequence is at least η, because $\mathscr{A}_{\text{ONL}}$ resets the room temperature to $T_{\text{des}}^{\min}$ at the beginning of each subsequence, whereas offline optimal algorithm does not. This induces a total disturbance cost of at least $(m - m^*)\eta$ to the optimal solution. The total cost of offline optimal algorithm is:

$$\text{Cost}(\mathbf{x}^*) \geq m^*\eta + (m - m^*)\eta = m\eta \tag{5.10}$$

Thus, $\text{Cost}(\mathbf{x}^*) \geq m\eta$, which is at least half of $\text{Cost}(\mathbf{x}_{\text{ONL}})$. □

CHAPTER 6

Simulation Studies

In this chapter, we present the results of the simulations that we ran to experimentally evaluate the performance of our algorithms. We use the classical ON/OFF algorithm as a baseline control model. In the classical ON/OFF technique (also known as bang-bang or hysteresis control), the wireless sensor sends an ON command to the air-conditioner whenever the room temperature reaches $T_{\text{des}}^{\max}$ and OFF command when the temperature drops to $T_{\text{des}}^{\min}$. First we compare the online solution against the baseline algorithm. We, then, provide a detailed cost comparison between the online and offline algorithms under different models of random thermal sources and different values of η.

In the first experiment, all three algorithms were run multiple times for different values of η to determine their relative performance against each other. Fig. 6.1 shows the results of the experiment. The input size during all experiments was set to 1000. As can be seen from the figure , the average cost ratio of the online algorithm against offline algorithm is always below 1.5 which is much better than the theoretical ratio of 2. It can also been seen that our algorithm always performs better than the classic ON/OFF control technique.

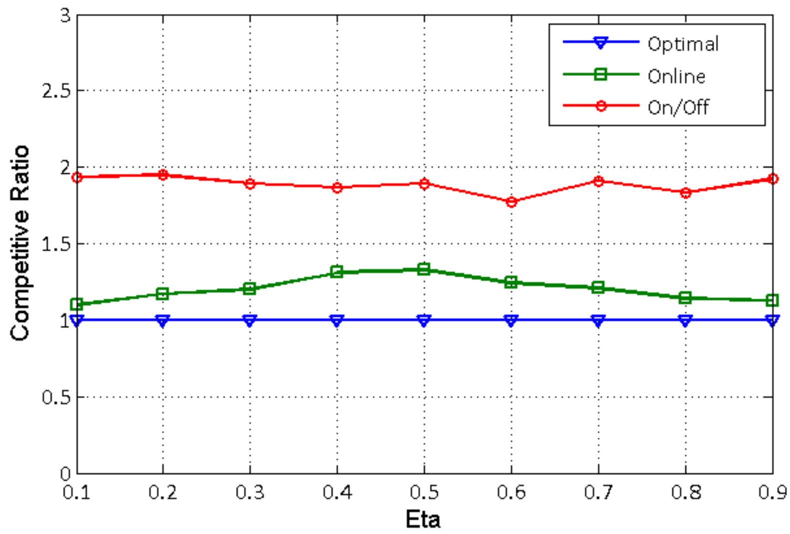


Figure 6.1: Simulation results showing the performance comparison between the online, the offline, and ON/OFF algorithms.

We now compare the performance of the online algorithm with the optimal offline algorithm under different models of random thermal sources. For the next experiment, we draw the random thermal sources from Poisson distribution. Poisson distribution is a one parameter distribution, where that parameter, λ, is both the mean and the variance of the distribution. Thus, we can change the behavior of random thermal source by changing λ. Poisson distribution is suitable in situations that involve counting the number of times a random event occurs in a given interval (e.g., time, distance, area etc.). We ran the simulations for different models of random thermal sources generated by varying the parameter λ. Fig. 6.2 shows the simulations results for $\lambda \in \{10, 20, 30\}$ and $\eta \in \{0.1, 0.2, ..., 0.9\}$. The vertical axis gives the ratio of the cost of the online algorithm's solution to the cost of the optimal solution and the horizontal axis represents the relative cost weighting of sending a control signal to the air-conditioner. By looking at each line, it can be seen that the cost ratio gets closer to one when the value of η approaches either zero or one. *This means that the online algorithm performs better when the relative weighting of sending a control signal is either very low or very high. It can also be observed that the performance of the algorithm improves as we decrease λ (i.e., reducing the random thermal disturbances).*

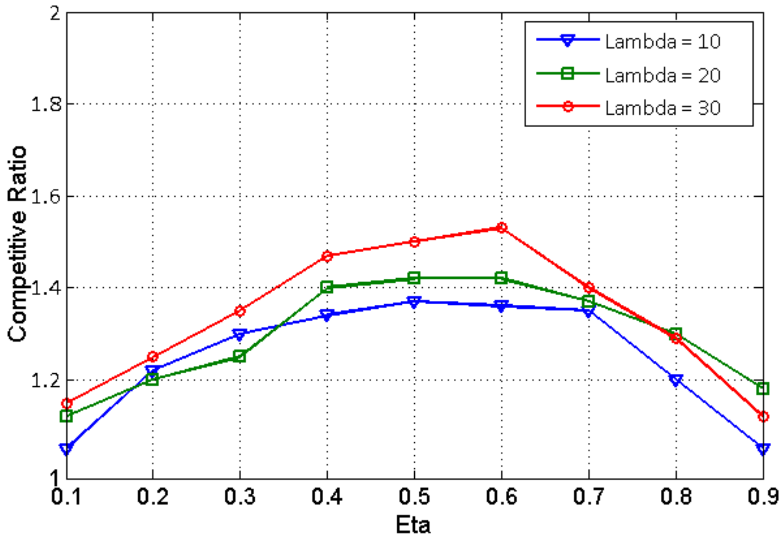


Figure 6.2: Competitive ratio of the online algorithm against the optimal algorithm when random thermal sources are drawn from Poisson distribution

Similar results were observed when the experiment was repeated, with random thermal sources drawn from Binomial distribution (see Fig. 6.3). Binomial distribution requires a parameter p, the probability of success. In our case, p is the probability of a random thermal source entering the room at a certain time. The results shown are for $p \in \{0.2, 0.5, 0.75\}$ and $\eta \in \{0.1, 0.2, ..., 0.9\}$. *Once again, as expected, the algorithm's performance improves as we reduce the value of p (i.e., the probability of occurrence of thermal disturbances).*

The simulation studies show that our online algorithm outperforms the baseline control method. However, simulations have a number of limitations. First, simulations involve the manipulation of a number of variables of a model representing

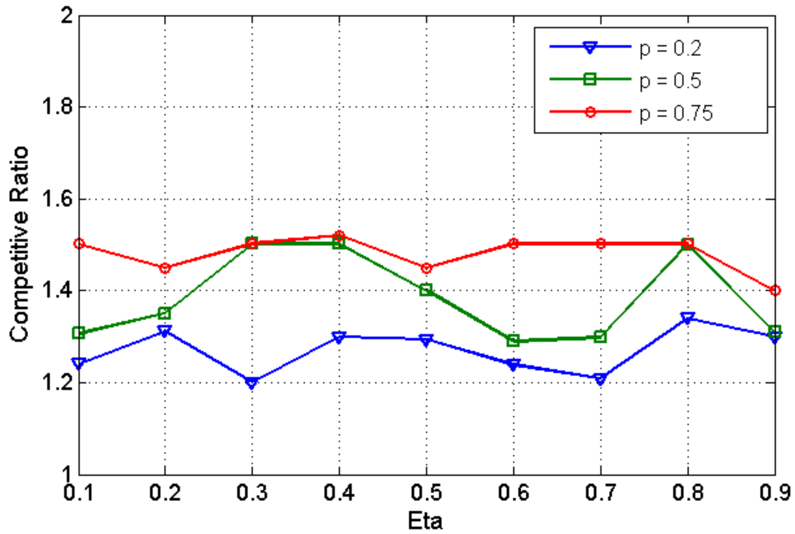


Figure 6.3: Competitive ratio of the online algorithm against the optimal algorithm when random thermal sources drawn from Binomial distribution.

a real system. However, it is possible that the reality of the system as a whole can be lost while manipulating of a single variable. Secondly, certain systems or components of a realistic situation are not transparent. Some factors have a lot of influence on the overall system, but they have indistinct relations in the overall system and can therefore not be represented in a model. Therefore, it is important to implement our control algorithms in real-world air-conditioning system and carry out an empirical study to evaluate its performance.

CHAPTER 7

Implementation

In this chapter, we present the empirical studies we conducted to evaluate the performance of our algorithm in a small-scale experimental setup using one air-conditioner. The algorithm's performance was evaluated under several control scenarios. The chapter includes an explanation of the experimental setup; a brief description of the hardware platform; a description of the control strategies and their relative performance; and discussion on the results.

7.1 Experimental setup

The experiment is setup in a room in a house using a custom wireless control system that includes a network of wireless temperature sensors and a controller. The size of the room is about 5m $\times$ 4m $\times$ 3.5m ($L \times W \times H$). A pictorial representation of our system is shown in Fig. 7.1. The figure shows approximate positioning of the hardware in the room.

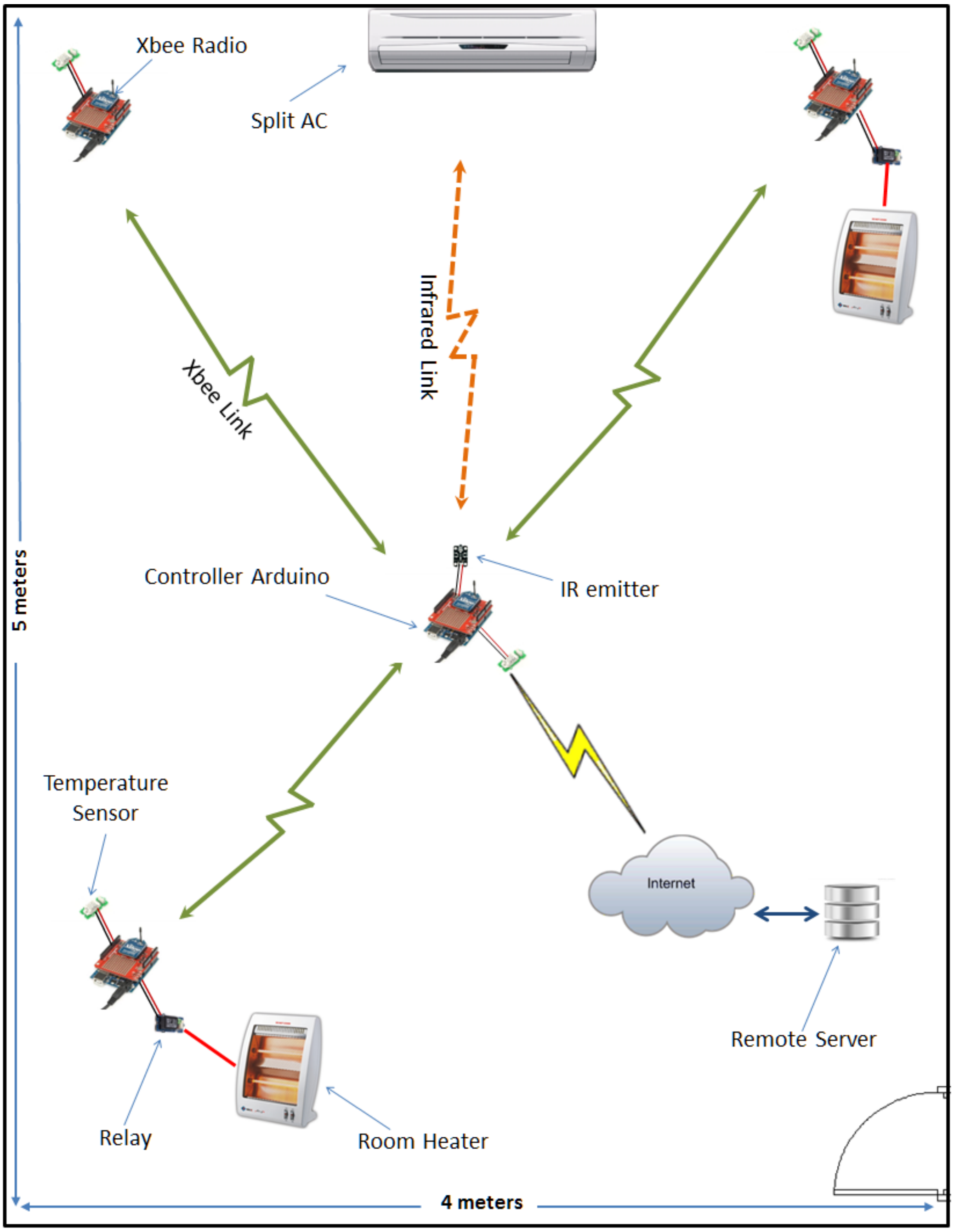


Figure 7.1: Pictorial representation of the experimental setup

The system comprises **(i)** an array of XBee enabled Arduino [1] boards equipped with temperature sensors, **(ii)** two Arduino controlled electric heaters, **(iii)** a spilt type air-conditioner, and **(iv)** a central controller Arduino. Arduino is chosen as the hardware platform because of its flexibility and ease of use for development of real-world control applications like in our case. It can receive input from a variety of sensors and can also control virtually any appliance. Arduino projects can be stand-alone (as in our case) or they can communicate with and receive commands from software running on a computer.

The Arduino boards in our system are programmed to measure temperature within the room. After collection, this information is transmitted to the controller Arduino via a wireless link. ZigBee [2] is used as the wireless communication protocol to send temperature data to the controller Arduino. To enable wireless communication via ZigBee protocol, each Arduino is equipped with an XBee radio module. Also, two Arduinos have 2000 W electric heaters connected to them. Heaters are used as random fluctuating heat sources and are controlled in a random fashion through relay by the Arduino they are connected to.

The primary function of the controller Arduino is to control the on/off functions of the air-conditioner unit according to the readings from the network of wireless temperature sensors. The controller Arduino is equipped with an XBee radio module, a temperature sensor, an Infrared (IR) emitter for sending actuation signals to the air-conditioner, and the control software. It was decided to control the air-conditioner through infrared because **(a)** it is wireless control method, and **(b)** it is non-invasive, thus requiring no retrofit. The controller Arduino analyzes the in-

[1] Arduino is an open-source electronics prototyping platform based on flexible, easy-to-use hardware and software. It's used for creating interactive objects or environments. The microcontroller on an Arduino board is programmed using the Arduino programming language and the Arduino development environment. For details go to www.arduino.cc

[2] ZigBee is a specification for a suite of high level communication protocols using small, low-power digital radios based on the IEEE 802.15.4-2003 standard for wireless home area networks. It's intended to be simpler and less expensive and is targeted at applications that require a low data rate, long battery life, and secure networking.

formation received from the other Arduinos over XBee network, which includes the temperature measurements and status of the heaters (ON/OFF). The controller then sends actuation signals over infrared link to the air-conditioner. The controller also periodically sends the temperature measurements, air-conditioner status, and information about the random heat sources to the remote server for storage. Please see Appendix A for a detailed explanation of the hardware platform development.

7.2 Actual experiments

A variety of experiments were conducted over a period of one week. Several control scenarios were tried by changing the input temperature signal to the algorithm. Evaluation of a scenario occurred over a twenty-four hour period. During the experiments, the room heaters were automatically turned on and off by the connected Arduinos in a random fashion. Any change in the status of heater was immediately sent to the controller Arduino via XBee link. In addition, each Arduino periodically transmitted temperature sensor readings via XBee link to the controller Arduino. The controller Arduino sent data to a remote server twice per minute. Finally, the temperature setpoints i.e. T_{des}^{min} and T_{des}^{max} were set to 23.5°C and 26°C respectively during the entire experiment in view of external weather. The following scenarios were evaluated. Our focus is on how to make use of the information available from a network of sensors, and how different methods of using the information affect energy performance and thermal comfort.

7.2.1 Average room temperature

In this scenario, the online algorithm running on the controller Arduino tries to maintain the average room temperature within the permissible range or deadband (i.e. T_{des}^{min} = 23.5°C, T_{des}^{max} = 26°C). The purpose of this scenario is to minimize aggregate discomfort in the room. The controller Arduino takes an average of all the temperature sensors deployed in the room and feeds the result as the input temperature signal to the online algorithm. It should be noted that there is no direct communication among individual sensors; individual sensors only send their temperature readings to the controller Arduino whenever there is a change in temperature.

Recall from chapter 5 that our online algorithm aims to find the optimal balance between the frequency of ON commands sent to the air-conditioner and the thermal comfort. This is achieved by balancing the cost of transmitting the ON command immediately with the cost of delaying the ON command. The wireless temperature sensors continuously track the change of temperature. When there is an arrival of a thermal source anywhere in the room (i.e. when a room heater is turned on), our online algorithm running on controller Arduino makes an estimate of the temperature impact of the thermal source and sets a timer τ such that when the timer expires, an ON command is sent to the air-conditioner. If a new thermal source is detected before the timer expires, the algorithm updates the timer accordingly. To be able to set a timer τ that does not result in thermal discomfort, we use trial-and-error to find a value for $\eta \in [0,1]$ that optimally balances the frequency of ON commands and thermal comfort (see eqn. (5.5) and (5.6)).

To maintain average room temperature in the permissible range, the air-conditioner is set to full swing mode by the controller Arduino so that cold air from the air-conditioner is propagated uniformly across the room. The data collected during the experiment is retrieved from the remote server and plotted in Fig. 7.2. The figure shows temperature readings from all four sensors, the ON/OFF status of the air-conditioner and heaters, and the timer (on the secondary y-axis). For the convenience of visualization, only a small portion of the collected is plotted (as indicated by the x-axis).

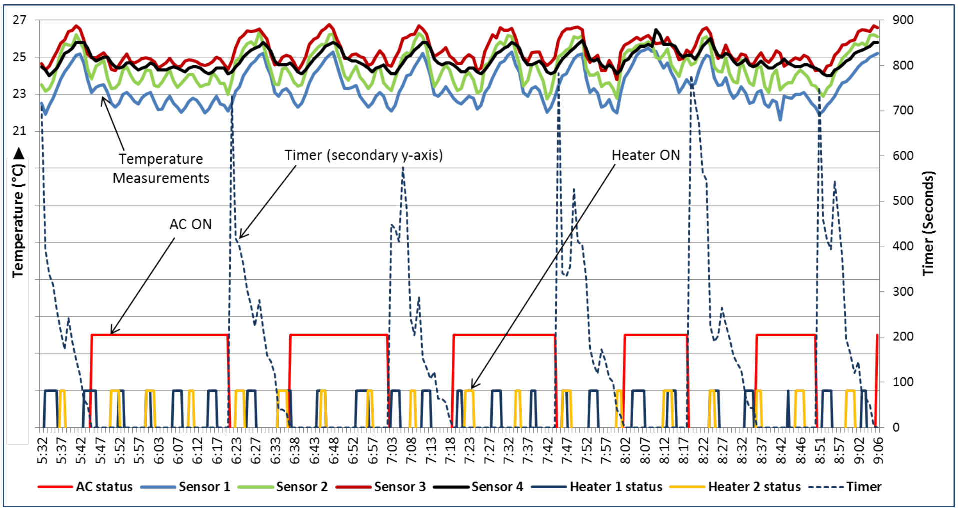


Figure 7.2: Data collected during *average room temperature* control scenario

7.2.2 Zone of interest

In this scenario, the online algorithm running on the controller Arduino focuses only on a zone of interest in the room (e.g. where people usually sit or where there is high population density and insufficient temperature). The algorithm maintains temperature inside the target zone in the permissible range. The difference from the previous scenario is that the algorithm considers the temperature readings only from sensors deployed in zone of interest, whereas readings from sensors outside the zone of interest are not taken into consideration during decision making. In the previous scenario, on the other hand, readings from all sensors were considered during decision making.

Similar to the previous scenario, individual sensors only communicate with the controller Arduino and not with one another. The algorithm~~s~~ sets and updates the timer τ in response to arrival of thermal sources in zone of interest. Also, the controller Arduino sets the air-conditioner to direct cold air flow towards the target zone. A small portion from the data collected during this experiment is plotted in Fig. 7.3. It should be noted that sensor 1 was deployed in the target zone.

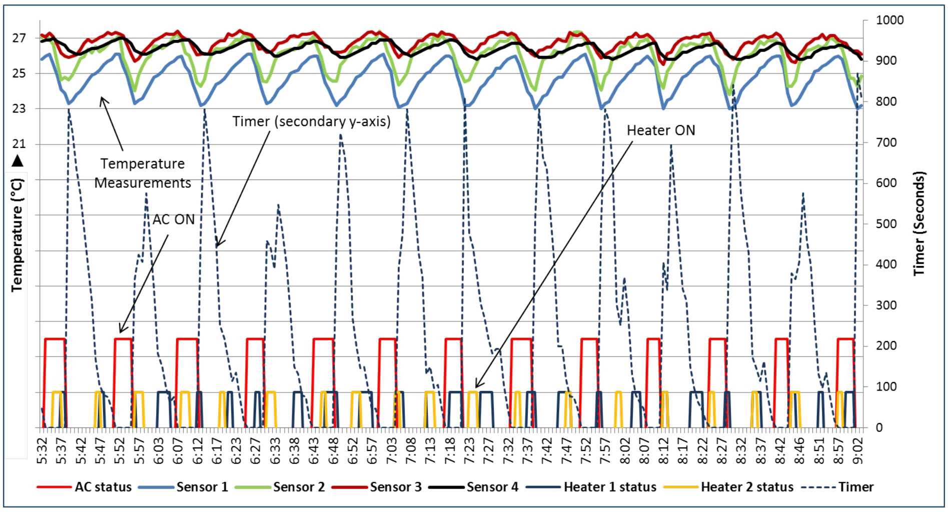


Figure 7.3: Data collected during *zone of interest* control scenario

7.2.3 Comparison with on-off control

In on-off control, the air-conditioner output is switched only when the temperature crosses the setpoint. The purpose of this scenario is to obtain performance data similar to the classical ON/OFF control method for comparison with the online algorithm. To make decisions, the controller Arduino considers the temperature readings only from the sensor deployed very close to the air-conditioner. The controller Arduino simply turns on the air-conditioner whenever the measured temperature from the sensor reaches T_{des}^{max} and turns it off when the temperature drops back to T_{des}^{min}. Like before, a portion from the data collected during this experiment is plotted in Fig. 7.4. It should be noted that Sensor 4 was deployed close to the air-conditioner.

7.2.4 Comparison with air-conditioner's default control

Our final scenario is to execute the air-conditioner's default control method for a twenty-four hour period. The controller Arduino performs no actuation/decision making. The wireless control network simply collects measurements from temper-

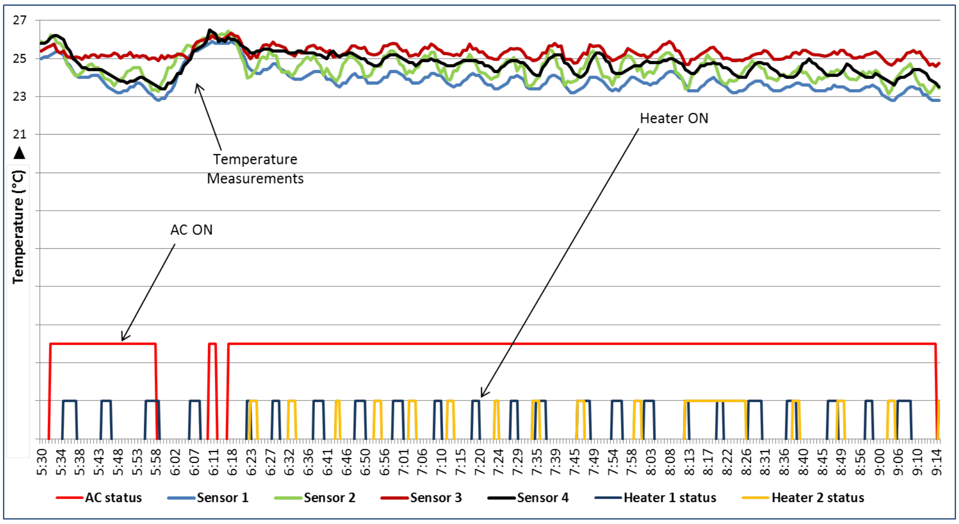


Figure 7.4: Data collected during *on-off* control scenario

ature sensors and sends it over the internet to the remote server for storage. Data collected during this final experiment is shown in Fig. 7.5. The temperature curves in the figure are relatively smoother compared to the previous control scenarios. This is because the air-conditioner in our experiment uses inverter compressor technology (variable frequency drive), where the system varies the compressor speed in response to temperature changes. Inverter based air-conditioners do not work by maintaining the temperature within the deadband and keep it relatively constant instead (see section A.5 of Appendix A for details). A temperature of 24°C was chosen as the setpoint which is roughly the average of T_{des}^{min} and T_{des}^{max} used in previous control scenarios.

7.3 Calculation of air-conditioner's energy consumption

To calculate the energy consumption by the air-conditioner in case of first three control scenarios, we assume a fixed-speed compressor operation that only operates either at 0% or 100% capacity. This is because our algorithm works by keeping

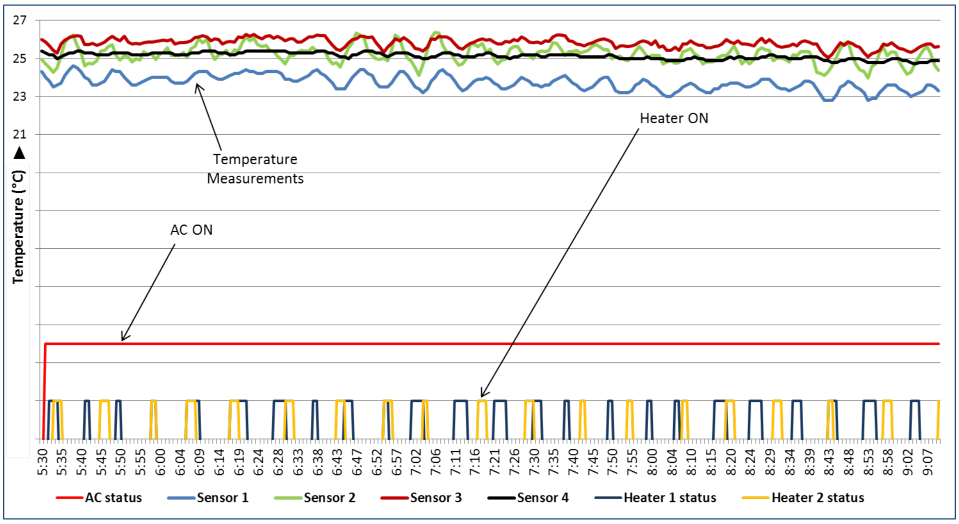


Figure 7.5: Data collected during *air-conditioner's default* control scenario

the air-conditioner either on or off. The air-conditioner in our experiment, however, has a variable-speed compressor. Therefore, we try to achieve full capacity operation by choosing the lowest available setpoint. We use the principle that when the difference between room temperature and setpoint is high, inverter-based air-conditioners operate at nearly full capacity (see section A.5 of Appendix A). For the first three control scenarios, the difference between the overall average temperature and the setpoint temperature T_{des}^{min} is more than 7°C (see the difference between the second and third rows in Table 7.1), therefore we assume that the air-conditioner operates at 100% capacity in case of the first three control scenarios. On the other hand, in case of the default control scenario, we assume 50% operational capacity because the average and setpoint temperatures are close to each other. (see section A.5 of Appendix A for the justifications behind our assumptions.) We multiply the total air-conditioner running time (2nd row in Table 7.1) by the capacity (3rd row) to get the total energy consumption (4th row). The plotted results are presented in Fig. 7.6.

Table 7.1: Calculation of air-conditioner energy consumption

	online-avg	online-zone	on-off	default
AC ON Duration	17.51 hrs	6.09 hrs	18.62 hrs	24 hrs
Overall Avg Temp	24.57°C	25.75°C	24.55°C	24.84°C
Setpoint T_{des}^{min}	17°C	17°C	17°C	24°C
Estimated Capacity	100%/6.9 kW	100%/6.9 kW	100%/6.9 kW	50%/3.45 kW
Energy Consumption	120.82 kWh	42.02 kWh	128.49 kWh	82.8 kWh

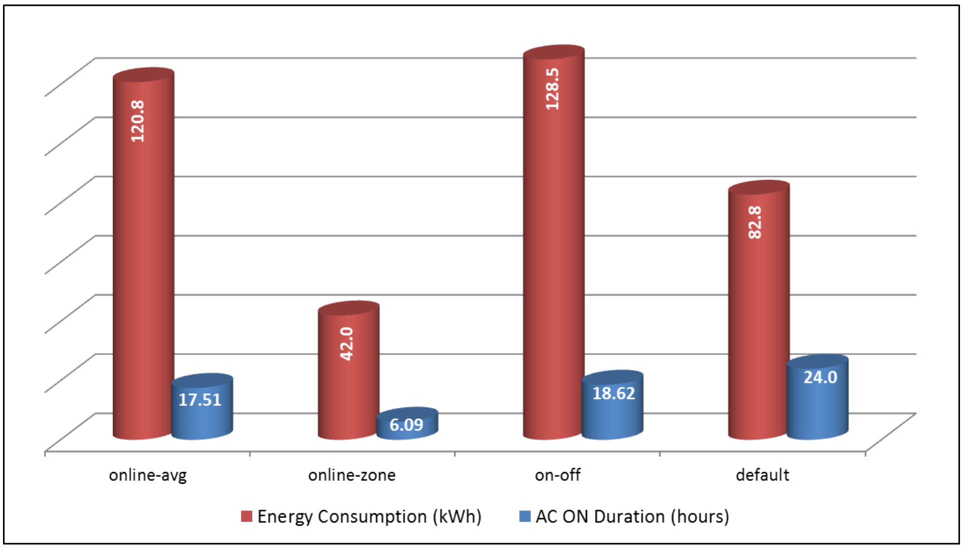


Figure 7.6: Comparative energy consumption by air conditioner for control scenarios

7.4 Calculation of total thermal comfort and sensor network energy consumption

We use the total thermal disturbance caused by each control scenario as a measure of its thermal comfort. A higher thermal disturbance means lower thermal comfort and vice versa. Recall from chapter 4 that thermal disturbance at a given time is the difference between T_{des}^{max} and the actual room temperature. Figure 7.7 shows the total thermal disturbance caused by each scenario during its twenty-four hour evaluation period. For each scenario, it shows the thermal disturbance for each sensor as well overall disturbance.

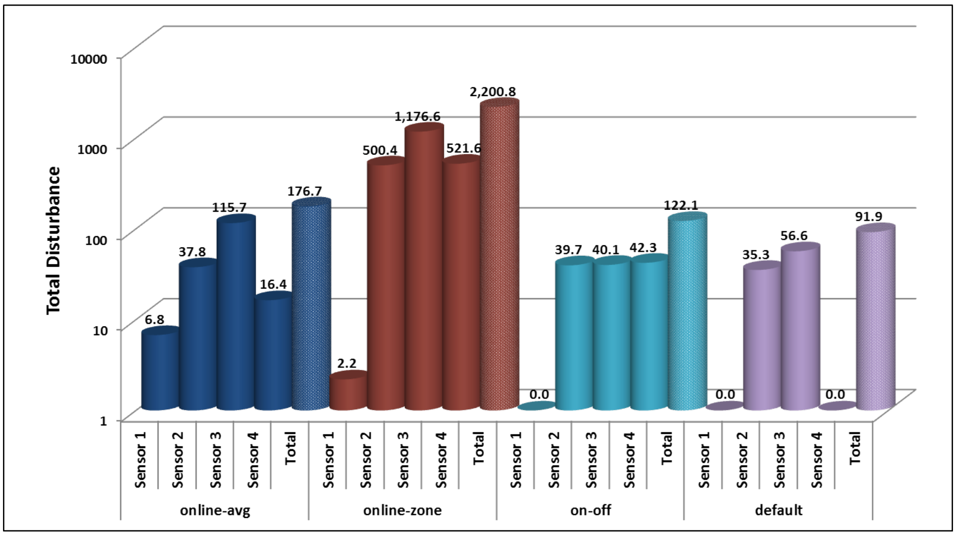


Figure 7.7: Comparative thermal disturbance

Similarly, the sensor network energy consumption is measured in terms of its communication frequency or the number of ON commands sent to the air-conditioner. Fig. 7.8 shows the number of ON commands sent by the controller for the first three scenario. Recall that no commands were sent to the air-conditioner in the default scenario.

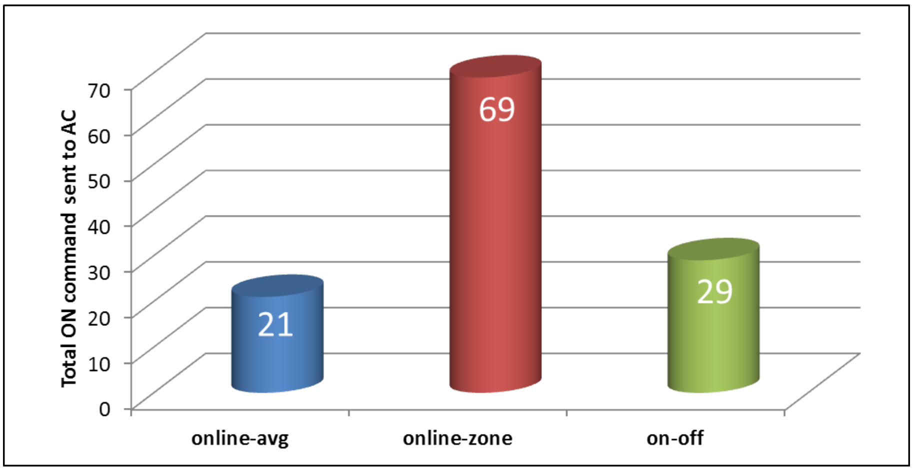


Figure 7.8: Comparison of total ON commands sent to the air-conditioner

7.5 Observations

1. For the first control scenario (i.e., online algorithm with *average room temperature*), the readings from all temperature sensors follow a similar pattern i.e., change in temperature is uniform across all sensors for the entire duration of the scenario (Fig.7.2). This is because chilled air was uniformly distributed across the room and also the algorithm considered readings from all sensors while making decisions.

2. The air-conditioner output switching frequency is significantly higher in case of second control scenario (i.e., online algorithms with *zone of interest*). This is because of smaller area of focus which results in faster cycling between T_{des}^{min} and T_{des}^{max} (see the temperature readings from sensor 1 in Fig. 7.3).

3. Fig. 7.9 shows the variations in average room temperature over time for each scenario. We can observe that the average room temperature is higher for *zone of interest* scenario. This is because the algorithm maintains thermal comfort only within zone of interest and ignores area outside the zone, thus resulting in higher average temperature.

4. In case of the first two control scenarios, it can be observed that the timer is directly affected by random heat sources. The timer's value is decreased/increased in response to activation/disappearance of heat sources (Fig. 7.2, 7.3).

5. The sensors do not exhibit uniform behavior when the *on-off* control scenario is in effect (Fig. 7.4). It can be observed that Sensor 3 is less responsive to the air-conditioner as compared to other sensors. The reason is that the air-conditioner makes control decisions based on only one sensor deployed close to the air-conditioner. Note that the air-conditioner was set to auto mode to ensure autonomous operation and prevent any external influence.

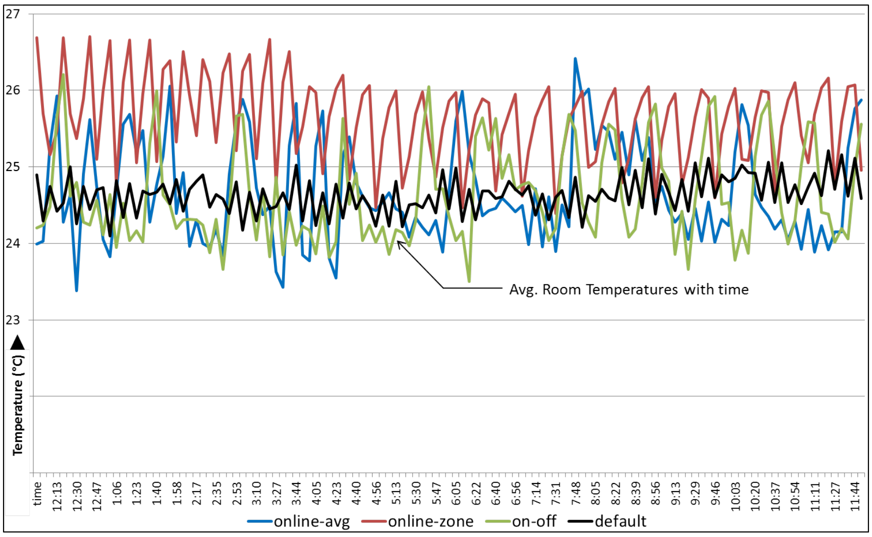


Figure 7.9: Average room temperature comparison between control scenarios

6. The *default* control scenario maintains comparatively constant average room temperature (Fig. 7.9) due to its inverter-based compressor operation. However, like the *on-off* control scenario, the sensors do not follow uniform behavior. For example, Sensor 1 and 2 show slight swings in temperature while Sensor 3 and Sensor 4 exhibit rather stable temperature patterns (Fig. 7.5).

7. Looking at the air-conditioner's energy consumption (Fig. 7.6), it is obvious that *zone of interest* control scenario results in the least energy consumption, followed by the air-conditioner's default control scenario. The simple on-off scenario is most expensive with respect to energy consumption.

8. Finally to shed some light on the trade-off between thermal comfort and energy consumption of wireless sensors, it is observed that the number of ON commands sent by *zone of interest* control scenario is almost three times as high as the ON commands sent by other two scenarios (Fig. 7.8). Whereas, for the same scenario, the thermal disturbance in the zone of interest (i.e. sensor 1) is very low (Fig 7.7).

CHAPTER 8

Conclusion and Future Work

While intelligent systems for smart buildings have been a popular research topic, online optimization approach has been explored to a lesser extent. In this thesis, we investigated a new breed of research problems by applying online algorithms to wireless sensor based smart building control. We provide the first study of optimizing the trade-off between the battery lifetime of wireless sensor and the effectiveness of HVAC remote control in the presence of uncertain fluctuations in room temperature. We present both an effective optimal offline algorithm and a 2-competitive online algorithm and evaluate their performance through simulations. We also implement and evaluate our control algorithms in real-world air-conditioning system and conclude the following based on our observations:

1. The specific control scenario can significantly affect the air-conditioners' energy consumption as well as overall thermal comfort. In *zone of interest* scenario, we demonstrated that it is possible to achieve upto 50% reduction in energy consumption and still provide comfortable environment only where

necessary. However, it may result in thermal discomfort outside the zone of interest.

2. The battery consumption of the wireless sensors greatly depends on the control algorithm. This is evident from the difference in the number of ON commands sent to the air-conditioner between the control scenarios.

3. The battery life time of the wireless sensors also depends to some extent on the rate of cycling between T_{des}^{min} and T_{des}^{max}, which in turn depends on external weather and thermal characteristics of the room. The faster the rate of cycling, the higher the frequency of the control commands sent to the air-conditioner and vice versa.

4. The sensor network energy consumption is directly linked with thermal comfort. Trying to improve thermal comfort will increase sensor network energy consumption and vice versa. It is, therefore, important to find a good trade-off between the two conflicting goals.

There are plenty of research opportunities to extend the results of this work to a more general context. So far, we devised a deterministic online algorithm. It is well-known that randomized online algorithms can exhibit both improved theoretical competitive ratio and practical performance. For the on-going work, we will study randomized online algorithms for wireless sensor controlling air-conditioning systems, and evaluate their performance.

In a general setting, there may be multiple sensors and multiple air conditioning systems. Intelligent coordination among sensors can enable optimized control over multiple system parameters (e.g., temperature, wind, ventilation). This interaction among multi-input and multi-control systems in a networked setting will be a challenging yet important research problem.

Several other possibilities can be explored with our system; it may be possible to minimize consumption during peak hours by simply shifting energy consumption by pre-cooling or pre-heating the thermal space ahead of peak hours, and then allowing the temperature to drift gradually during a high price period.

Another research direction is to use integrated sensors (CO_2, PIR, humidity) to exercise control according to human behavior and room conditions. For example, the algorithm can make online decisions regarding turning on/off the air-conditioner in unoccupied zones. Moreover, our wireless control system can easily be integrated with building managements systems for demand responsive air conditioning control.

APPENDIX A

Hardware Platform Setup

In this appendix, we outline the development procedure of our hardware platform. Our system comprises several Arduinos connected through a wireless XBee network to the controller Arduino which communicates with the air-conditioner via an infrared (IR) link. The system also includes two Arduino-controlled room heaters. We discuss important aspects of the system including (1) setting up an XBee wireless network, (2) designing an Arduino with temperature measurement and heater control, (3) designing the controller Arduino, (4) decoding the IR protocol used between the air-conditioner and the remote control, (5) calculating air-conditioner energy consumption, and (6) configuring the remote server.

A.1 Configuring XBee network

To equip an Arduino with wireless communication capability, it must have an XBee radio module. However, before connecting the XBee to the Arduino, we have to configure it. This means that each XBee needs to have a device (self) ID and a network ID. The device ID must be unique for each XBee whereas the network ID must be the same for all XBees otherwise they will not be able to communicate with each other. The XBee modules can be configured as follows:

- Mount the XBee module on an XBee Explorer USB and connect it to a computer as shown in Fig. A.1

Figure A.1: An XBee module mounted on XBee Explorer USB

- Launch X-CTU software, select appropriate COM port, and then click on the *Modem Configuration* tab and click on the read button (Fig. A.2). Set the network ID and device ID as shown. Also set the communication mode to FFFF to change the XBee module to broadcast mode. To finish the configuration, click on the write button to store the new settings on the XBee module.

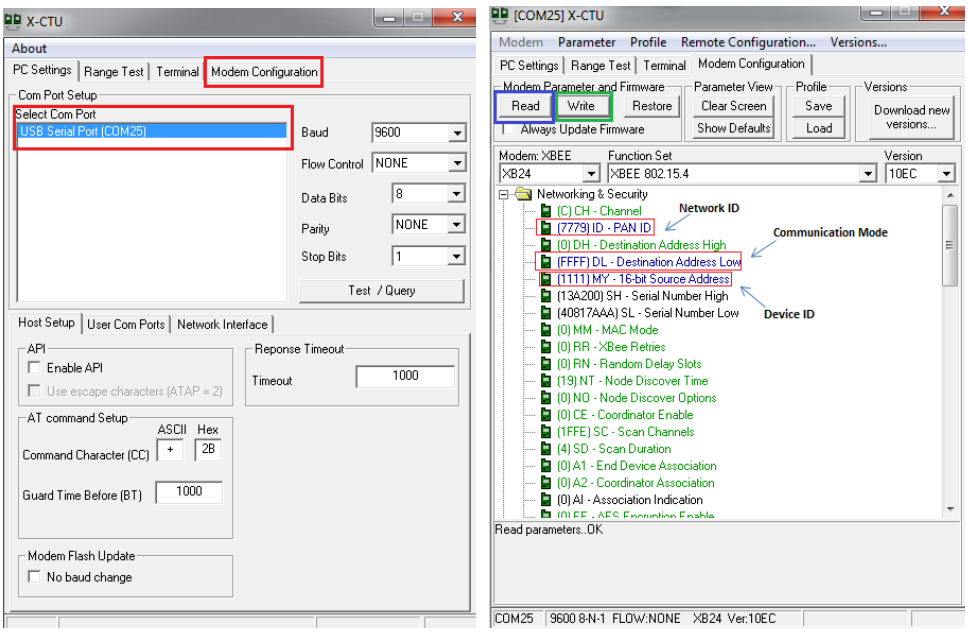


Figure A.2: XBee Radio Module Configuration through X-CTU

A.2 Sender Arduinos

In order to equip an Arduino with wireless communication capabilities, we connect a properly configured XBee module to it. An XBee shield is mounted on the Arduino to simplify the task of interfacing the XBee module with the Arduino. A snapshot of an XBee-enabled Arduino with a connected temperature sensor is shown in Fig. A.3.

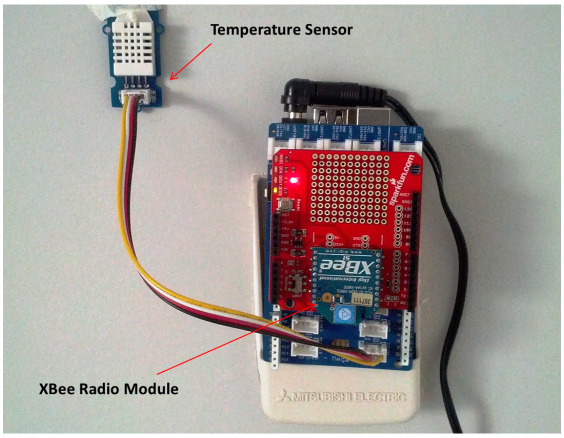


Figure A.3: An XBee-enabled Arduino with a connected temperature sensor

Recall that the room heaters used in the experiments is controlled by an Arduino using a relay. Live wire of the heater is connected to a relay which makes it possible to control the heater simply by turning the relay on and off. Fig. A.4 shows an XBee-equipped Arduino with a temperature sensor and heater.

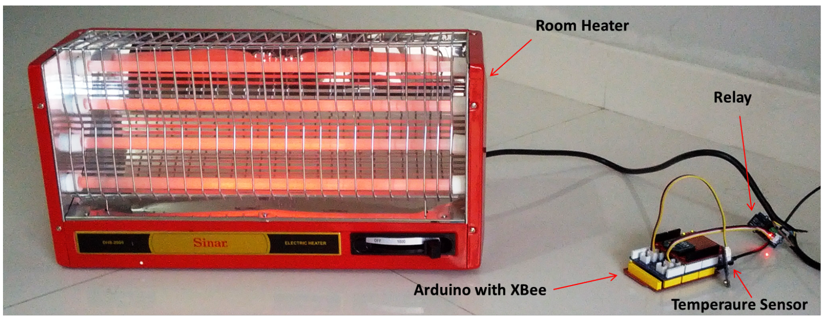


Figure A.4: An XBee-enabled Arduino with a room heater and temperature sensor

A.3 Central controller

The central controller implements the air-conditioning control strategies. It is actually a combination of two Arduino boards – *Arduino Ethernet board* and *Arduino Uno board*. Two Arduino boards have to be used instead of one because the infrared (IR) library for Arduino had several conflicts with other Arduino libraries. Accordingly, a separate Arduino board is used whose only responsibility is to send IR commands to the air-conditioner. See Fig. A.5 for a snapshot of the actual controller that we designed and developed.

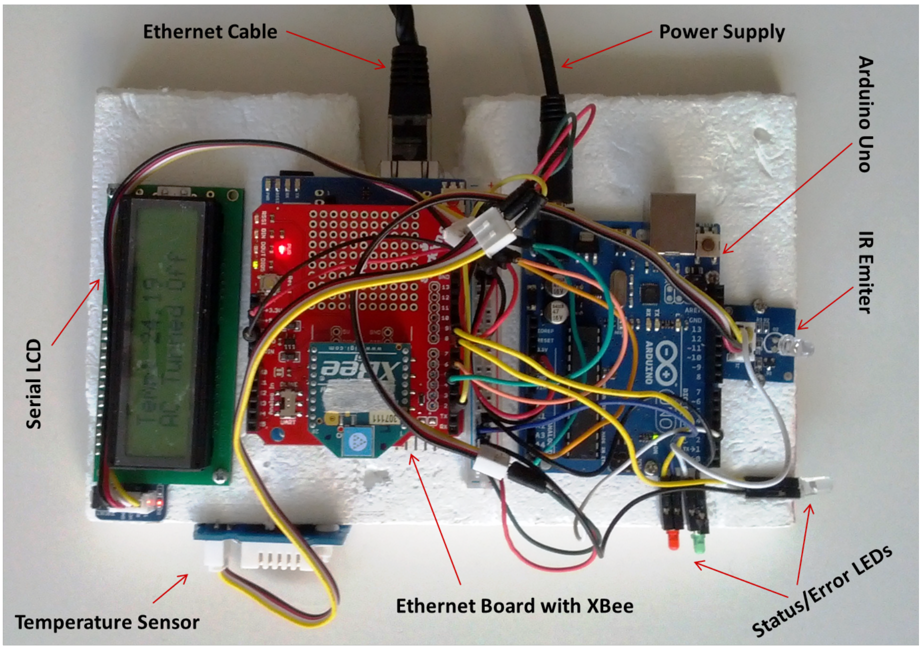


Figure A.5: A snapshot of the actual controller

The main tasks performed by the Arduinos are described below:

a)- Arduino Ethernet board: It has the following duties:

1. Receiving data from other Arduinos over XBee network. The board is equipped with an XBee radio module to enable wireless communication via XBee.

2. Execution of the control strategy and send commands to the attached Ar-

duino Uno for onward transmission to the air-conditioner.

3. Sending data over the internet to a remote server for storage in a database.

The board is equipped with a temperature sensor so that it can also measure temperature for control purpose and/or sending it to the remote server. Additionally, a small LCD display is connected to the board which displays status/error messages.

When powered on, the Arduino Ethernet board first performs various initialization related tasks like fetching the remote server address, establishing connection with the server, activating XBees network etc. Once the initialization is complete, it executes the control strategy and, if necessary, sends a control signal to the air-conditioner. Whenever it receives new temperature measurements and/or heater status data, it again executes the control strategy and sends the control signal accordingly.

b)- Arduino Uno board: Its sole responsibility is to send control commands to the air-conditioner over IR link. An IR emitter is attached to the Arduino Uno which enables sending all the IR commands that are sent by remote controller. To achieve this, the IR protocol used by the remote controller has been decoded as described in the next section. The Arduino Uno sends the appropriate IR control signal to the air-conditioner based on the command it receives from the Ethernet board over I2C bus. Arduino Wire library is used to transfer data/commands from the Ethernet board to Arduino Uno via I2C bus.

A.4 Decoding infrared protocol

Before we can send infrared (IR) commands to the air-conditioner from Arduino, we first need to crack the protocol of the IR remote control. We use an IR receiver connected to Arduino to receive and decipher the IR commands sent by the remote control. Mitsubishi air-conditioner was used in the experiments, therefore the decoding process is applicable to Mitsubishi remote controls. With minor modifications, the procedure can be adapted to decode IR protocols used by other vendors.

The air-conditioner remote control protocol is quite different from typical TV, DVD, satellite receiver, and other remote control protocols. That is because the settings are stored on the remote control itself rather than the air-conditioner. This means that whenever a button is pressed, the remote control sends the complete set of parameters such as temperature, fan settings, swing, and others.

After analyzing different codes emitted by the original remote control, we were able to understand the codes and generate them ourselves. Now, we can exercise fine-grained control over the air-conditioner. We can set temperature, fan speed, and air flow direction by sending the appropriate IR command. Whenever a button on the remote control is pressed, a total of 20 bytes are sent as specified by Mitsubishi remote control protocol. Table A.1 lists the details for each byte. The example row in the table is the sequence of bytes in the IR signal when the OFF button is pressed on the remote control.

Table A.1: Structure of IR packet sent by Mitsubishi remote control

Byte	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Description	Length of Remaining Packet	Start (HIGH)	Start (LOW)	Communication (SHORT)	Communication (LONG)	Actual Command Length	Actual IR Command													
Example	19	69	33	9	24	14	196	211	100	128	0	5	192	240	188	0	0	0	12	44

A.5 Calculation of air-conditioner energy consumption

We used a split-type air-conditioner in our experiments (see Table A.2 for specifications[1]).

Table A.2: Specifications of the air-conditioner used in the experiments

Model	Mitsubishi MS-E24VD
Capacity	6.9 kW/2.0 ton
Indoor Upper Operating Limit	32°C Dry Bulb / 23°C Wet Bulb
Indoor Lower Operating Limit	21°C Dry Bulb / 15°C Wet Bulb
Outdoor Upper Operating Limit	52°C Dry Bulb
Outdoor Lower Operating Limit	21°C Dry Bulb

The air-conditioner uses inverter technology, where the inverter receives information from sensors monitoring operating conditions, and adjusts the revolution speed of the compressor, which directly regulates air-conditioner output. When the room temperature is higher than the set-point, the air-conditioner runs on higher capacity in order to quickly bring down the temperature. Once the room temperature drops to the desired temperature, the inverter lowers the air-conditioner capacity and start consuming the same amount of energy while maintaining the temperature at desired level. The process is shown in Fig. A.6[2]. By looking at the measured capacity, it can be seen that the air-conditioner runs at roughly 50% capacity on average when it reaches the setpoint. Thus, the energy consumption of the air-conditioner in our system, when operated for 24 hours, can be calculated as follows:

$$\begin{aligned}\text{Power Consumption} &= \text{Operating Capacity} \times \text{Rated Capacity} && \text{(A.1)}\\ &= 50\% \times 6.9\text{ kW} = 3.45\text{ kW}\\ \text{Energy Consumption} &= \text{Power Consumption} \times \text{Duration (hours)} && \text{(A.2)}\\ &= 3.45\text{ kW} \times 24\text{ hours} = 82.8\text{ kWh}\end{aligned}$$

[1] Source: http://www.tochalelectric.com/userfiles/files/MS-E24VD/Catalogue/MS-E24VD.pdf
[2] Source: http://www.mitsubishielectric.com/bu/air/technologies/inverter.html

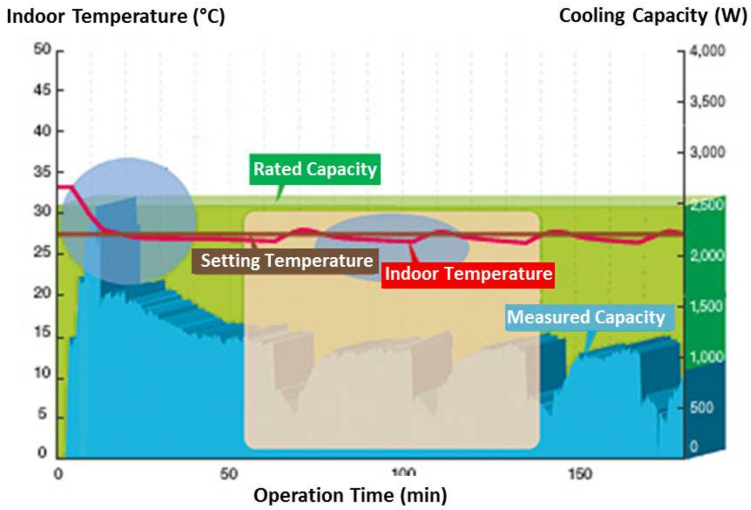
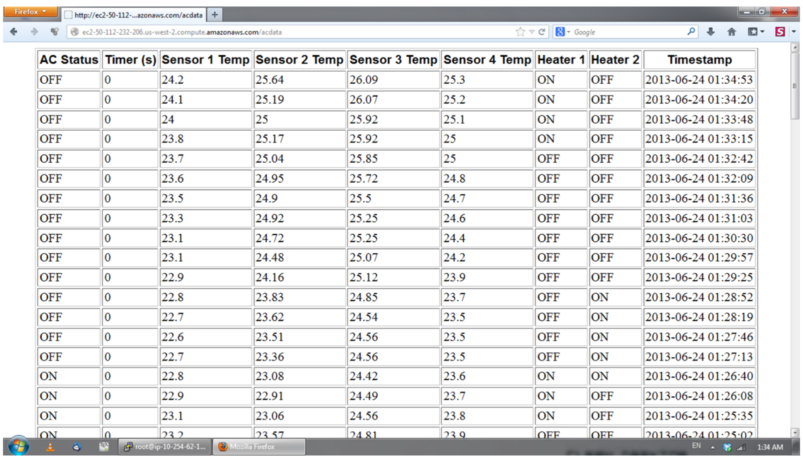


Figure A.6: Air-conditioner operation control with inverter technology

A.6 Configuring remote server

As mentioned previously, the controller Arduino periodically sends data to a remote server where it is stored for later analysis. A dedicated Amazon EC2 server has been set up for this purpose. The server basically runs two PHP scripts: one to receive the data sent by the controller Arduino and store it in a MySQL database and the second script to display live data to the user via a web browser (see Fig. A.7).



AC Status	Timer (s)	Sensor 1 Temp	Sensor 2 Temp	Sensor 3 Temp	Sensor 4 Temp	Heater 1	Heater 2	Timestamp
OFF	0	24.2	25.64	26.09	25.3	ON	OFF	2013-06-24 01:34:53
OFF	0	24.1	25.19	26.07	25.2	ON	OFF	2013-06-24 01:34:20
OFF	0	24	25	25.92	25.1	ON	OFF	2013-06-24 01:33:48
OFF	0	23.8	25.17	25.92	25	ON	OFF	2013-06-24 01:33:15
OFF	0	23.7	25.04	25.85	25	OFF	OFF	2013-06-24 01:32:42
OFF	0	23.6	24.95	25.72	24.8	OFF	OFF	2013-06-24 01:32:09
OFF	0	23.5	24.9	25.5	24.7	OFF	OFF	2013-06-24 01:31:36
OFF	0	23.3	24.92	25.25	24.6	OFF	OFF	2013-06-24 01:31:03
OFF	0	23.1	24.72	25.25	24.4	OFF	OFF	2013-06-24 01:30:30
OFF	0	23.1	24.48	25.07	24.2	OFF	OFF	2013-06-24 01:29:57
OFF	0	22.9	24.16	25.12	23.9	OFF	OFF	2013-06-24 01:29:25
OFF	0	22.8	23.83	24.85	23.7	OFF	ON	2013-06-24 01:28:52
OFF	0	22.7	23.62	24.54	23.5	OFF	ON	2013-06-24 01:28:19
OFF	0	22.6	23.51	24.56	23.5	OFF	ON	2013-06-24 01:27:46
OFF	0	22.7	23.36	24.56	23.5	OFF	ON	2013-06-24 01:27:13
ON	0	22.8	23.08	24.42	23.6	ON	ON	2013-06-24 01:26:40
ON	0	22.9	22.91	24.49	23.7	ON	OFF	2013-06-24 01:26:08
ON	0	23.1	23.06	24.56	23.8	ON	OFF	2013-06-24 01:25:35
ON	0	23.2	23.57	24.81	23.9	OFF	OFF	2013-06-24 01:25:02

Figure A.7: A snapshot of live data displayed via a web page

APPENDIX B

Proof of Lemma 1

In this section, we prove Lemma 1 that we used in chapter 4. The differential equations are again listed here:

$$\frac{\mathrm{d}\tilde{T}(t)}{\mathrm{d}t} = \frac{1}{\mathsf{c} \cdot M_{\mathrm{air}}} \cdot \left(\frac{\mathrm{d}Q_{\mathrm{in}}(t)}{\mathrm{d}t} - \frac{\mathrm{d}Q_{\mathrm{ac}}(t)}{\mathrm{d}t} \right) \tag{B.1}$$

$$\frac{\mathrm{d}Q_{\mathrm{in}}(t)}{\mathrm{d}t} = \frac{T_{\mathrm{od}} - \tilde{T}(t)}{R_{\mathrm{eq}}} \tag{B.2}$$

$$\frac{\mathrm{d}Q_{\mathrm{ac}}(t)}{\mathrm{d}t} = \frac{\mathsf{c} \cdot M_{\mathrm{ac}} \cdot (\tilde{T}(t) - T_{\mathrm{ac}})}{E_{\mathrm{ac}}} \tag{B.3}$$

Where $\frac{\mathrm{d}Q_{\mathrm{in}}(t)}{\mathrm{d}t}$ is the heat flowing into the room from outside environment and $\frac{dQ_{ac}(t)}{dt}$ is the chilled air flowing from air-conditioning system into the room. By substituting, Eqn. (B.2) and Eqn. (B.3) into Eqn. (B.1), we obtain

$$\begin{aligned}\frac{\mathrm{d}\tilde{T}(t)}{\mathrm{d}t} &= \frac{1}{\mathsf{c}\cdot M_{\mathrm{air}}}\cdot\left(\frac{T_{\mathrm{od}}-\tilde{T}(t)}{R_{\mathrm{eq}}}-\frac{\mathsf{c}\cdot M_{\mathrm{ac}}\cdot(\tilde{T}(t)-T_{\mathrm{ac}})}{E_{\mathrm{ac}}}\right)\\ &= \frac{E_{\mathrm{ac}}\cdot T_{\mathrm{od}}-E_{\mathrm{ac}}\cdot\tilde{T}(t)-R_{\mathrm{eq}}\cdot\mathsf{c}\cdot M_{\mathrm{ac}}\cdot(\tilde{T}(t)-T_{\mathrm{ac}})}{\mathsf{c}\cdot M_{\mathrm{air}}\cdot R_{\mathrm{eq}}\cdot E_{\mathrm{ac}}}\\ &= \frac{E_{\mathrm{ac}}\cdot T_{\mathrm{od}}+R_{\mathrm{eq}}\cdot\mathsf{c}\cdot M_{\mathrm{ac}}\cdot T_{\mathrm{ac}}}{\mathsf{c}\cdot M_{\mathrm{air}}\cdot R_{\mathrm{eq}}\cdot E_{\mathrm{ac}}}\\ &\quad-\frac{E_{\mathrm{ac}}+R_{\mathrm{eq}}\cdot\mathsf{c}\cdot M_{\mathrm{ac}}}{\mathsf{c}\cdot M_{\mathrm{air}}\cdot R_{\mathrm{eq}}\cdot E_{\mathrm{ac}}}\cdot\tilde{T}(t)\end{aligned}\tag{B.4}$$

Let

$$\begin{aligned}\mathsf{C}_1 &= \frac{E_{\mathrm{ac}}\cdot T_{\mathrm{od}}+R_{\mathrm{eq}}\cdot\mathsf{c}\cdot M_{\mathrm{ac}}\cdot T_{\mathrm{ac}}}{\mathsf{c}\cdot M_{\mathrm{air}}\cdot R_{\mathrm{eq}}\cdot E_{\mathrm{ac}}}\\ \mathsf{C}_2 &= \frac{E_{\mathrm{ac}}+R_{\mathrm{eq}}\cdot\mathsf{c}\cdot M_{\mathrm{ac}}}{\mathsf{c}\cdot M_{\mathrm{air}}\cdot R_{\mathrm{eq}}\cdot E_{\mathrm{ac}}}\end{aligned}$$

Then, Eqn. (B.4) can be written as:

$$\frac{\mathrm{d}\tilde{T}(t)}{\mathrm{d}t} = \mathsf{C}_1-\mathsf{C}_2\cdot\tilde{T}(t)$$

By rearrangement,

$$\frac{\mathrm{d}\tilde{T}(t)}{\frac{\mathsf{C}_1}{\mathsf{C}_2}-\tilde{T}(t)} = \mathsf{C}_2\cdot\mathrm{d}t$$

Integrating both sides with respect to t,

$$-\log\left|\frac{\mathsf{C}_1}{\mathsf{C}_2}-\tilde{T}(t)\right| = \mathsf{C}_2\cdot t+C$$

By substituting $t = 0$ (i.e., initial condition), we obtain

$$
\begin{aligned}
-\log \left| \frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(t) \right| &= \mathsf{C}_2 \cdot t - \log \left| \frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(0) \right| \\
e^{\mathsf{C}_2 \cdot t} &= \frac{\frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(0)}{\frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(t)} \\
\tilde{T}(t) &= \frac{\mathsf{C}_1}{\mathsf{C}_2} - \left(\frac{\mathsf{C}_1}{\mathsf{C}_2} - \tilde{T}(0) \right) \cdot e^{-\mathsf{C}_2 \cdot t} \qquad \text{(B.5)}
\end{aligned}
$$

This concluded the proof as Eqn. (B.5) is the same as Eqn. (4.4).

APPENDIX C

Calculation of Room Thermal Resistance

The building thermal model used in this research (during the theoretical part and simulations) requires the total equivalent (also called lumped) thermal resistance, R_{eq}, of the entire room. Therefore, we include a simple example on how to calculate R_{eq} using the rooms dimensions, number and sizes of windows and the type of insulation used in walls. Table C.1 shows the room geometry and insulation details used for calculation of R_{eq}.

From the values in Table C.1, we can calculate the equivalent resistances of the walls as follows.

$$R_{Wall} = \frac{L_{Wall}}{k_{Wall} \times Wall_{area}} \tag{C.1}$$

Table C.1: Room geometry and insulation details

Description	**Value**
Room length (Len_{room})	10 m
Room width (Wid_{room})	5 m
Room height (Ht_{room})	4 m
Roof pitch (Pit_{roof})	40
Number of windows ($Num_{windows}$)	4
Height of windows ($Ht_{windows}$)	1 m
Width of windows ($Wid_{windows}$)	1 m
Wall insulation having glass wool (L_{walls})	0.2 m
Window insulation ($L_{windows}$)	0.01 m
Thermal conductivity of walls (K_{walls})	0.038
Thermal conductivity of windows ($K_{windows}$)	0.78

Where,

$$\begin{aligned} Wall_{area} = {} & (2 \cdot Len_{room} \cdot Ht_{room}) + (2 \cdot Wid_{room} \cdot Ht_{room}) \\ & + [2 \cdot (1/\cos(Pit_{roof}/2)] \cdot (Wid_{room} \cdot Len_{room}) \\ & + [(\tan(Pit_{roof}) \cdot Wid_{room})] - Window_{area} \end{aligned}$$

Similarly, the equivalent resistance of windows is calculated as:

$$R_{Window} = \frac{L_{Window}}{k_{Window} \times Window_{area}} \tag{C.2}$$

Where,

$$Window_{area} = Num_{windows} \cdot Ht_{windows} \cdot Wid_{windows}$$

From Eqns. C.2 and C.1, R_{eq} is calculated as.

$$R_{eq} = \frac{R_{Wall} \times R_{Window}}{R_{Wall} + R_{Window}} \tag{C.3}$$

APPENDIX D

Sensor Power Consumption

In order to maximize the battery life-time of wireless sensors, it is important to understand the energy consumed by each component of a wireless sensor node. Therefore, we provide power consumption data for each unit (i.e., transceiver, micro-controller, and sensor) in common wireless sensor nodes (see Tables D.1-D.3). The power consumption survey was originally carried out by [5].

Table D.1: Power Consumptions of Transceivers and in Common Wireless Sensors.

Transceiver Model	**Transmission (mA)**	**Reception (mA)**	**Sleep (mA)**
TR1000	12	3.8	0.0007
CC1000	10.4	7.4	0.03
CC2500	21.6	12.8	0.0004
nRF2401A	10.5	18	0.0004
CC2420	17.4	18.8	0.4
RF230	14.5	15.5	0.00002
MC13192	30	37	0.5
JN5121	45	50	0.0004

Table D.2: Power Consumptions of MCUs in Common Wireless Sensors.

MCU Model	**AT163**	**AT128**	**80c51**	**MSP430**	**HCS08**
Active (mA)	5	5.5	4.3	1.8	4.3
Sleep (mA)	0.025	0.015	0.19	0.00512	0.0005

Table D.3: Power Consumptions of Sensor Module in Common Wireless Sensors.

Sensor Module	**SHT15**	**TSL2561**	**ADXL202**
Function	Humidity, Temperature	Light	Accelerometer
Current (mA)	0.55	0.24	0.6

From the tables, it is evident that radio communication is most energy-intensive among the three operations (i.e., sensing, processing, and communication). Specifically, the transceiver power consumption can get as high as 28 times compared the power consumption of micro-controller (see Table D.1 and D.2). The ratio becomes even higher when compared to the power consumption of the sensor modules. For these reasons, we aim to maximize the battery life-time of the wireless sensor by optimizing the update frequency of the control commands sent to the air-conditioner.

APPENDIX E

Key Notations used in the thesis

Table E.1: Key Notations used in the thesis

Notation	Definition
$\tilde{T}(t)$	Ambient room temperature at time t (unit: degree Celsius)
T_0	Initial ambient room temperature at time $t = 0$
T_{od}	Outdoor temperature
T_{ac}	Temperature of the cold air from air-conditioner
M_{air}	Total air mass inside the room
M_{ac}	Air mass flow through air-conditioner (Kg/hr)
E_{ac}	Air conditioner efficiency
c	Heat capacity of the air at constant pressure
R_{eq}	Equivalent thermal resistance of the entire room
$W(t)$	Sequence of impulsive thermal sources
w_{i}	Level of thermal intensity entering the room at time t
a	Sequence of arrivals of impulsive thermal sources
$T_{\text{des}}^{\text{max}}$	Maximal desirable temperature
$T_{\text{des}}^{\text{min}}$	Minimal desirable temperature
$T_{\tau}(t)$	Temperature of thermal sources
X	Set of decision variables
x_{k}	Time that the k_{th} ON command is issued by the wireless sensor
$\mathscr{D}(\mathbf{x})$	Thermal disturbance given decision variable x
$[x]^{+}$	max(x, 0)
$T_{\text{t}_\text{k}}(t)$	Temperature of the room after k_{th} ON command
η	Weight assigned to balance the update frequency and the thermal comfort
$\mathscr{A}_{\text{OFL}}$	Offline Algorithm
$\text{Cost}[i, j]$	Minimum cost when the last and second to last ON command are transmitted at time t_{i} and $t_{\text{i}-\text{j}}$ respectively
$\text{Cost}_{\text{min}}[i]$	Minimum cost when the last ON command is transmitted at time t_{i}
$\text{idx}[i]$	Array to record j when $\text{Cost}_{\text{min}}[i] \leftarrow \text{Cost}[i, j]$
σ_k	Set of thermal sources arrived between the $(k-1)$-th and the k-th ON commands
$\mathscr{A}_{\text{ONL}}$	Online Algorithm
$\mathscr{D}_{ij}(\tau)$	Total thermal disturbance accumulated from the start of the sub-sequence to the latest arrival
t_{j}	The time when the timer was first set after transmission of the last ON command
λ	Mean and variance of the Poisson distribution
p	Success probability. A parameter required by Binomial distribution

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