Energy-Efficient Thermostats for Room-Level Air Conditioning

Milan Jain
Indraprastha Institute of Information Technology Delhi
milanj@iiitd.ac.in

Abstract
Room-level air conditioners (also referred as ACs) consume a significant proportion of total energy in residential and small-scale commercial buildings. In a typical AC, occupants specify their comfort requirements by manually setting the desired temperature on the thermostat. Though commercial thermostats (such as Tado) provide basic energy-saving features, they neither consider the influence of external factors (such as weather) to set the thermostat temperature nor offer advanced features such as monitoring the fitness level of AC. In this paper, we discuss grey-box modeling techniques to enhance existing thermostats for energy-efficient control of the ACs and provide actionable and corrective feedback to the users. Our study indicates that the enhancements can reduce occupants’ discomfort by 23% when maximising the user experience, and reduce AC energy consumption by 26% during the power-saving mode.

Author Keywords
Smart thermostat; Comfort; Feedback; Fault Detection

Introduction
Efficient and optimised usage of heating and air conditioning devices - a major power consuming appliance, can save significant energy across residential and commercial buildings [4]. Unlike big commercial buildings, people pre-
fer window and split air conditioners (ACs) in residential and small-scale commercial which comes with an inbuilt thermostat for the occupants to mention their comfort requirement in the form of thermostat temperature. When thermostat embedded within the AC senses that room temperature is close to a lower threshold, the thermostat shuts down the compressor - a major power consuming component of the AC. Correspondingly, when the room temperature attains the upper threshold, the thermostat again turns on the compressor. Even though the control logic of thermostat drives the AC energy consumption and maintains user comfort, the AC manufacturers design the thresholds based on lab tests performed with numerous assumptions about the room and its thermal environment.

In addition to that, the inbuilt thermostats:

1. need manual intervention - they rely on tenants to set the thermostat temperature.

2. are unaware about the future - the thermostats are incapable of leveraging the readily available information such as weather forecast.

3. are unaware about the user comfort - as the thermostats regulate the room temperature based on lower and upper thresholds, there is no way to monitor the impact of set temperature on user comfort.

4. neglect the influence of weather conditions - The thermostats assume a highly insulated room environment with negligible influence of weather conditions, however, the room temperature gets affected by the change in weather conditions.

5. are incapable of monitoring the AC fitness level - undetected faults usually make an appliance irreparable and useless. A smart thermostat capable of monitoring the fitness level of AC can help user in avoiding such instances.

The existing commercial thermostats ([24], [25]) allow users to operate their AC locally as well as remotely (from any other location) through their smartphones, to reduce manual intervention. Additionally, the commercial thermostats can also pre-cool the space by monitoring the GPS location of the user. However, even the commercial thermostats fail to address many issues (of an inbuilt thermostat), as stated above. To further understand the perception of people towards the existing thermostats, we interacted with few residents and as per a user, "Ahmm, setting a thermostat temperature is quite challenging task. I come home, feeling very hot and start the AC at 23... then in some time it becomes very cold and I turn it off... and after some time, turn it on again (may be at a higher temperature). You never know what to set AC on.... therefore, during night I fix my AC at 24-25 and use blanket... at some point I feel cold and take the blanket, after few minutes I start feeling hot and remove the blanket. Though, it's annoying but that's the best way I have figured out till now..."

In this study, we explored grey-box modelling techniques to enhance smart thermostats for energy-efficient control while ensuring user comfort, and also provide actionable and corrective feedback to the occupants for optimal AC usage. First, we proposed a comfort-energy knob (for existing commercial thermostats) to maximise energy savings while ensuring the user comfort. Our analysis indicates that such a knob can reduce residents’ discomfort by 23% when optimising comfort, and save 26% energy in power-saving mode. Next, we studied that the temperature information is sufficient to infer much useful infor-
mation regarding an AC for the users - such as energy consumption, the number of compressor cycles - with an accuracy of around 85%. Lastly, we designed Greina - an online framework to identify the early symptoms of gas leakage in an AC. In our analysis over 90 outlets, Greina detected 86% faults at least a week in advance when compared with manual reporting. One must note that, in all the studies, we only sensed room temperature, and gathered climatic conditions from a cloud based weather service, which represents a genuinely low-cost and scalable transition from smart to smarter thermostats.

Related Work
Programmable thermostats were one of the initial attempts to save energy in central Heating, Ventilation and Cooling (HVAC) units. Later, Lu et. al. [18] proposed smart thermostat to learn residents’ occupancy patterns and control the HVAC. Nest [20] is one such commercial smart thermostat which is available readily available in the market. Studies also evinced the feasibility of energy efficiency in HVAC by using reactive and predictive control of the thermostats based on occupancy [7, 14]. However, one must note that control based on occupants’ schedule might lead to inefficient outcomes because tenant’s routine is inconsistent [22, 16]. Besides, studies based on central HVAC is inapplicable to an AC, primarily due to design and operational variations between the two.

Specifically for ACs, manufacturers introduced intelligent and web-based ACs [25, 24] with numerous modes of operations (such as sleep mode) along with smartphone based control. Li et. al. [17] proposed control algorithm to optimise the duty-cycles of an AC compressor. However, these studies (or products) neither consider the impact of weather conditions, nor analyse the influence of a particular set temperature on tenants’ comfort. Furthermore, none of the above mentioned studies monitor the fitness level of AC which is equally critical for the optimised usage of an AC. In independent studies, Ganu et. al. [6] and Palani et. al. [21] analysed the electricity signature of ACs to find the unusual patterns; but the approach requires user to setup a power meter to monitor AC energy consumption, which is costly and a tedious process than the installation of a smart thermostat.

System Design
The thermal behaviour of a space primarily depends on the non-intuitive thermodynamics of the room (Figure 1), however, it is hard to monitor each factor affecting the room temperature. Therefore, studies [19, 23] explored Grey Box Modelling where sensor data is leveraged to tune the parameters of a lumped thermal model. Figure 2 presents the resistive-capacitive (RC) implementation of one such lumped thermal model of a room divided into n thermal regions. Here, capacitors depict the thermal capacity of a particular area and resistors indicate the heat transfer between any two regions (including the wall and external conditions). The number of parameters of a lumped thermal model is directly proportional to the number of regions in a room (n). As tuning involves the actual (temperature) data from a room, the adjusted parameters present an approximate thermal behaviour of the room.

Given the benefits, we used grey-box model to design the thermostat and the architecture primarily comprises of three layers - 1.) input layer (user, sensor, and model), 2.) learning layer, and 3.) the application layer (Figure 3) [10]. The thermostat regularly tunes the model parameters to accommodate changes in weather conditions, user activities (in the form of thermal noise), and various other dynamics of the room. The system utilises the tuned thermal model to estimate the room (or region-wise) temper-
The application layer takes the estimates to then ensure energy-efficient control, actionable feedback for the users, and predictive maintenance of the AC.

**Energy-Efficient Control**

People feel comfortable in a range of temperature. Ideally, a thermostat should report the users, “What temperature settings will provide them personal comfort and the cost efficiency?”. We proposed enhancing smart thermostats by adding a Comfort-Energy Trade-off (CET) knob, realised through an optimisation framework which assists users in balancing their comfort and the savings without worrying about the right set temperature [13]. Motivated by Lake Thermal Stratification [3], we divided a room into three regions (Figure 1) - Low Impact Region (lir), Moderate Impact Region (mir), and High Impact Region (hir).

Here, hir corresponds to the area in proximity of the AC, facing direct and maximal impact of the cold air coming from the AC. Next, mir is the region where occupants spend their significant time and often have an indirect effect of AC cooling, while lir primarily includes the corner spaces of the room. The regions are assumed to be separated by a thin layer of air having negligible thermal mass. The model is an extension of a 2nd order thermal model [5] and considers conductive heat transfers due to the difference in temperature of the region (under consideration) and the adjacent spaces such as weather conditions, wall (facing outside), neighbouring regions, and the AC. We assume negligible heat transfer through adjacent rooms within the home. The thermostat (Figure 4) uses the tuned thermal model, set temperature, and CET to then automatically vary the thermostat temperature. Our analysis indicates that the enhancement can reduce occupants’ discomfort by 23% when maximising the user experience, and AC energy consumption by 26% during
the power-saving mode.

**Actionable Feedback**

Automatically varying the thermostat temperature can sometimes either result in false positives and waste significant energy, or false negatives which can make occupants uncomfortable [1]. On contrary, a feedback system allows occupants to override the control logic and specify their preference based on the suggestions. Therefore, we proposed PACMAN - to predict (prior-usage) and estimate (post-usage) AC energy consumption by only sensing the room temperature (Figure 5) [11, 12].

The advanced algorithm of PACMAN leverages a single-zone thermal model which assumes uniform temperature across the room - a single value indicates the room temperature. A single zone thermal model considers the effect of AC cooling and external temperature while accounting for all other internal and external sources of heat transfer as thermal noise in the room. The learned parameters assist PACMAN in mapping the ambient information (room temperature) with AC energy consumption that otherwise would require plug-level monitoring. The proposed system ensures occupants’ participation by providing power consumption feedback to them at successive phases of the AC usage. In our analysis, the proposed system achieved an average accuracy of 85.3% and 83.7% in estimating and predicting AC energy consumption, respectively, across all the homes.

**Detecting Gas Leakage**

Air conditioners often break down due to ageing and irregular maintenance. A broken AC wastes significant energy and usually fails to maintain desired temperature for the users. While users promptly identify the sudden failures, they usually fail to sense the early symptoms of slow time-varying faults. Refrigerant gas leakage is an example of slow time-varying defect where coolant leaks
through the coils (and valves) and leakage slowly dimin-
ishes the cooling capacity of the AC. Besides degrading
the equipment life, gas leakage results in energy wastage
(between 5%-15%), never attains the desired tempera-
ture, and makes environment hazardous for the living be-
ings [2]. To the best of our knowledge, none of the exist-
ing commercial thermostats or existing studies (proposing
smart thermostats) deal with diagnosing gas leakages.

We proposed a scalable and low-cost fault detection en-
gine Greina - that monitors ambient information (room
temperature and door status) to identify the early symp-
toms of gas leakage. The proposed framework leverages
transfer learning to ensure fault detection even when data
is inadequate for training. In addition to that, the online
algorithm of Greina ensures that model adapts to tem-
poral and spatial diversities in the environment. For per-
formance evaluation, we gathered data from 90 outlets
of a retail enterprise for one year. In our analysis, Greina
detected 86% faults at least a week in advance, when
compared with manual reporting. Furthermore, if main-
tenance team had employed Greina, the company could
have saved 2x energy while minimising the risk to stored
food items by keeping the room 5°C-10°C colder every
day, when AC had refrigerant leakage.

Discussions
In this paper, we discussed three major enhancements
in smart thermostat which can provide region-specific
comfort, actionable feedback, and fault diagnosis by only
sensing ambient information from the room. However, one
must also note that the current studies neither deals with
the thermostat design nor its mobile application. Previ-
ous studies show that human-centric prototypes of such
devices (and applications) can significantly influence the
outcomes. We keep the thread open for the concerned

community.

Similarly, the wide adoption across the community estab-
lishes the reason behind the choice of metrics and func-
tions in the existing framework; they are the nut and bolts
of the proposed system. Tightening them might boost the
performance of designed thermostat and the community
is encouraged to study their variants in enhancing the
proposed framework. Moreover, climate, users’ attitude
(towards energy savings), and many other factors differ
significantly across the geographies. Though the shown
numbers are an indication of better comfort along with
notable energy savings, there can be considerable dis-
crepancy across (and within) the countries.

Furthermore, there still exist multiple open research prob-
lems for future exploration. The occupants’ location (whether
they are home/away) can empower the smart thermostats
to run model predictive control (MPC) for dynamic set
temperature variation in the ACs. Another interesting ap-
plication exists in small-scale commercial units - such as
restaurants and bank branches - which often deploy multi-
ple ACs and possess a tremendous potential for energy
 savings [8, 9]. The installed ACs typically run on their
full capacities without accounting for cooling impact from
neighbouring ACs, present in the same room. Though
Karmakar et. al. [15] proposed coordinated scheduling of
multiple ACs to reduce the peak power consumption, en-
hancing the proposed algorithm can also assist in better
grid management.

Conclusion
Room-level air conditioners are designed to maintain a
suitable temperature for the occupants in relatively small
rooms, especially in residential and small-scale commer-
cial buildings. The smart thermostat provides limited
energy-saving features but possess significant scope for enhancements. In this paper, we discussed grey-box techniques for smart thermostats to ensure energy-efficient control of the AC, actionable feedback for the occupants, and refrigerant leakage detection to avoid any permanent damage to the appliance. Our analysis over real-world data shows that the proposed enhancements are effective in significantly reducing the AC energy consumption while ensuring the user comfort. In addition to energy-efficient control, the proposed thermostat is powerful enough to provide actionable and corrective feedback to the user with an accuracy better or comparable to state of the art techniques.

REFERENCES

1. Nipun Batra, Manoj Gulati, Amarjeet Singh, and Mani B Srivastava. 2013. It’s Different: Insights into home energy consumption in India. In Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings.

2. Michael R Brambley, Philip Haves, Sean C McDonald, Paul Torcellini, David G Hansen, David Holmberg, and Kurt Roth. 2005. Advanced sensors and controls for building applications: Market assessment and potential R&D pathways. Technical Report. Pacific Northwest National Laboratory (PNNL), Richland, WA (US).

3. Jonas MK Dake et. al. 1969. Thermal stratification in lakes: analytical and laboratory studies. Water Resources Research (1969).

4. Lucas W Davis et. al. and Paul J Gertler. 2015. Contribution of air conditioning adoption to future energy use under global warming. Proceedings of the National Academy of Sciences (2015).

5. T Dewson, B Day, and AD Irving. 1993. Least squares parameter estimation of a reduced order thermal model of an experimental building. Building and Environment (1993).

6. Tanuja Ganu et. al. 2014. SocketWatch: an autonomous appliance monitoring system. In 2014 IEEE International Conference on Pervasive Computing and Communications (PerCom).

7. Srinivasan Iyengar, Sandeep Kalra, Anushree Ghosh, David Irwin, Prashant Shenoy, and Benjamin Marlin. 2015. iProgram: Inferring Smart Schedules for Dumb Thermostats. In Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments.

8. Milan Jain. 2016. Data driven feedback for optimized and efficient usage of decentralized air conditioners. In Pervasive Computing and Communication Workshops (PerCom Workshops), 2016 IEEE International Conference on.

9. Milan Jain. 2017a. Decision support system for room level air conditioners. In Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers.

10. Milan Jain. 2017b. ThermalSim: A Thermal Simulator for Error Analysis. arXiv preprint arXiv:1708.04524 (2017).

11. Milan Jain and Amarjeet Singh. 2014. PACMAN: predicting AC consumption minimizing Aggregate energy consumption. DSpace at IIIT-Delhi (2014).

12. Milan Jain, Amarjeet Singh, and Vikas Chandan. 2016. Non-intrusive estimation and prediction of
residential ac energy consumption. In *Pervasive Computing and Communications (PerCom)*, 2016 IEEE International Conference on.

13. Milan Jain, Amareet Singh, and Vikas Chandan. 2017. Portable+: A Ubiquitous And Smart Way Towards Comfortable Energy Savings. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* (2017).

14. Rachel Kalaimani, Milan Jain, Srinivasan Keshav, and Catherine Rosenberg. 2017. On the Interaction between Personal Comfort Systems and Centralized HVAC Systems in Office Buildings. *arXiv preprint arXiv:1710.02064* (2017).

15. Gopinath Karmakar, Ashutosh Kabra, and Krithi Ramamritham. 2013. Coordinated scheduling of thermostatically controlled real-time systems under peak power constraint. In *IEEE Real-Time and Embedded Technology and Applications Symposium 2013 (RTAS 2013)*.

16. Wilhelm Kleiminger, Silvia Santini, and Friedemann Mattern. 2014. Smart heating control with occupancy prediction: how much can one save?. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*.

17. Bin Li et. al. 2010. Optimal on-off control of an air conditioning and refrigeration system. In *American Control Conference (ACC)*, 2010.

18. Jiakang Lu et. al. 2010. The smart thermostat: using occupancy sensors to save energy in homes. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*.

19. Henrik Madsen et. al. 1995. Estimation of continuous-time models for the heat dynamics of a building. *Energy and Buildings* (1995).

20. Nest. 2015. Nest. (2015). [https://nest.com/](https://nest.com/).

21. Kartik Palani, Nabeel Nasir, Vivek Chil Prakash, Amandeep Chugh, Rohit Gupta, and Krithi Ramamritham. 2014. Putting smart meters to work: Beyond the usual. In *Proceedings of the 5th international conference on Future energy systems*.

22. Therese Peffer, Marco Pritoni, Alan Meier, Cecilia Aragon, and Daniel Perry. 2011. How people use thermostats in homes: A review. *Building and Environment* (2011).

23. Peter Radecki and Brandon Hencey. 2012. Online building thermal parameter estimation via unscented Kalman filtering. In *American Control Conference (ACC)*, 2012.

24. Sensibo. 2016. Sensibo. (2016). [https://www.sensibo.com](https://www.sensibo.com).

25. Tado. 2016. Tado. (2016). [https://www.tado.com/en/](https://www.tado.com/en/).