Energy-Efficiency Potential of Behavioral Initiatives: An Experimental Case Study from Brunei

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ABSTRACT

In several warm-climate countries, loads from air-conditioners constitute more than half of the energy consumed by residential buildings. Therefore improving the end-use efficiency of AC electricity consumption can yield significant benefits in terms of minimizing demand and energy subsidies, mitigating impacts of climate change, improving grid stability, and reducing the need for new investments in generation and transmission assets.

In this work, we estimate savings that can be achieved through behavioral energy efficiency initiatives for residential households in a country with tropical climate. With the help of a pilot instrumentation covering different types of homes, we quantify the achievable savings from running ACs at higher set point temperature without sacrificing comfort and turning them off when not in use. Our analysis results indicate that simple behavioral adjustments can in fact deliver aggregate savings of about 19% as compared to business-as-usual energy consumption without much discomfort to residents.

KEYWORDS

Set point temperature, Energy Efficiency, Behavioral Initiatives

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1 INTRODUCTION

Brunei is a small oil rich nation located on the northern coast of Borneo island in Southeast Asia's Malay Archipelago. Brunei's per capita power consumption is about 9.3GWh, which is one of highest in the region. Similarly, Brunei's per capita CO_2 emissions average to about 24.4 metric tons, which are higher than those of USA or China [21]. Two dominant drivers of high energy consumption in Brunei are warm weather and government subsidies. The climate in Brunei is tropical equatorial. Temperatures generally remain high throughout the year with an average of about 28°C. The relative humidity is commonly high as well varying between 70 − 100%. As a consequence, more than 60% of energy used by homes and offices is spent on space cooling. Moreover, electricity in Brunei is largely subsidized and generated from locally produced natural gas. Therefore residential tariff is low and varies in a block structure with an average of about 0.06BND/kWh (≈ 0.04USD) [4].

EIA forecasts that the world energy consumption will grow by 56% between 2010 to 2040, with majority of the demand expected to grow in non-OECD countries [22]. In fact, Brunei's electricity requirements are expected to double by this time from 3.9TWh in 2010 [17]. Therefore in line with several progressive nations, energy-efficiency and conservation in all sectors has been outlined as a core objective by the government in its Vision 2035 [10]. The focus of this work is on sustainability and energy efficiency in the residential sector. Households contribute more than 38% of all energy consumed in Brunei [4], which is much higher in proportion as compared to other nations.

Broadly, residential energy efficiency initiatives tend to be classified into two groups – Technical and Behavioral. The technical programs include the use of more energy efficient appliances such as inverter Air-conditioners, compact-fluorescent lighting, insulation retrofits, and so on. Although technical programs can help mitigate energy demand, it has been observed that savings from these tend to saturate eventually [11]. In order to realize the full potential of energy efficiency, these programs need to be complemented with behavioral programs that engage with customers and help them make adjustments without sacrificing comfort. These include adjusting set point temperature, lowering the temperature of hot water for washing and showers, turning-off appliances that are not in use, and so on. Availability of smart thermostats & controls, IoT sensors, low-cost sub-metering of residential appliances or circuits along with social media and mobile apps are essentially helping consumers make such behavioral changes in order to save energy [12]. In addition to reducing customer bills, energy efficiency programs can reduce aggregate demand and emissions, improve grid stability, and deliver ancillary benefits to multiple stakeholders and long-term cumulative savings for governments that subsidize energy consumption and production [13].

This work estimates savings that can be achieved through behavioral energy efficiency initiatives for residential customers in Brunei. Our results are based on a pilot study involving 8 sample

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Table 1: Smart Homes Considered for the Experimentation

Home	Avg. monthly consumption (kWh)	No. of ACs	No. of Monitored ACs	No. of People	No. of Rooms
A1	6250	8	3	20	17
B1	3300	9	3	7	15
B2	3500	10	2	4	18
B3	3300	8	5	13	13
C1	2100	4	4	5	7
C2	1500	5	3	5	9
C3	1500	13	4	5	15
D1	833	4	4	3	6

homes, which were instrumented with smart sensors that record energy consumption of home appliances along with external context information such as motion, light, and temperature. These sensors reported measurements to a cloud server where the data was processed so that household residents could view their energy consumption patterns and statistics on their tablets. We use sensor data along with controlled experiments conducted in collaboration with residents to estimate the savings potential of two key behavioral initiatives: (i) Running ACs at a higher set point temperature, and (ii) Turning-off ACs when not in use. Our results indicate that these two simple initiatives can yield aggregate savings of about 19% in Brunei as compared to business-as-usual scenario. In particular, the key contributions of our work are as follows:

1. With the help of real measurements, we present empirical results that clearly demonstrate changes in AC energy consumption and occupant comfort as a function of changes in set point temperature, AC operating mode, ambient temperature, and humidity.

2. We infer occupancy in household rooms by applying density based clustering on motion sensor measurements. We then estimate wasted energy by computing time durations when ACs are left turned on for long durations without anyone being present in the room. These results were subsequently validated using feedback from the household residents.

3. Based on results inferred for sample homes, we estimate savings for Brunei. Our experimental results and techniques may be utilized to evaluate the achievable savings potential of behavioral initiatives for several Asian countries with warm and humid climates and help influence government policies on energy efficiency.

Rest of the paper is organized as follows. Section 2 presents prior work. Section 3 gives details about the sample pilot homes and their instrumentation. Section 4 presents techniques and results for estimating savings that could be achieved by minimizing wastage. Section 5 presents experimental results on savings that can be achieved from changes in set point temperature and AC operating modes. Section 6 estimates aggregate savings potential and finally, section 7 presents conclusions and directions for future work.

2 RELATED WORK

Energy efficiency in buildings is an active area of research. A number of studies have focussed on proactive control of HVAC systems due to their high contribution in the energy consumption of commercial and office buildings [15, 16]. [3] shows that occupancy-based HVAC control can yield savings of up to 15% in large office buildings. A large body of work on smart homes and home energy management systems leverages IoT sensing to improve energy efficiency [12, 18]. A number of IoT startups have come up in this space, which offer services to instrument homes and help consumers become energy aware and minimize their consumption [1, 2]. However, relatively less effort has been targeted towards quantifying the actual achievable savings through technical or behavioral energy efficiency initiatives in the residential sector. Our work attempts to bridge this gap.

[20] attempts to quantify savings that can be achieved by retrofitting residential geysers in South Africa. Similarly, [6] assesses the savings potential of replacing home appliances such as lighting, ceiling fans, and TVs with their efficient counterparts in India. Our work on the other hand focusses on behavioral energy efficiency initiatives with respect to ACs. [5] analyzes the effect of real-time pricing to increase the efficiency of the power grid. [9] estimates the savings potential of demand response for industrial and commercial customers in Delhi while [14] compares savings achieved through different DR strategies applied to pilot residential customers in Europe. [7, 8] estimate the potential of energy-efficiency from residential, commercial, and industrial buildings in US. Our work is a step in a similar direction targeted towards residential customers in South Asia. However, unlike prior work, we use data from real pilot experiments to quantify savings from behavioral initiatives.

3 EXPERIMENTAL SET UP IN BRUNEI

3.1 Description of the Pilot Homes

A sample of 8 homes were selected for instrumentation and data analysis for 3 months in order to estimate savings achievable from behavioral initiatives. Each home had multiple rooms fitted with room ACs along with other appliances such as freezers, refrigerators, heaters, and washing machines. The homes were chosen based on their willingness to participate in the pilot and taking into account factors such as their consumption history, floor & site area, number of rooms, and ACs so as to obtain a representative sample of the statistical population of Brunei. In particular, 4 categories of homes were considered. Category *A* included homes with consumption above 5MWh/month, category *B* with 3-5MWh/month, category *C* with 1-3MWh/month and lastly category *D* included homes with consumption below 1 MWh/month. Table 1 gives details of all participating homes.

3.2 Instrumented Devices and Data Sources

The pilot homes were instrumented with 3 types of custom built sensors: *BPlug, BSense, and BSend,* which record measurements once every 10 seconds and transmit these over a secure WiFi link to the cloud server.

BSend is a smart meter that measures the total consumption of the home along with other electrical parameters such as line voltage, current drawn by each phase, and power factor.

BPlug is a smart plug that sits between an appliance and wall-socket and measures the power consumption of the connected appliance. Additionally, it senses line voltage, current, power and other electrical parameters associated with the appliance.

BSense is a smart sensor which senses motion, ambient temperature, humidity, light, and sound. These parameters can be correlated with the AC consumption in rooms to warn consumers of possible wastage of power.

As the number of appliances and rooms in the homes were high, eight appliances were metered with BPlugs and six rooms were instrumented with BSense in each home. The BSend in each home measured the aggregate consumption. In order to increase energy awareness and promote conservation, pilot households were provided with tablets to visualize the data related to their kWh consumption at different time granularities. The participants were able to view the aggregate kWh consumption, energy costs, consumption of metered appliances, and their ranking relative to other pilot participants.

3.3 Analysis of Energy Consumption

Fig 1 shows the benchmark pie charts that demonstrate the weekly breakdown of energy consumption in pilot homes, as measured by Bsend and Bsense devices. We observe that ACs constitute at least 50% of total consumption, as some of the unmonitored ACs fall in the ’others’ category. This is followed by fridges/freezers and water boilers/water heaters, which are second and third highest category of consuming appliances respectively. There is significant difference in the consumption of ACs versus all other appliances. Therefore improving the end-use efficiency of AC consumption even by a small percentage can yield significant savings. In [4], the authors

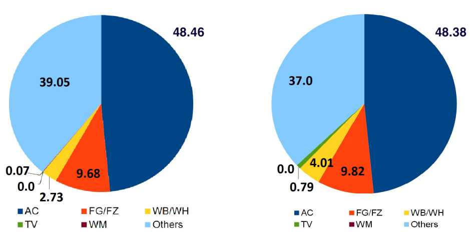

Figure 1: Benchmark pie charts showing weekly breakdown of energy consumption for two pilot homes in categories B & C: (i) AC, (ii) FG/FZ: Fridge/Freezer, (iii) WB/WH: Water Boiler/Water Heater, (iv) TV, and (v) WM: Washing Machine. The ’Others’ category consists of unmonitored appliances.

have observed that 64% of domestic electricity is consumed by ACs in Brunei. The next two sections are devoted to analysis of AC consumption in pilot homes and estimation of savings achievable from behavioral initiatives.

4 POTENTIAL SAVINGS FROM EFFICIENT USE OF ACS

One way to measure the efficiency of AC usage is to infer if there was at least one occupant in the room when the AC was turned on. Clearly, keeping the ACs turned on over a long period of time, in unoccupied rooms leads to wastage of energy. Therefore to estimate efficiency and potential savings, we first infer occupancy of individual rooms using the motion sensor data reported by the installed BSense devices.

4.1 Occupancy Estimation based on Motion Sensor Data

Each BSense device reports a binary field known as ’Motion Detection Status’ (MDS), which is defined as follows:

$$MDS(t) = \begin{cases} 1 \text{ , if any motion is detected at time } t \\ 0 \text{ , Otherwise} \end{cases}$$

MDS binary timeseries measured by one of the BSense devices is shown in Fig. 2(a). We observe that there are certain time periods when a series of activities is detected by the Bsense device, implying the likelihood of the room being occupied. Similarly, there are other time periods with little or no motion detected, implying the likelihood of low or no occupancy. Therefore the main challenge is to partition time into continuous segments, such that each segment accurately corresponds to occupied or unoccupied time periods. To address this challenge, we use unsupervised machine learning techniques. More precisely, we apply DBSCAN algorithm to cluster the MDS binary time series so that each cluster corresponds to a contiguous block of time when the room was occupied.

DBSCAN [19] is a density based clustering algorithm capable of identifying clusters of arbitrary shape. It takes two parameters as input: *eps* and *MinPts*. *eps* denotes the distance to merge two subclusters while *MinPts* denotes the minimum number of points needed to form a subcluster. For our specific application, since we are temporally clustering the MDS timeseries, *eps* denotes the distance in time. We experiment with 3 different values of *eps*: 30min, 45min and 60min. We set *MinPts* to be 4 based on experimentation. At a high level, this means that the algorithm determines dense regions of 1s in the MDS time series and merges two regions if the minimum distance between centers of those regions is less than *eps*. Fig 2 shows the original and clustered MDS time series. Fig 2(a) shows the raw MDS time series that is measured. Fig 2(b) and (c) show the clustered time series obtained by applying DBSCAN with *eps*=30min and *eps*=60min respectively. Each cluster infers a contiguous time period when there may have been at least one occupant in the room where the AC was operating. As expected, clustering with the *eps*=30 generates more clusters, each of small time durations, as compared to *eps*=60. Based on feedback from household residents, we found that *eps*=45min yields the most accurate occupancy information of rooms.

4.2 Usage Score and Potential Savings

Once we obtain the occupancy of rooms using the above approach, we classify the AC usage into two categories:

- *Good Usage*: This is the amount of energy used by the AC when the room was inferred as occupied.
- *Bad Usage*: This is the amount of energy used by the AC when the room was inferred as unoccupied. Clearly, bad usage is the amount of AC energy that is wasted.

Next we calculate the AC Usage Score (ACUS) for each AC during a given time period as:

$$ACUS = \frac{good\ usage}{good\ usage + bad\ usage} \times 100\%$$

A higher score implies higher efficiency of AC use (i.e. less wastage). Note that ACUS is dependent on occupancy inference. As *eps* is

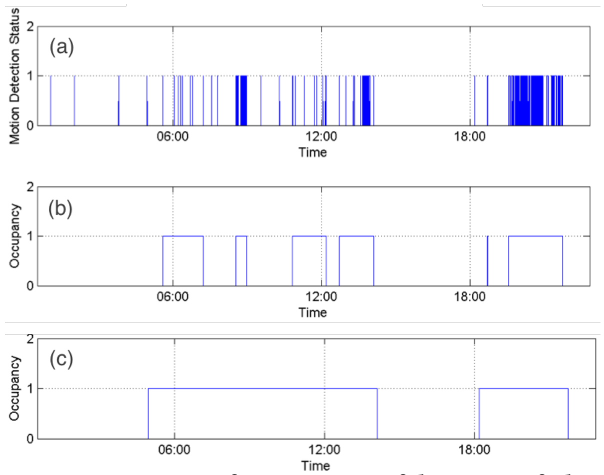

Figure 2: Occupancy inference in one of the rooms of a home with different values of *eps*. (a) Raw binary MDS time series, and (b)-(c): Clustered MDS time series indicating when the room was occupied and unoccupied with *eps*=30min and 60min respectively.

increased, individual cluster sizes increase yielding better scores. Figure 3 shows an example of good and bad usage, based on the estimated occupancy.

During night time when household residents are generally asleep, although the room is occupied and AC is turned on, motion reduces. However, we observed in experiments that the minor occasional movements captured by BSense during night are sufficient to detect occupancy by using the right values of *eps* and *MinPts*. Therefore the night time AC use by occupants is classified as good usage.

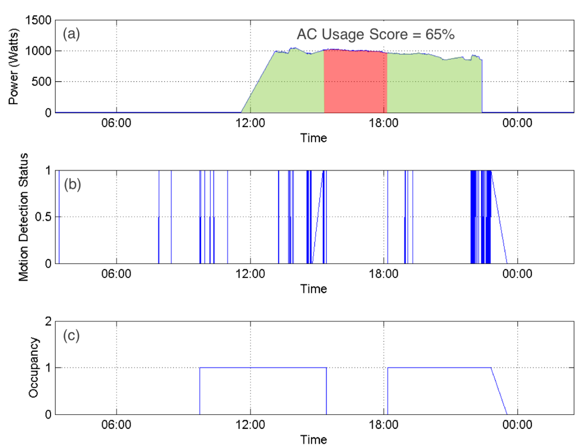

Figure 3: AC energy consumption Vs. occupancy for one of the rooms in a home. (a) AC energy consumption with good and bad usages highlighted in green and red respectively along with ACUS, (b) Raw MDS time series used to estimate occupancy, and (c) Clustered MDS time series indicating when the room was occupied and unoccupied for *eps* = 60min.

Once the good and bad usages for individual ACs in a home are computed, we combine them to compute home level AC usage score as $ACUS_h$ =

$$\frac{\text{sum of good usage over all monitored ACs}}{\text{sum of good and bad usage over all monitored ACs}} \times 100\% \quad (1)$$

Table 2: AC Usage Scores (ACUS) for all homes computed over the duration of pilot study (for different values of *eps*)

Home Category	*eps* = 30 min.	*eps* = 45 min.	*eps* = 60 min.
A	77.48	83.98	89.37
B	69.94	81.85	88.96
C	73.99	83.63	88.36
D	48.81	60.17	68.01
Average	69.76	80.08	86.17

Table 3: Potential Savings from efficient use of ACs across Brunei (for different values of *eps* in mins).

	eps = 30	*eps* = 45	*eps* = 60
Average ACUS (%)	69.76	80.08	86.17
Wastage (%)	30.24	19.92	13.83
Potential Savings (%)	15.12	9.96	6.92
Energy Savings (GWh/day)	0.24	0.16	0.11
Savings (BND/day)	0.039 M	0.026 M	0.018 M
Savings (BND/year)	14.43 M	9.48 M	6.59 M

Based on the above equation, we compute the efficiency of AC consumption for all pilot homes considering measurements collected over the course of the pilot study lasting 3 months. The results are grouped by category and shown in Table 2.

As bad usage corresponds to inefficient use of ACs, a natural question is how much energy could have been saved across Brunei by minimizing bad usage, i.e. if users were to turn off ACs in unoccupied rooms. Observe in Table 2 that the average AC usage score across pilot homes varies from 70-86% based on *eps*, which implies that about 14-30% of the energy used by ACs is being wasted. However, it may not be possible to save all the wasted energy due to several reasons including users being unresponsive, possible discomfort incurred to re-cool the room after the AC is turned off and turned back on, and low savings possible during night time when residents are asleep. Therefore assuming only half of the wasted energy could be saved, Table 3 estimates savings possible across Brunei. The calculations are based on the fact that the total domestic AC consumption in Brunei is about 1.63GWh per day [4]. Although the cost of energy is subsidized for households, the actual generation cost of energy is approximately 0.16BND/kWh, which is used to estimate the dollar savings.

We observe that 6.92-15.12% of energy could be saved simply by turning-off ACs when they are not in use. These figures can increase awareness and motivate household residents to conserve more energy. Moreover, they can help other stakeholders such as the government, which subsidizes energy, to deploy smart occupancy sensors in homes that prompt users or automatically turn-off ACs in unoccupied rooms.

5 POTENTIAL SAVINGS FROM CHANGES IN SET POINT TEMPERATURE AND AC OPERATIONAL MODES

Brunei being a tropical country, the humidity and temperature are commonly high. The temperature during the day is higher than in the night. Humidity on the other hand is lower during the day but higher in the night. ACs act to maintain the indoor temperature and humidity within thermal comfort bounds set by the user. Figure 4 demonstrates changes in the indoor temperature and humidity (as measured by BSense), as a function of AC power consumption. The ambient temperature and humidity as measured by weather underground, are also shown for reference.

Most ACs installed in pilot homes were rated between 1 and 2HP, which could operate in three modes: COOL, DRY, and FAN. The residents most commonly used the COOL mode with a set point temperature kept between 21-23°C. In the COOL mode, the compressor and the fan work to continuously maintain the room temperature at the specified set point. The power consumed by the AC is maximum in this mode and a function of the difference between set point and ambient temperature. In the DRY mode, the AC acts to reduce humidity in the room, thereby improving comfort. The compressor runs for short durations and the fan runs at low speeds, resulting in less consumption of energy. Therefore DRY mode may be a more efficient option to use during night times in Brunei when the humidity is higher but the temperature is lower. In the FAN mode, the compressor is completely off and this mode may not be suitable for countries such as Brunei. In order to estimate savings that can be achieved by changing the set point temperature or by running the AC in DRY mode, we conducted several controlled experiments, which included soliciting feedback from the household residents.

5.1 Changes in AC operating mode: Experiments with two ACs in a hall

The first set of experiments were performed in a hall with two ACs, which had a rating of 2 horse power each. During the first 3 days of the week, the ACs were run in COOL mode from 2-9PM at a set point temperature kept between 21-23°C. For the next three days, they were run in COOL mode as before from 2-7PM, but this was followed by a period of DRY mode from 7-9PM with a set point of 25°C (The ACs did not have the option of changing the set point in DRY mode). Fig. 4 plots measurements for one of the ACs for one day when it was set in COOL mode 21-23°C. We observe that the instantaneous power consumption exceeds 2kW. The indoor temperature and humidity both reduce when the AC is turned on at 2PM. Fig. 5 plots measurements for one of the ACs for one day when it was in COOL mode 21-23°C followed by DRY mode 25°C. We observe that the overall energy consumption decreases by a good margin in DRY mode. We also begin to see compressor on-off cycles and the humidity is maintained at a comfortable level of about 40%. However, the temperature gradually increases in this mode. In order to estimate changes in the comfort level, household residents were also asked to rate their comfort on a scale of 1-10, with 10 being the most comfortable condition. Table 4 shows changes in the comfort index as well as energy consumed in kWh/hour based on the 6-day experiment. We observe that the energy consumption reduces by about 42% from the business-as-usual scenario of COOL 21-23°C mode to DRY 25°C mode. However the comfort level, as solicited from occupants, also decreases by about 27%. Therefore DRY mode may be an option for running ACs for short durations, especially at night when the ambient temperature is not high.

Table 4: Hall AC experiment involving changes in AC operating mode: Reduction in energy consumption & comfort

Mode & Set Point	Approx. Duration	Average kWh/hr	Average Comfort Index
COOL 21-23°C	2:00 – 9:00 PM	4.54	10
COOL 21-23°C	2:00 – 7:00 PM	4.62	10
DRY 25°C	7:00 – 9:00 PM	1.93	7.3
% Reduction from COOL to DRY mode		42%	27%

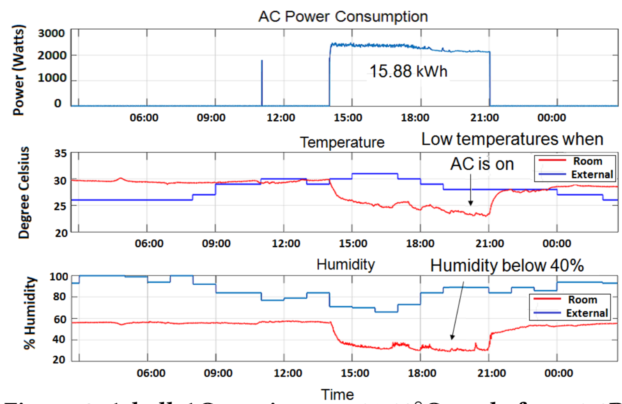

Figure 4: A hall AC run in COOL 21-23°C mode from 2-9PM for a day, consuming about 15.88kWh.

5.2 Changes in set point: Experiments with bedroom AC

The next set of experiments were performed using a bedroom AC in one of the pilot homes. In these experiments, the AC was run in COOL mode at different set point temperatures varying from 21°C to 25°C. The experiments were conducted over a course of 3 weeks in March

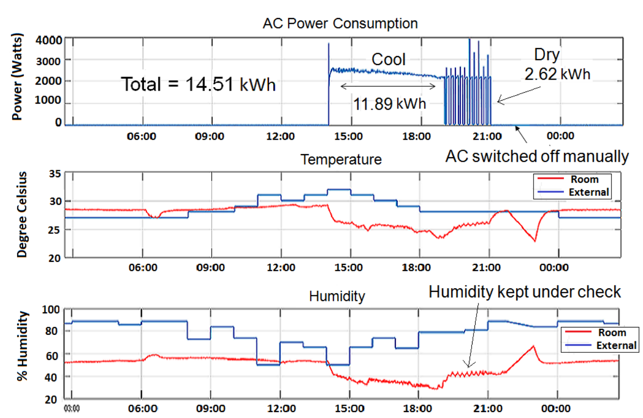

Figure 5: A hall AC run in COOL 21-23°C mode from 2-7PM followed by DRY 25°C mode from 7-9PM, consuming about 11.89 and 2.62kWh respectively.

Table 5: AC experiment results involving set point changes: Reduction in energy consumption without discomfort

Date (dd/m)	Set Point Temp	Duration	Wh/hr	Comfort Index
30/3	21°C	8:20 – 10:10 PM	918.87	10
28/3	22°C	7:50 – 10:20 PM	905.52	10
18/3	23°C	8:15 – 09:35 PM	905.18	10
20/3	24°C	7:40 – 10:30 PM	852.64	10
21/3	25°C	8:20 – 09:40 PM	819.45	9

Table 6: Results from AC experiment involving set point changes: Potential savings across Brunei

Set Point Temp change	Savings (Wh/hr)	Savings (%)	Daily Savings (MWh)	Yearly Savings (Million BND)
(21° → 23°C)	44.60	4.92	80.41	4.70
(21° → 24°C)	59.11	6.52	106.55	6.22
(21° → 25°C)	103.64	11.43	186.83	10.91
(22° → 23°C)	27.19	3.06	49.97	2.92
(22° → 24°C)	41.70	4.69	76.63	4.48
(22° → 25°C)	86.23	9.70	158.48	9.26
(23° → 24°C)	14.51	1.68	27.50	1.61
(23° → 25°C)	59.04	6.85	111.93	6.54
(24° → 25°C)	44.53	5.25	85.87	5.02

Table 7: Combined Savings

	eps = 30		eps = 45		eps = 60	
Set point Changes	Yearly GWh	Yearly M-BND	Yearly GWh	Yearly M-BND	Yearly GWh	Yearly M-BND
(21° → 23°C)	115.11	18.42	85.84	13.73	68.59	10.98
(21° → 24°C)	123.21	19.71	94.43	15.11	77.48	12.40
(21° → 25°C)	148.08	23.69	120.81	19.33	104.75	16.76
(22° → 23°C)	105.68	16.91	75.84	12.13	58.26	9.32
(22° → 24°C)	113.93	18.23	84.60	13.53	67.31	10.77
(22° → 25°C)	139.30	22.29	111.5	17.84	95.12	15.22
(23° → 24°C)	98.71	15.79	68.45	10.95	50.62	8.09
(23° → 25°C)	124.87	19.98	96.20	15.40	79.31	12.69
(24° → 25°C)	116.79	18.68	87.63	14.02	70.45	11.27

at different times of the day, different weather conditions, and based on the availability of residents. Table 5 shows the experimental schedule and observations for a couple of days. We observe that the energy reduces with increase in set point temperature as expected. Moreover, the user comfort index remained high between 9-10 over the course of experiments implying that such adjustments can be implemented without sacrificing comfort. Table 6 presents the average energy reductions from set point changes based on 3 weeks of measurements. Based on these values, aggregate savings across Brunei are shown. The calculations are based on the fact that approximately 1.63GWh of energy is consumed per day by domestic ACs in Brunei and the generation cost of energy is about 0.16 BND/kWh. We observe that 6.8-11.4% of energy can be saved by maintaining the set point at 25°C as compared to business-as-usual scenario of 21-23°C. Thus engaging users to change their set points can yield significant savings for the government in terms of reduced cost of subsidies.

6 COMBINED SAVINGS FROM CHANGES IN SET POINT AND TURNING OFF ACS IN UNOCCUPIED ROOMS

We can now combine the effects of reducing wastage, as explained in section 4, with changes in set point temperature to calculate the aggregate savings potential of these two behavioral initiatives. Let t_c denote the total consumption in kWh per day, s_e denote percentage savings from reduced wastage (refer Table 3), and s_t denote percentage savings from changes in set point temperature (refer Table 6). Then the total savings in kWh can be estimated as Total Savings = $t_c \times [s_e + (1 - s_e) \times s_t]$. The combined savings in terms of energy and costs for different values of eps are shown in Table 7. We observe that 13.72-24.82% of energy can be saved by both maintaining the set point at 25°C and turning-off the ACs while not in use.

7 CONCLUSION

In countries with warm and humid climate, improving the efficiency of AC use can yield multiple benefits such as minimizing the cost of energy subsidies, mitigating impacts of climate change, and reducing the need for new generation and transmission investments.

This work estimates savings that can be achieved through two behavioral energy efficiency initiatives in Brunei: Turning-off ACs in unoccupied rooms and adjusting AC set point temperature. Using data from a pilot study involving different types of instrumented homes, we estimated occupancy in rooms and analyzed if AC energy was being wasted. We studied how AC energy consumption and comfort levels vary as a function of set point and AC operating mode. Our analysis shows that about 6.9-15.1% of the energy in Brunei homes can be saved by simply turning off ACs when they are not in use. Moreover, about 6.8-11.4% of energy could be saved by running ACs in COOL mode at a set point of 25°C (as compared to business-as-usual scenario of 21-23°C), without impacting comfort. Jointly, these two initiatives can deliver aggregate savings of 13.72-24.82%, with an average of about 19%. To realize the full potential of these savings, systems that engage users along with IoT and smart home automation may be required.

In future work, we plan to apply machine learning to forecast savings that may be achieved by increasing set points by different amounts, based on forecasted temperature and humidity. We also plan to estimate the savings potential of behavioral initiatives in other countries in South Asia as well as estimate savings that can be achieved by improving the efficiency of electricity generation and distribution in these countries.

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