No-frills Water Comfort for Developing Regions

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ABSTRACT

In developing countries, majority of the households use overhead water tanks to have running water in their taps. These water tanks are exposed to the elements, which usually render the tap water uncomfortable to use, given the extreme subtropical weather conditions. Externally weatherproofing these tanks to maintain the groundwater temperature is short-lived, and only results in a marginal (0.5 – 1 °C) improvement in tap water temperature. We propose Ashray, an IoT-inspired, intelligent system to minimize the exposure of water to the elements thereby maintaining its temperature close to that of the groundwater. Ashray learns the water demand patterns of a household and pumps water into the overhead tank only when necessary. The predictive, machine learning based, approach of Ashray improves water comfort by up to 8 °C in summers and 3 °C in winters, on average. Ashray is retrofitted into existing infrastructure with a hardware prototyping cost of $27, whereas it can save up to 16% on water heating costs, through reduction in natural gas consumption, by leveraging groundwater temperature. Our proposed system, Ashray, can positively impact the lives of millions of people in developing countries.

KEYWORDS

water comfort, machine learning, water usage forecasting

1 INTRODUCTION

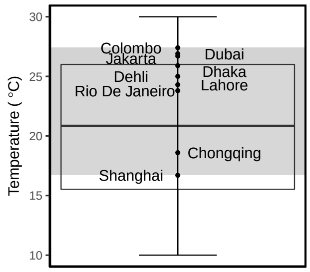
Background. *Thermal comfort*, i.e., satisfaction with the thermal environment, is an important factor that determines human productivity and wellbeing [23, 29, 46]. This is more so as unprecedented climatic changes are taking place, and we are witnessing ever more frequent, severe, and deadly, heatwaves and cold spells. Thermal comfort could mean the difference between life and death for the most vulnerable population groups, i.e., infants, the elderly and people with chronic health conditions as observed during recent heatwaves gripping regions across Europe, Asia, Australia and the Americas. For instance, the heatwave of 2003, which affected many European cities, resulted in approximately 70,000 excess deaths [6, 27, 38]. In France alone, a third of the recorded deaths, roughly 5000 in just 9 days, were attributed exclusively to heatstroke [6, 35]. In addition to causing strokes, heat was also found to aggravate cardiovascular diseases as well as psychiatric and pulmonary illnesses [27]. A detailed analysis of the European heat waves has revealed that people who had air conditioning at their homes or visited cool places during the heat of the day experienced better outcomes [6]. Similarly, people who cooled off by taking extra showers were found to be at a lower risk of death [6].

Except for the oil rich countries in the Middle East and North Africa, air conditioning is generally the least affordable option in regions where it is most desirable, such as, Sub-Saharan Africa (SSA), South Asia, and Indonesia for example [31]. Hence, in developing countries, air conditioning is a rarity, both at homes and in public spaces. For instance, Pakistan, SSA and many ASEAN[1] countries have the lowest per capita access to air conditioning [39]. This makes these regions vulnerable to the deadly effects of heat waves, which are projected to become more frequent in the years to come. For example, in 2015, a deadly heat wave claimed approximately 3500 lives in India and Pakistan [10]. In the absence of affordable air conditioning, people frequently splash water on exposed parts of the body (face, neck, forearms etc.) and take showers to ward off heat, especially in the pre-monsoon dry season when the maximum day-time temperature often exceeds 45 °C. Thus, maintaining tap water temperature within human comfort ranges is essential.

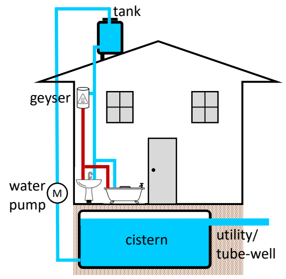
While optimal thermal comfort through air conditioning has been extensively studied [1, 5, 30, 42, 48], water comfort has *not* received the same level of attention. This is particularly important for developing countries, where unlike the US and Europe, water supply is intermittent and unreliable. Households typically require large residential cisterns, which act as receptacles for water delivered by the public water supply or directly from community tube-wells. By and large, water is supplied at groundwater temperature due to underground distribution and storage networks. The residential cisterns are used to replenish rooftop water tanks that provide running water. These overhead tanks are usually made of plastics and exposed to the elements, which inevitably impacts the temperature of the stored water, thereby rendering tap water uncomfortable and potentially unsafe for use [18].

Problem. In the US and Europe, homes are directly connected to a continuously pressurized, on-demand, water source provided by a publicly owned water utility that delivers running water to each household at *near* constant groundwater temperature. In these regions residential cisterns are extremely rare; the water supply network is reliable enough that the cost of a cistern is generally not worth the benefit. The remarkably constant ground water temperature, which approximately equals the annual mean temperature of

[1] Association of South East Asian Nations comprising of Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand and Vietnam.



(a) Groundwater temperature



(b) Water distribution

Figure 1: Water supply in developing regions. (a) Box and whisker plot constructed from groundwater temperatures of 400 cities. The region under study is highlighted in grey. Water is not delivered at these temperatures in taps. (b) Household water distribution in developing regions. A large cistern acts as receptacle for water supply. This water is pumped into an overhead tank to provide running water.

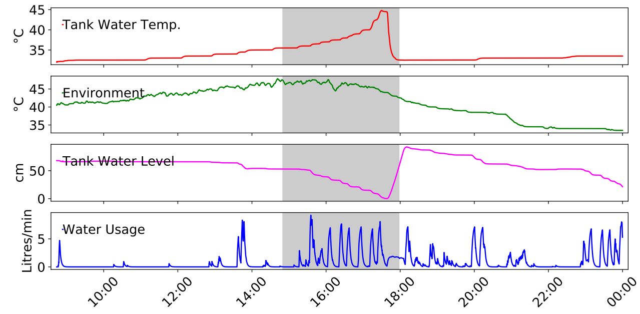
the locality [36], makes it comfortable to use both in summers and winters.

On the contrary, developing countries in the east, such as China, India, Bangladesh, Pakistan, Sri Lanka, UAE and many others, which account for more than half of the world's population, present a completely different scenario. Fig. 1a shows the calculated groundwater temperature of several cities in the region under study. Unfortunately, in this region, water is not delivered in the taps at these temperatures. As the water supply is intermittent: a few hours per day or even a few hours per week, large residential cisterns are mandatory.

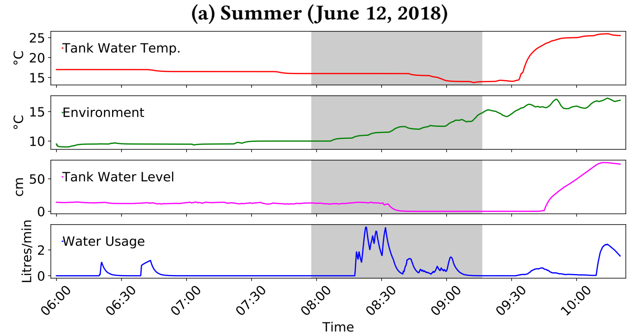
To have running water in taps, most households in this region employ a two-reservoir water system, as shown in Fig. 1b. A rooftop tank that is filled either on-demand or according to a fixed schedule by pumping water from a underground cistern. The scorching summer heat in these regions can render tap water from overhead tanks unusable during the day, as shown in Fig. 2. Similarly, in winters, the water temperature falls significantly below human comfort range. The latter issue may be dealt with by using a water heating system, which may be costly but solves the problem. However, there is no obvious solution for the former.

A cheap and effective solution to this problem holds a much greater significance for developing countries where in the absence of affordable air conditioning, people often splash water to achieve thermal comfort and ward off the dry summer heat. The root cause of this problem is the inevitable exposure of overhead tanks to direct sunlight and the heat during the day, which sends the water temperature soaring. Existing solutions may include weatherproofing water tanks, either through constructing concrete tank structures, which are costly and beyond the affordable reach of the majority of the population; or via external insulation of overhead tanks, which is short-lived and ineffective.

Challenges. In order to achieve thermal comfort from tap water, its temperature must be maintained as close to groundwater as possible. This can only be achieved if the exposure of water to the elements is minimized during daytime, for example, by minimizing



(a) Summer (June 12, 2018)



(b) Winter (January 11, 2019)

Figure 2: Empirical observations of diurnal household tap water usage and temperature variations. The groundwater temperature is 23 °C and replenishment is performed arbitrarily by the user. Tap water can get extremely uncomfortable both in summers and in winters as highlighted by the shaded regions. The rooftop tank water temperature is dramatically impacted when it is filling up with groundwater.

the amount of time for which the water resides in the overhead tank. To build a system that can accomplish this goal, we need to thoroughly understand both water usage patterns and the impact of diurnal variations in ambient temperature on tank water. This can be challenging due to the following factors:

- *Lack of systems*: There is a lack of off-the-shelf integrated systems with appropriate sensors for measuring and communicating, preferably via wireless, the required variables, such as water temperature and flow rate. Available water sensors only report coarse-grained water flow measurements.
- *Lack of data*: As a direct consequence of lack of appropriate systems, there is no data available for initial benchmarking and analysis. In order to gain insights into the problem, extensive data must be collected and analyzed first.
- *Cost restrictions*: For a successful roll out, the cost of the final solution must be within the affordable range of ordinary consumers. Moreover, the long term savings and benefits offered by the proposed solution should preferably offset its deployment cost.

Solution. We propose Ashray[2], a machine learning based system that maintains tap water temperature as close to that of groundwater as possible in order to enhance its capacity for providing maximal thermal comfort. Ashray achieves this by minimizing the amount of time for which ground water resides in the overhead tank before its consumption by the household, consequently, minimizing its exposure to the elements (heat, sunlight, etc.). To that end, Ashray learns the water consumption behavior of the household and pumps water into the overhead tank only when it predicts imminent water requirement. Ashray comes equipped with sensors that measure water consumption and temperatures both in the overhead tank and of the ambient environment. These measurements are periodically sent to a local compute unit, which employs a machine learning algorithm to learn the water consumption behavior of the household as well as the impact of ambient temperature on the temperature of water in the overhead tank. Ashray dynamically adapts its pumping schedules to account for diurnal variations in temperature. For example, in summers pumping is performed more frequently during the day than at night.

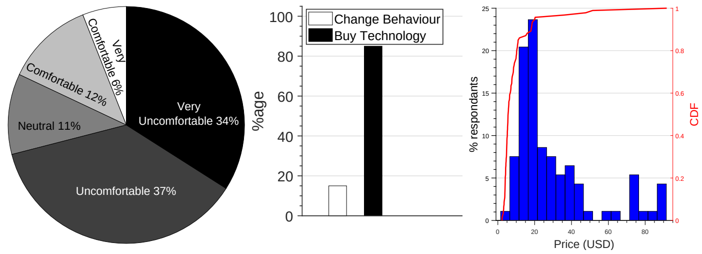
The main contributions of our work are as follows:

- We build a water sensing platform that measures water consumption, ambient temperature and the temperature of water in the overhead tank. These measurements are reported wirelessly to a local compute unit. Our platform comes with a rechargeable battery backup to ensure continuous operation as electric supply is intermittent in some target regions.
- We deploy this platform in three homes in the city and outskirts of Lahore, Pakistan for over a year to collect >30 million data points that capture seasonal variations in water consumption. We perform an in-depth analysis of this data and unveil usage patterns. Further, we model overhead tank temperatures amid changing weather conditions.
- We develop models for water consumption using machine learning techniques. We show that the consumption of water in a household can be accurately modeled and forecasted using Gaussian Mixtures and Hidden Markov Models (MoG-HMM). Using these forecasting models, Ashray predicts future water consumption and pumps water into the overhead tanks just before its imminent use.

Benefits. The results that we have gathered after deploying the complete Ashray system indicate that, on average, tap water temperature can be reduced by up to 8 °C in summers and increased by up to 3 °C in winters, depending upon the annual mean temperature of the locality. This translates into thermal comfort during summers and energy savings in winters, which is discussed in detail in Section 5. According to our estimates, the energy savings in winters amount to around 0.339 MMBtu[3] or equivalently to 8 m^3 reduction in natural gas consumption, resulting in a 16% saving on water heating costs for a typical household. Although this may not sound very significant for a single household, yet the aggregated savings of natural gas (or electricity) on a regional level would be substantial, bearing a positive impact on the resources, economies and the environment of these regions. This is more so as most of these developing regions are densely populated and thermally stressed, making them more vulnerable to the effects of climate change due to CO_2 emissions.

[2] Or *Asrai*- Translucent water creatures in English folklore that melt when exposed to sunlight. We draw an analogy because we want to protect water's ability to provide thermal comfort from being eroded by exposure to sunlight and other elements.

[3] One million British thermal units or Btu, where 1 Btu ≈ 1054 Joules.



(a) Summer (b) User Willingness (c) Desirable cost

Figure 3: Feeler survey: Most respondents are uncomfortable with tap water temperature, and are willing to buy a technical solution at an affordable price.

2 OVERVIEW

Designing and conducting a survey that aims to gauge the views of a population spread across multiple continents is resource intensive. Hence, instead of a statistically sound and intensive survey, we conducted a "feeler" survey in two regions, UAE and Pakistan. UAE has a large diverse community of expatriates, which allowed us to gauge the views of people from multiple developing countries in the regions including Bangladesh, China, India, Srilanka, and the UAE itself where this is an acute problem. The survey was useful for us to ascertain (i) whether there is an acknowledgement of the problem in the target population, and (ii) assess the cost of a marketable solution. We present the results of that survey before summarizing Ashray in a nutshell.

2.1 Survey

The survey's respondents were inquired about their perception of tap water comfort on a five point Likert-scale ranging from "very comfortable" to "very uncomfortable". The survey consisted of the following questions:

- How comfortable are you with your household tap water temperature in summers?
- How comfortable are you with your household tap water temperature in winters?
- Would you buy an off-the-shelf solution that provides water comfort?
- If so, how much are you willing to pay for the solution?
- Are you willing to change your water usage timings?

The survey was conducted online to ensure maximal geographic coverage for the regions of interest considered in this study. We solicited the responses of 156 volunteers (62% male, 38% female, age range 15-80). The results of the survey are shown in Fig. 3. We can observe that the wide majority of the respondents did not find

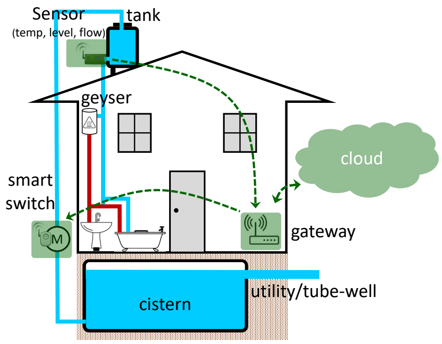


Figure 4: Ashray retrofitted water distribution system.

the tap water in their households comfortable for use in summers (see Fig. 3a). A similar trend in responses was observed for winters.

A sizable fraction of the respondents, 18% in summers to be precise, also reported their satisfaction with the tap water. Of those who perceived their tap water to be uncomfortable, most were willing to buy an off-the-shelf technology to improve their water comfort without having to change their water usage timings or behavior. Whereas, a small minority was willing to make changes to their water usage patterns, for example by taking baths late at night or very early in the morning, to get better thermal comfort from their tap water (see Fig. 3b). Finally, Fig. 3c shows the cost, in USD, that most respondents were willing to pay for a solution. Affordability was an important consideration in the design of Ashray and feedback from potential users on the acceptable cost provided an estimate of the maximum cost of our proposed solution.

2.2 Ashray in a Nutshell

Ashray aims to provide water comfort by retrofitting the existing household water distribution system in developing regions with IoT elements, as shown in Fig. 4. These elements include a sensor, a smart switch, and a processing unit. The IoT sensor is deployed at the outlet of the overhead tank to measure (i) the water discharge out of the tank, (ii) the water temperature inside the tank, (iii) the ambient temperature, and (iv) the water level inside the tank. These measurements are periodically transmitted via a wireless medium to a processing unit (gateway), which is a Raspberry Pi (RPi) in our experimental setup but could be easily replaced by any computing hub such as a wireless access point. Water discharge measurements from the IoT sensor are used to first learn, and then predict water usage. Whereas, the measurement data on water temperature and level is used to quantify the thermal characteristics, i.e., heat transfer rate, of the overhead tank. Our machine learning algorithms, as we discuss in Sec. 4, operate in real time on the gateway device, such as a RPi, but may also be hosted on a cloud for long term analysis of the data, provided a robust internet connection to the cloud is available. The algorithm decides when, and for how long, to actuate the water pump through a wireless smart switch.

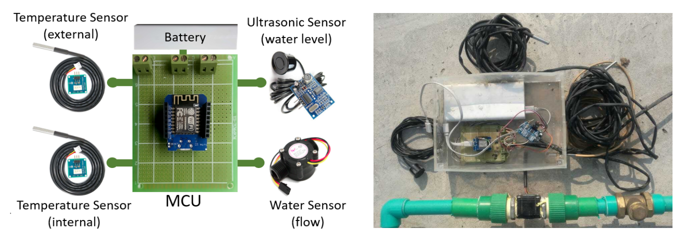
We next expand on the two key elements of Ashray, that is, the IoT device and the machine learning algorithms.

Name	Flow	Level	Water temp	Env temp	Wireless comm	Battery	Price (USD)
Ashray	✓	✓	✓	✓	✓	✓	27
AMR15 W [51]	✓	-	-	-	✓	-	10
MULTICAL® [25]	✓	-	✓	-	✓	✓	237
WATERON [24]	✓	-	-	-	✓	✓	-
K24 Flow Meter [33]	✓	-	-	-	-	-	21

Table 1: Ashray vs other water sensors: feature comparison.

Component	Price ($)
ESP32 + wifi [13] × 2	0.98
Temp Sensors [12]	0.84
Flow Sensor [14]	3.52
Level Sensor [15]	3.71
Battery+Charger [16, 17]	1.97
Relay [3]	1.49
Gateway [2]	10.00
Pack. & assembly	4.00
Total	**26.51**

Table 2: Ashray cost breakup.



(a) Sensor Architecture. **(b) Ashray in Action.**

Figure 5: Ashray sensor architecture (a) and installation at the outlet of of the overhead tank (b).

3 ASHRAY → WATER SENSOR

Justification. Although a variety of water sensors (or meters) are available off-the-shelf, yet they do not fulfill all our requirements, i.e., measure water level in the tank, water discharge from the tank, as well as the temperatures, both inside and outside the tank. This information is required to provide sufficient features for building a robust forecasting algorithm using machine learning techniques. Additionally, the sensor must be easy to deploy and sufficiently cheap to meet the expectations of an ordinary user as highlighted in Sec. 2.1.

As shown in Table 1, existing solutions fall short of meeting our requirements. MULTICAL [25] is the closest match to our requirements but is prohibitively costly. Our choice of components ensures that all the requirements of Ashray are met at a substantially lower hardware cost compared to MULTICAL [25], as shown in Table 2. These are per-component prototyping costs which may further be reduced in bulk purchases, in mass production and with application specific hardware design.

Architecture. The IoT sensor is attached to the outlet of the water tank. It comprises of the following components, which are shown in Fig. 5.

(1) A *Water Flow Sensor* that measures the *water discharge*, i.e., the volumetric flow rate of the water flowing out of the overhead tank. We use a Hall effect based DN25 flow sensor [49]. It can measure flow rates within the range 1 litres/min to 60 litres/min, which is adequate for capturing tap water usage in homes.
(2) A waterproof *Ultrasonic Sensor* to measure the water level inside the overhead water tank that is attached to the ceiling of the tank. We use JSN-SR04T Integrated Ultrasonic Ranging transducer [43] with a measurement range of 600 centimeters that is sufficient to capture the water level inside commonly used overhead water tanks.
(3) Two *Temperature Sensors*, which are installed both inside and outside of the tank for sensing water and ambient temperatures, respectively. We use DS18B20 sensor [9], which has an operating range from −55 °C to 125 °C.

As shown in Fig. 5a, these sensors are interfaced with a WiFi enabled ESP-8266 MCU [11], which polls the sensors every 5 seconds and then transmits the measurement data to the gateway for further processing.

Most developing countries are struggling to meet their growing energy demands, often resulting in intermittent supply of electricity to most households. Hence, our IoT sensor comes equipped with a 12 hours rechargeable battery [34], which is sufficient for the typical duration of power blackouts in these regions. The sensor is housed in a weatherproof package to protect it from the elements.

Besides the IoT sensor, Ashray also needs to remotely actuate the water pump based on the output of its forecasting algorithms. For this purpose, we have developed a smart switch module with an ESP8266 MCU that is interfaced to a solid state relay. The relay can handle up to 40 amperes, which is sufficient to power the household water pumps. Communication between the gateway and the smart switch happens via the HTTP protocol.

Deployment. The IoT sensor was initially deployed in two homes (A and B) in Lahore city, with varying number of tenants and fixtures, for data collection. Lahore, the second largest city of Pakistan, is a large metropolis of over 10 million inhabitants where the two-reservoir water distribution system is most prevalent. The sensor has been successfully collecting data since May 2018 with no down time. Home A has five tenants, two adult males (aged 28 and 57 years) and three adult females (ages 20, 22 and 25 years). Home B has seven tenants, two adult males (aged 25 and 40), three adult females (27, 35, and 60 years) and two children (aged 7 and 9 years). This deployment allows us to observe the water consumption behavior over a sufficiently long period of time to build models for forecasting using machine learning techniques. We demonstrate subsequently in Sec. 5.2 that this deployment is sufficient in scale for building robust forecasting algorithms.

4 ASHRAY → WATER USAGE FORECASTING

Ashray relies on accurate water usage forecasting to determine water pumping schedules. A generic pumping model was dismissed early on because often small amounts of residual water in the overhead tank is highly impacted by the elements, as shown in Fig. 2. Thus, we perform a rigorous analysis of the data to unveil underlying patterns for selecting the most appropriate forecasting algorithm. We present a statistical analysis of the collected data in Sec. 4.1, and subsequently build a forecasting model in Sec. 4.2.

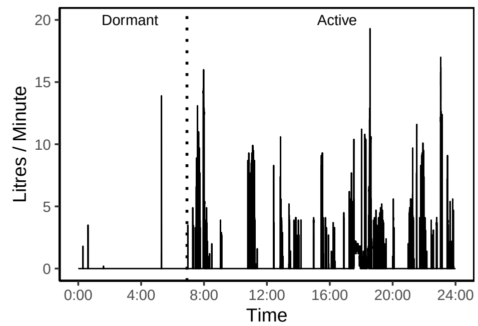


Figure 6: Sample daily water usage pattern. Two distinct spans of water usage are observed.

4.1 Analyzing Water Usage

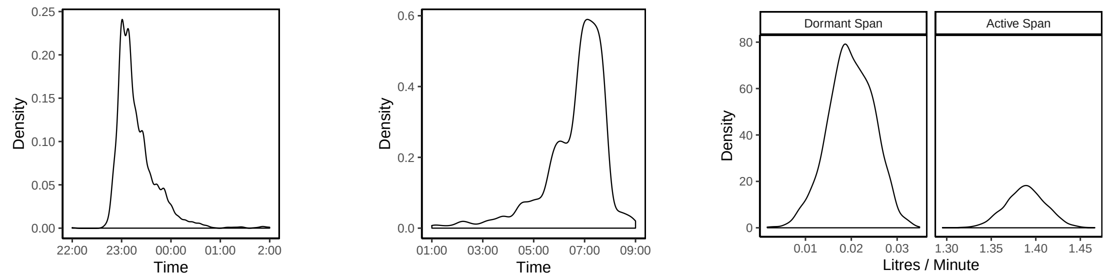
Usage Spans. Fig. 6 shows water usage for a single day, and is typical of the usage pattern we observe throughout the year. A descriptive analysis of the data suggests that there are two distinct spans of water usage: *dormant* and *active*. We can see a relatively dormant period from midnight to early morning and an active period that lasts throughout the day with different average water usage, potentially requiring different models for accurate forecasting within each span. This requires a clear demarcation of the *changepoint* between these spans.

Identifying changepoints is a well studied problem in statistics. Our year long data consists of over 30 million data points that we have divided into daily chunks. The two distinct daily spans advocate using a Bayesian technique. We therefore apply Markov Chain Monte Carlo (MCMC) techniques using the Metropolis-Hastings algorithm. We use the PyMC3 library for implementing the MCMC technique [41].

Fig. 7 shows the outcome of MCMC. The active span for home A commences between 0700 and 0800 hrs, as shown in Fig. 7b, and ends between 2300 and 2400 hrs., as shown in Fig. 7a. The sample pdf of the water usage in each span are shown in Fig. 7c. We have two substantially distinct means, reinforcing the requirement for separate models during the active and dormant spans.

Usage Patterns. Every household can have different usage patterns depending upon the type of activities and the number of occupants. We therefore analyzed the distribution of water usage, as shown in Fig. 8. Fig. 8a indicates that there are multiple peaks (i.e., a multi-modal distribution) for different rates of water usage, mapping to different household chores. The higher peaks on the left show the most commonly observed usage patterns—*routine* usage, extracted and expanded in Fig. 8b. Whereas, the tail of the data shows rarely observed usage patterns—*abnormal* usage, extracted and expanded in Fig. 8c.

Applying an IQR (inter quartile range) analysis confirms a relatively long tail, as shown in Fig. 8d: The routine activities use less than 10.6 litres/min (with an average below 5 litres/min) whereas, abnormal usage can go as high as 20 litres/min.

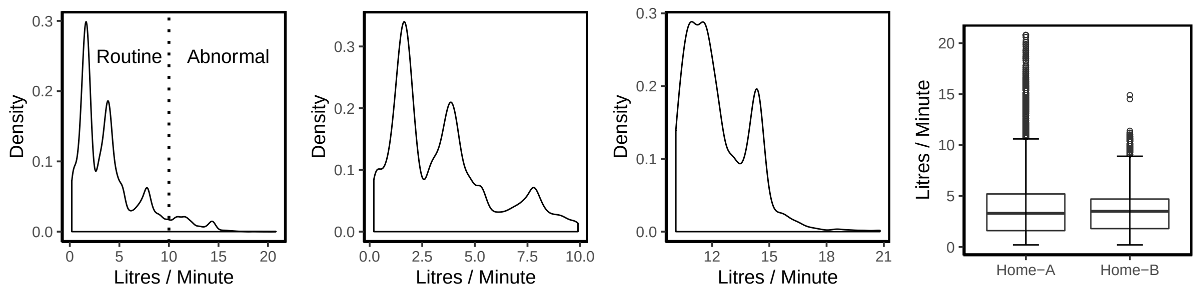


(a) Sample pdf of dormant span starting time

(b) Sample pdf of active span starting time

(c) Sample pdf of *mean* water usage in Dormant and Active span

Figure 7: MCMC analysis for identifying *changepoints* between Dormant and Active spans.



(a) Distribution of overall usage

(b) Routine usage of water for home A

(c) Abnormal usage of water for home A

(d) Box plot of home A and B

Figure 8: Daily water usage patterns for homes A and B. A multi-modal usage pattern was observed.

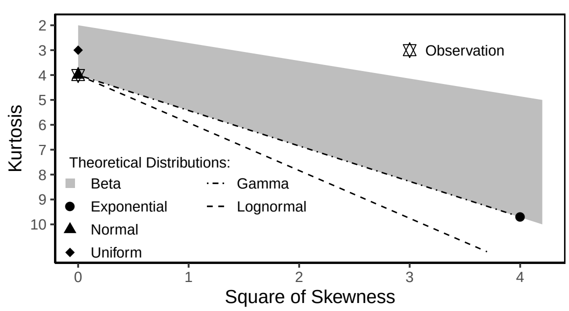


Figure 9: Cullen and Frey plot for finding the best fit distribution. Gaussian is the best candidate distribution.

To model this multi-modal usage pattern, we segmented data around each peak and identified the distribution of each segment. Fig. 9 shows the Cullen and Frey plot [8] for a sample segment. We can easily conclude that the best candidate distribution is Gaussian for each peak. To further verify that the Gaussian distribution is indeed a good fit for all segments, we perform *qq* (quartile-quartile) analysis on all these segments using a Gaussian distribution as a theoretical reference. Fig. 10 shows the *qqnorm* plots for four of these segments, as a sample, corresponding to the two highest and the two lowest peaks. We can clearly observe that Gaussian distribution is indeed a good fit. We observed the same outcome for all peaks in the data.

We can thus conclude that the entire data set is a mixture of Gaussian distributions. This makes a MoG-HMM (mixture of Gaussian Hidden Markov Model) based machine learning algorithm a suitable candidate for modeling and usage forecasting.

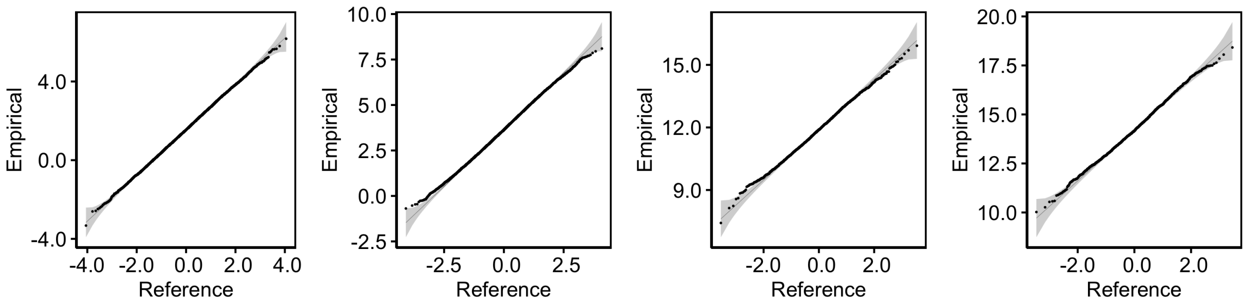
4.2 Forecasting

Model. Our daily water usage forecasting model is shown in Fig. 12. The *inputs* to the model are: (i) instantaneous water usage in liters per minute, and (ii) time of the day. The *output* is the predicted water usage in the next interval. At the highest level, the model consists of two states, active (A_s) and dormant (D_s). Within each state, water usage can either be routine (M_r) or abnormal (M_a), as discussed in Sec. 4.1, and these states predict water usage.

To differentiate between M_r and M_a, we employ a usage classifier. Our classifier is itself based on a HMM, which determines the matching probability of current water usage (D) with both the models. Thus, the output of the classifier can be describe as below:

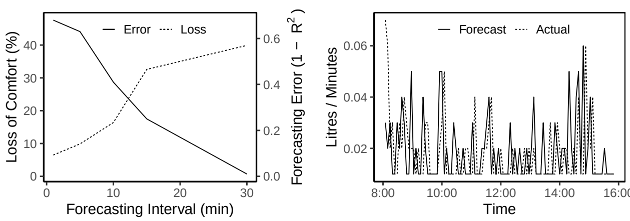
$$model = \underset{m \in \{\mathcal{M}_a, \mathcal{M}_r\}}{\operatorname{argmax}} \quad (D|m)$$

Thus, the overall model is MoG-HMM with a Gaussian usage pattern within each state of the active and dormant spans.



(a) qqplot of water usage under 2.5 litres **(b) qqplot of water usage between 2.5 and 6.5 litres** **(c) qqplot of water usage between 11 and 13 litres** **(d) qqplot of water usage between 13 and 16 litres**

Figure 10: *qq* plots for the two highest and two lowest peaks. Gaussian distribution is the best fit for each segment.



(a) Best forecasting interval **(b) Forecasting model accuracy**

Figure 11: Forecasting interval and accuracy.

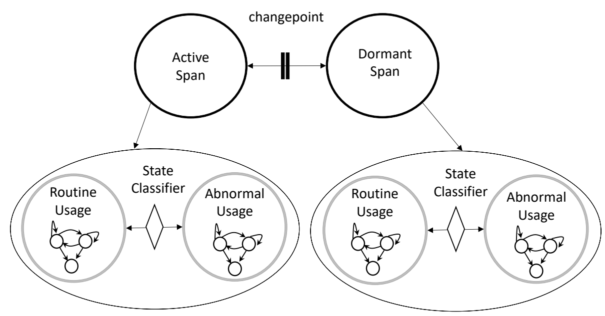


Figure 12: Daily water usage forecasting model.

Forecasting Interval. An important aspect of the model is to determine how often to forecast water usage as we schedule water pumping accordingly. Multiple conflicting parameters need to be balanced for identifying an optimal interval. First, *forecasting error* is impacted by the forecasting interval. The smaller the interval, the better the expected accuracy. Second, forecasting interval impacts the comfort level, which we define as *loss of comfort* in terms of a percentage deviation from groundwater temperature. For example, very short forecasting intervals result in pumping only small amounts of water into the overhead tank, impacting the residual water temperature insignificantly. Third, for each forecasting interval we need to decide whether or not to turn on the water pump. A very small interval may cause *short cycling* of the water pump, causing it physical damage. Thus, the forecasting interval is a function of these three parameters, as described below:

Forecasting Interval= f(Short Cycling, Forecasting Error, Comfort Level)

We dynamically update the forecasting interval as these parameters may be different in different regions and times of the day. For example, a larger interval may suffice for the dormant span whilst the impact of elements is moderate, similarly a relatively smaller interval may be necessary for the active span wherein a greater impact of elements is expected during the day. Fig. 11a shows the results for a given usage pattern in an active span. We can see that an interval of approximately 13 minutes balances loss of comfort against forecasting error, while easily satisfying the short cycling requirements of the water pump.

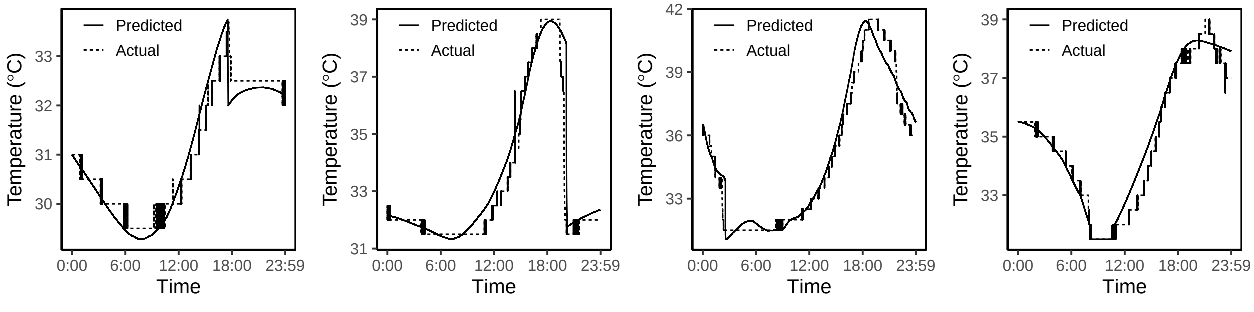
Forecasting Accuracy. To evaluate the accuracy of the forecasting model, we computed the R-squared metric for the entire data set, and obtained a score of 0.9 for both homes. In order to visually ascertain the accuracy of results, Fig. 11b overlays the actual and forecasted water usage patterns for a span of eight hours. The forecasting is indeed accurate, justifying the correct selection of models made during the analysis.

Forecasting errors may potentially result in stock outs of the overhead tank. We cater for this by defining a minimum level of water that must be maintained in the tank. Similar to two-position control [40], the water pump is automatically turned-on with an updated forecast once the water falls to that level.

5 EVALUATION

We evaluate Ashray both by simulation and in deployment. The simulation assesses the performance of Ashray over a wide range of conditions driven by traces collected from our sensor deployment. We then report the results from a full fledged deployment of Ashray in another home to validate the simulation results. Our key results indicate that using Ashray translates into:

- up to 8 °C reduction (in summer) and 3 °C increase (in winter) in tap water temperature, making it more comfortable for the household. In many cases, the reduction in tap water temperature during summers can be helpful in preventing



(a) June 6, 2018 **(b) June 7, 2018** **(c) June 12, 2018** **(d) June 20, 2018**

Figure 13: Tank model vs empirical measurements. Water temperature is accurately predicted for a range of different inputs.

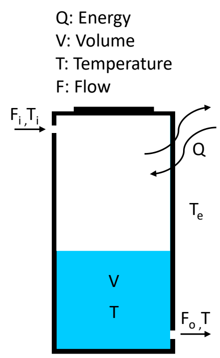


Figure 14: Overhead tank model.

scalding due to prolonged exposure to relatively hot tap water.

- at most only 0.6 °C worse from an *oracle*: an ideal prediction that knows in advance when and how much water will be used, but is impossible to implement in practice.
- up to 16% reduction on heating costs for an average household in our country as water is supplied to the geyser at a relatively higher temperature in winters; thus requiring relatively less heating. This can potentially translate into massive gas savings if Ashray is adopted on a regional scale.

5.1 Ashray Performance in Simulation

The simulation of Ashray requires two inputs. First, household water usage patterns. For this purpose, we use traces from our sensor deployment, as described in Sec. 3. Second, the ambient temperature and radiation traces of a given region. We use traces for the year 2018 provided by *Time and Date AS* [47] and Meteoblue [32]. Both these inputs are used to derive an overhead tank model, as described below.

5.1.1 Overhead Tank Model. When the water pump is turned on, water flows into the overhead tank at flow rate F_i and temperature T_i. This water mixes with the stored water in the tank, resulting in a change in volume and temperature of the water inside the tank . Water flows out of the tank at a rate F_o and temperature T_o through the outlet. Since we assume a homogeneous mixture of water, i.e., incoming water is instantaneously mixed with existing water in the tank, water temperature observed at the time of usage is equal to tank's internal water temperature ($T_o = T$).

For a given residual volume V and temperature T of water inside the tank and external temperature T_e, energy flows into the tank if T_e is greater than T and out of the tank otherwise, as depicted in Fig. 14. Let the total change in energy of the tank be Q, which depends on the net flow of energy into the tank. As a first order approximation, we can model the rate of change in Q using Newton's law of cooling:

$$\dot{Q} = \dot{Q}_{F_i} - \dot{Q}_{F_o} + \dot{Q}_d \tag{1}$$

where, $\dot{Q}_{F_i}$ is the rate of energy inflow due to F_i at T_i, $\dot{Q}_{F_o}$ is the rate of energy outflow due to F_o at T_o, and $\dot{Q}_d$ is the rate of change in energy due to the difference between T_e and T. For an object of mass m, specific heat C, and temperature T, its total energy will be $Q = mCT$. We know that $m = \rho V$ where ρ is the density of the object. Therefore:

$$\rho \dot{V}CT = \rho F_i C T_i - \rho F_o C T_i + \dot{Q}_d$$

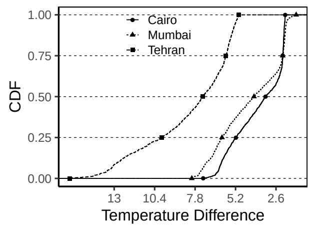
F_i and F_o are the flow rates of incoming and outgoing water, respectively

$$\dot{VT} = F_i T_i - F_o T + \frac{\dot{Q}_d}{\rho C}$$

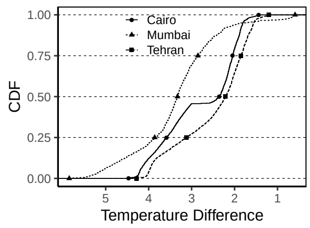
which gives

$$V\dot{T} + T\dot{V} = F_i T_i - F_o T + \frac{\dot{Q}_d}{\rho C} \tag{2}$$

Accuracy. We implemented the tank model using equation 2 and compared its accuracy with the empirical measurements of the sensor deployment. As a sample, Figure 13 shows a comparison between the predicted and measured daily water temperature in the overhead tank on four different days. We can observe that the model accurately predicts the water temperature for a range of different inputs.



(a) Summers (July 2018)



(b) Winters (Nov. 2018)

Figure 15: Temperature difference between Ashray and ground truth for two months. Ashray improves water comfort across various climatic regions. The average improvement in °C is 8.15, 3.68, 4.21 in summers and 2.49, 2.79, 3.36 in winters for Tehran, Cairo and Mumbai, respectively.

5.1.2 Simulating Ashray. To measure the general impact of Ashray in various cities, we require their respective ground water temperatures. Note the groundwater temperature remains near constant throughout the year [36].

Fig. 1a provides groundwater temperatures of over 400 cities. In order to scale down the evaluation, we group temperatures from Fig. 1a using k-means clustering. We exclude cities with groundwater temperatures below 15 °C as these typically do not represent the target developing regions. The k-means clustering results in three clusters with *means* 17.26 °C, 21.96 °C, and 26.89 We then find the nearest matching city for these three clusters, resulting in Tehran (17 °C), Cairo (21.4 °C), and Mumbai (27.1 °C). We use these three groundwater temperatures along with the usage patterns of home A to simulate the tank water temperature with and without Ashray. For brevity, we refer to the tank temperatures without Ashray as *ground truth*, i.e., water is pumped routinely by the household as per previous practice.

Benchmarks. Apart from the ground truth, we use three approaches to benchmark Ashray performance:

- *Two-position control*, which is a common method used in industry to control water level in tanks. In this strategy, a lower and an upper threshold is defined and the water pump is turned on and off at these two levels, respectively.
- *Manual Optimization* of the user schedule. Since water is typically pumped into the overhead tank once per day, we find an optimal daily time for pumping water once that would yield the best water temperature. This is to see whether a simple intervention in manual scheduling can impact water comfort.
- *Oracle* is a theoretically perfect forecasting model that knows water usage patterns and daily temperature variations a priori to maximize water comfort. However, as these patterns cannot be known in advance, implementing this approach is not possible in practice.

Results → water comfort. Fig. 15 shows the cumulative distribution of the difference of tap water temperature between Ashray and the ground truth in summer and winter for Tehran, Cairo and Mumbai. Note that the positive difference in temperature shows the improvement offered by Ashray in °C. We can clearly see that Ashray improves water comfort in all observations in both summers and winters. In more than 50% observations, the improvement in summers is at least 6 °C for Tehran and 3 °C for Cairo and Mumbai. This is a substantial improvement in the target region, where a single °C improvement in water temperature matters, as is evident by the widespread use of costly but ineffective external insulation techniques among most households.

Table 3 shows the detailed simulation results for all approaches. We note the following key observations:

- Ashray offers relief in scorching weather conditions when the ground truth temperature reaches dangerous levels, which can be harmful to households. This can be observed by comparing the *max* columns of Ashray and ground truth in summers.
- The water temperature offered by Ashray is at most 0.6 °C worse than that of an ideal oracle, which deterministically knows future usage. Note that the oracle is also not able to deliver the water at groundwater temperature due to the dead level constraint that requires a minimum water level to be maintained in the tank.
- Ashray's performance is understandably dependent on the input water temperature and weather. The lower the temperature of the input water in summers, the more comfortable is Ashray's tap water, and vice versa in winters.
- Standard non-predictive approaches, such as two-position control, offer minimal advantage in terms of water comfort as they are not optimized for achieving it.

Results → energy savings. In winters, Ashray supplies water to the geyser at a relatively higher temperature, implying less heating effort to attain the desired temperature. To evaluate energy savings, an approximate geyser model can be describe as follows: Let V be the volume of the geyser, which is always filled to capacity with water at a desired temperature T_g. On using a volume of water with mass m, let $T_{g'}$ be the new temperature of the water in the geyser after cold water from the overhead tank mixes with it. As $T_{g'} < T_g$, therefore, in order to maintain the desired temperature, T_g, the geyser fires up to heat the water in its tank. In the steady state, the amount of heat, Q, required to achieve the desired temperature is given by $Q = mc\Delta T$, where $\Delta T = T_g - T_{g'}$. Using this model, we estimate the volume of natural gas required to generate Q.

We compare the energy consumption of the geyser with and without Ashray to accrue the corresponding benefits. The intuition is that, in winters, supply of water at a higher temperature to the geysers by Ashray would require less heating to maintain the desired tap water temperature. For the results shown in Fig. 15b, the amount of gas required to heat water using a geyser is decreased by 8 m^3 when using Ashray. This translates into an average monthly saving of 16% on water heating costs for a single household.

In summary, Ashray promises to provide near optimal thermal comfort in simulation. The next section validates these simulation results in a *real world deployment*.

5.2 Ashray Performance in Deployment

Settings. We validate the simulation results by deploying Ashray in home C, which is located in the outskirts of Lahore, 70 kms from

Cities	Temperature	Summer (°C)					Winter (°C)				
		Oracle	Ashray	Ground Truth	Two Position	Manual Opt.	Oracle	Ashray	Ground Truth	Two Position	Manual Opt.
Mumbai (27 °C)	min	27.18	**27.28**	**29.00**	27.09	29.00	24.90	**24.25**	**20.42**	22.00	20.33
	max	30.39	**31.08**	**35.87**	38.00	38.53	27.00	**27.00**	**24.00**	24.83	25.45
	mean	28.17	**28.62**	**32.29**	34.33	32.87	25.96	**25.43**	**22.42**	23.83	23.54
Cairo (21 °C)	min	21.14	**21.27**	**23.00**	21.00	23.00	19.12	**18.85**	**15.87**	18.02	15.37
	max	24.83	**25.34**	**30.13**	31.98	32.00	21.00	**21.00**	**18.00**	20.21	18.00
	mean	22.61	**23.01**	**26.16**	25.47	26.67	19.86	**19.21**	**17.10**	17.54	16.91
Tehran (17 °C)	min	18.45	**19.02**	**23.00**	16.59	16.00	13.92	**13.65**	**10.79**	11.90	10.45
	max	25.55	**26.01**	**36.39**	32.98	35.89	16.00	**15.45**	**14.00**	14.50	14.00
	mean	20.63	**21.03**	**28.87**	27.09	26.00	14.73	**14.31**	**12.28**	12.75	11.95

Table 3: Ashray vs the rest. Ashray is near optimal (compare Ashray & Oracle columns) and outperforms non-predictive conventional approaches.

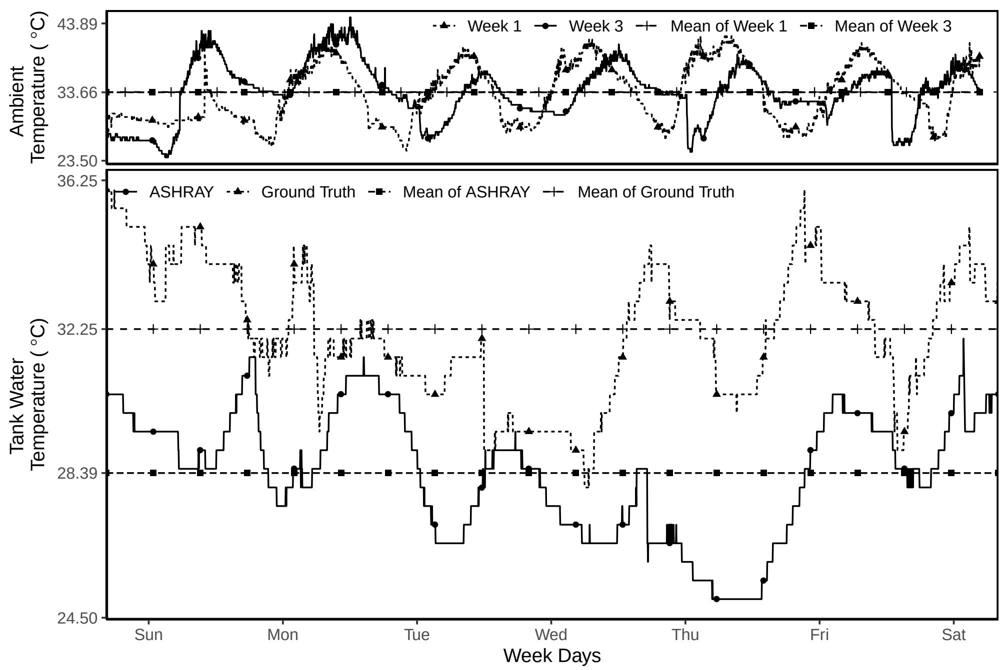


Figure 16: Ashray performance in deployment. Simulation results are validated for week long spans with similar average ambient temperatures (see the top graph). On average, Ashray achieves 4 °C reduction in tank water temperature (see the bottom graph).

homes A and B. The deployment in a different home also allows us to validate our machine learning model, which was trained using data traces from other homes (A and B), on a largely unseen water consumption behavior. Home C hosts one adult male (aged 65), two adult females (aged 40 and 60) and three children (aged 8, 13 and 16). The overhead tank in home C can store 250 gallons of water, which is directly pumped from a ground reservoir. The groundwater temperature is 23 °C. We activate Ashray after a brief two-week training period in July 2019. Our baseline for comparison is the ground truth sans Ashray, i.e., routine pumping by the household.

Also, note that it is not possible to simultaneously compare the two approaches for the same time-frame, as any given approach dictates the pumping schedule, which in turn, determines the tap water temperature. Thus, only one approach can be active at a given time. A fair comparison would be to take two reasonably long time-frames with approximately similar average ambient temperatures, and measure the difference between their tap water temperatures.

Results. Fig. 16 compares the tap water temperature of Ashray (in week 3) with the ground truth (in week 1). Here ground truth corresponds to actual empirical measurement without Ashray. The mean difference in ambient temperatures for week 1 and week 3 is negligible; guaranteeing a fair base for comparison. We can clearly observe that Ashray consistently maintains a lower average temperature, and conclude that the simulation results carry over to the deployment. Please note that a point-by-point comparison in Fig. 16 is not valid because the data is from two different time-frames.

Nonetheless, we can confidently conclude that Ashray models are indeed robust and water comfort is guaranteed across a wide range of conditions.

6 DISCUSSION

No-frills. Ashray is a no-frills water comfort system in the sense that it makes a valiant effort to provide water comfort by preserving the groundwater temperature, without spending energy on directly heating or cooling water. However, its performance is strongly dependent on the temperature of water in the underground cistern, which typically remains constant throughout the year and is close to the groundwater temperature. A future version of Ashray may also consider meeting tighter comfort bounds in scheduling as well as benefit from solar radiation to heat water in overhead tanks in winters.

Ashray does not account for the temperature effects of water flow in pipes, as most deployments in the region are based on PVC (polyvinyl chloride) pipes. PVC pipes offer better thermal insulation, are cheaper, last longer, and have vastly replaced GI (galvanized iron) pipes for plumbing. Moreover, these pipes are typically installed inside walls, further insulating them against the elements and minimizing any impact on water temperature.

Target regions typically rely on gravity based water flow in household water distribution and ASHRAY retrofits into these systems for providing comfortable running water. Other potential solutions, such as using a pressure pump that can supply water directly to taps are costly and may require redesigning existing water networks. Further, they would necessitate uninterrupted supply of electricity, which is not to be expected in target regions.

Related Work. Related work on the subject can be divided into two broad categories, i.e., *water comfort* and *water conservation*.

Comfort: Water comfort has been largely studied in the context of minimizing energy consumption of hot water provisioning in winters. For instance, Circulo [22] learns patterns of hot water usage in a home and circulates hot water only when it is highly likely to be used. This approach reduces *hot water circulation* costs in homes by 30% without increasing water wastage by households while waiting for hot water. Water circulation pumps can incur more than $1000 per year in energy costs, and hence do not represent a plausible choice for the regions considered in this paper. Similarly, a smart water heater (SWH) [45] has been proposed to reduce heat losses through piping: delivering lower temperature water whenever possible. SWH uses data fusion techniques to infer the fixture being used, the mixed water temperature at the fixture, and the pipe volume for that fixture. After learning a model for each fixture, it solves a control optimization problem to decide when and at which temperature to deliver water to minimize energy consumption without sacrificing the thermal comfort of the user. SWH can reduce water heating costs in homes by 8 to 14%.

Both Circulo and SWH try to minimize the costs associated with using hot water in homes while ensuring the thermal comfort of the household. However, both these solutions are useful only in winters. On the contrary, Ashray tries to deliver water comfort in summers, which is critical to the health and well-being of the common household, as discussed in Section 1, owing to the extreme summer temperatures experienced by the regions under consideration. Similarly, in winters, Ashray reduces the cost of heating water by leveraging ground water temperature.

Conservation: Household and irrigation water conservation [50] is important to: ensure the sustainability of fresh water reserves, save energy on water treatment and distribution, and preserve fresh water habitats.

An important aspect of water conservation is understanding water consumption. Various solutions have been offered to enable a household to understand its water consumption and make informed decisions regarding water conservation. For instance, eco-feedback [19] and persuasive displays [28] have been proposed to create household awareness on where water use occurs, whether such use is excessive and what steps can be taken to conserve water. Likewise, HydroSense [21], a single-point pressuring sensor that is installed within a home's water infrastructure supports both the identification of activity as well as the estimation of the amount of water being used at individual water fixtures. Work on HydroSense has been extended further to make the sensor self-powered through energy harvesting [7] as well as critically examine the feasibility of using pressure-based sensing and determine water usage activities in real world deployments [20]. Similar in spirits, WaterSense [44] uses motion sensors to automatically infer how many fixtures are in each room, and how much water each fixture uses. NAWMS [26] is a self-calibrating system that provides information on when, where, and how much water is being used. The system uses wireless vibration sensors that are attached to pipes and, hence, does not require either plumbing or any special expertise for its installation. Waterbot [4] is a system that informs and motivates behavioral changes at the sink for the purpose of increasing safety, hygiene and water conservation. Slightly different in nature, RoyalFlush [37] detects toilet overflows to avoid damage to property such as furniture and appliances.

These works on water conservation are both complementary and orthogonal to Ashray. We do not see any specific need for a fine-grained fixture-level water usage estimate in Ashray as it only influences the schedule of water pumping into the overhead tank, which serves as a common water source for all fixtures.

7 CONCLUSIONS

In developing regions, the use of overhead tanks in water distribution networks causes water to loose its groundwater temperature. We present an affordable solution for the masses, Ashray, which delivers near groundwater temperature in taps using simple IoT retrofits and forecasting models developed using machine learning techniques. Ashray improves thermal comfort by up to 8 °C in summers and 3 °C in winters. Additionally, it reduces heating costs in winters by supplying running water to the geyser at a relatively higher temperature. Our performance evaluation, using both simulations and deployment, confirms these benefits.

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