An Interactive Context-aware Power Management Technique for Optimizing Sensor Network Lifetime

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Abstract: A key problem in sensor networks equipped with renewable energy sources is deciding how to allocate energy to various tasks (sensing, communication etc.) over time so that the deployed network continues to gather high-quality data. The state-of-the-art energy allocation algorithm takes into account current battery level and harvesting energy and fairly allocates as much energy as possible along the time dimension. In this paper we show that by not considering application-context this approach leads to very high and uniform sampling rates. However, sampling the environment at fixed predefined intervals is neither possible (need to accommodate system failures) nor desirable (sampling rate might not capture an important event with desired fidelity). To that end, in this paper we propose a novel interactive power management technique that adapts sampling rate as a function of both application-level context (e.g., user request) and system-level context (e.g harvesting energy availability). We vary several key parameters including application request patterns, geographic locations, time slot length, battery end point voltage and evaluate the performance of our approach in terms of energy efficiency and accuracy. Our simulations use sensor data and system specifications (battery and solar panel specs, sensing and communication costs) from a real sensor network deployment. Our results show that the proposed approach saves significant amounts of energy by avoiding oversampling when application does not need it while using this saved energy to support sampling at high rates to capture events with necessary fidelity when needed. The computational complexity of our approach is lower ($O(n)$) than the state-of-the-art non-interactive energy allocation algorithm ($O(n^2)$).

1 INTRODUCTION

Sensor networks are revolutionizing the scientific applications by gathering data about the natural (Mainwaring et al., 2002)(Cerpa et al., 2001)(CRE, 2013)(GRE, 2015) and built environment data at unprecedented spatio-temporal granularity. A key problem in sensor networks is deciding how to allocate energy to various tasks (sensing, communication etc.) over time so that the deployed network continues to gather high-quality data. There has been extensive research in the area of power management and resource allocation algorithms in sensor networks. However, new challenges arise for sensors equipped with renewable energy sources (Chang and Bonnet, 2010). Fair energy allocation along time dimension in sensor networks with renewable energy is important in order to support constant operation. It has two implications: allocating as much energy as possible results in high frequency sampling and fair energy allocation over time results in sampling the environment at fixed rate. Our experience with real-world sensor network deployments in collaboration with limnologists and coral reef ecologists shows that the aforementioned high frequency fixed rate sampling technique does not work well in practice because of the following reasons.

Real-world Deployments Depend on Periodic Interaction to Maintain Optimal Sampling Regime: Sensor networks need periodic interaction primarily for the following two reasons. (A) Early identification of system failures: Sensor networks embedded in inhospitable environment are prone to fail for a variety of reasons such as biofouling, exposure to extreme temperature or humidity etc. (B) Identification of interesting trends: Both anticipated (nightly temperature drops) and unanticipated episodic events (typhoon, hurricanes etc.). At present the interaction is

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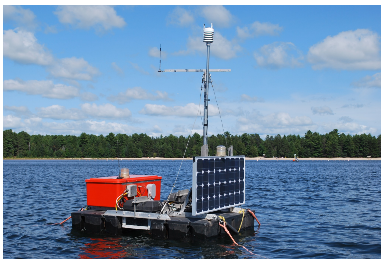

Figure 1: Buoy deployed in a lake located in northern Wisconsin, USA measuring several key limnological variables.

manual, where the domain scientists periodically look at the incoming data to ensure that it is generating science-quality data (Chang and Bonnet, 2010). Scientists also often explore the data to see if something interesting happened in last day or two and whether the current sampling rate is sufficiently capturing the events with necessary fidelity. At present, it is too complex to automate this process. This is both due to lack of priori knowledge of the all possible events and system failures and specifying and capturing all the interesting events and system failures. In addition, even if the events are known, programming and detecting all possible events makes the system prohibitively complex. In future, as machine learning algorithms will be more sophisticated and sensor networks become equipped with more computing power, we believe that this manual approach will be replaced by an automated system that requires no human interaction. Never the less, either a real end user or an automated system will interact with the deployed network on a periodic basis. In this paper we use the term ”user request” to denote both the request generated by human beings as well as automated systems.

Periodic Sampling at Fixed Rate Is Not Sufficient: Sampling the environment at fixed predefined intervals is neither reliable (need to accommodate system failures) nor desirable (current sampling rate might not capture an important event with desired fidelity) (Chang and Bonnet, 2010). We now explain this in detail. *Failure*: Suppose monitoring system monitors both temperature and humidity level at every 1 min. If either measurement is missing the other is useless. This indicates that the missing value should be compensated by either repeating a measurement within a few seconds. *Interesting events*: Consider an application that requires sampling a sensor at a high rate (i.e. 10 samples/seconds) when rain is detected and otherwise a much lower sample rate (i.e. 1 sample/minute). Scientists therefore want systems that can adapt sampling rates and meet their science requirements. Periodic sampling can often result in either oversampling (thereby wasting energy) or under sampling (thereby not capturing an event with necessary fidelity).

Setting Sampling Regime Is Often an Exploratory and Iterative Process: Scientists are often operating in unexplored territory and therefore setting up sampling rate is not a one-time process, but is an iterative and exploratory process. Scientists typically set the sampling rate to the best of their knowledge and then use the gathered data to adjust it. This process can take anywhere from few days to few months.

Based on these observations, we propose a novel interactive power management technique that adapts sampling rate as a function of both application-level context (e.g., user request) and system-level context (e.g harvesting energy availability and stored energy). We prove the energy-efficiency and accuracy of the proposed approach using data and infrastructure details (battery levels, sensing every consumption etc.) from a real-world deployment.

2 RELATED WORK

There has been considerable work in the area of sensor network reprogramming (Hui and Culler, 2004)(Levis and Culler, 2004)(Naik et al., 2007). These approaches are mainly designed for real network-wide software updates and are not suitable for more frequent sampling rate updates. The industrial automation systems or building management systems integrated with control system require guaranties for real-timeliness, functional safety, security, energy efficiency, etc (Chen et al., 2010). In these sensor-actuator networks resource allocation decisions are typically done in a centralized manner (at the plan data center). In contrast, we propose a fully distributed approach for energy allocation.

Context has been used extensively for efficient sensor network protocol design in the area of routing (Koo et al., 2009)(Zhou and Hou, 2007), cluster formation (Haque et al., 2009), and power management (Wood et al., 2008). Context aware power management protocol (Wood et al., 2008) proposed a context aware power management protocol considers heterogeneous energy sources in which some nodes are powered by batteries and others are plugged into wall. However, they do not consider green energy sources in their research. Solar energy allocation algorithm (Gorlatova et al., 2011) determines fair energy allocation along time dimension in systems with predictable as well as stochastic renewable energy inputs. Their energy allocation algorithm – Progressive Filling (PF) fairly allocates energy over time dimension and it has $O(n^2)$ computational complexity. PF algorithm starts from time slot 0 and increments its allocated energy by α until it reaches the target bat-

Table 1: Power specification for our deployment.

Device	Power consumption(W)
3G cost+Processing	5
Vaisala Weather Station	0.168
Sonde	3.372
Templine	0.42
Sensing cost	3.96

tery level. Since PF is the state-of-the-art energy algorithm, we use it to compare with the proposed interactive technique. In this paper we use interchangebly use PF algorithm and non-interactive technique. To the best of our knowledge, this is the first work that proposes a novel interactive power management technique that adapts sampling rate as a function of both application-level context (e.g., user request) and the system-level context (e.g harvesting energy availability).

Solar panels are frequently used in sensor networks because they can theoretically provide quite a bit of harvested energy. However, they are not a reliable, consistent source of energy because of the Sun's cycles and the everchanging weather conditions. To that end, short-term solar prediction algorithms (Kansal et al., 2007)(Piorno et al., 2009) have been studied. Exponentially Weighted Moving-Average (EWMA) (Kansal et al., 2007) algorithm relies on the assumption that the energy available at a given time of the day is similar to the energy generation observed at the same time on the previous days. The high prediction errors shown by EWMA when sunny and cloudy days alternate is due to the high impact that the weather conditions of the previous day have when estimating the energy generation for the current day. Weather-Conditioned Moving Average (WCMA) (Piorno et al., 2009) prediction algorithm avoids this effect by effectively taking into account both the current and past-days weather conditions.

3 SYSTEM MODEL

Our system consists of two components (1) field deployed sensor network (2) data center. The sensor network consists of a network of platforms (e.g. buoys or towers), which are large enough to house large solar panels and bulky batteries and an embedded computer to which multiple sensors (order of 30) are connected either via serial or Bluetooth link. The computer runs a low-power operating system and is equipped with one or more network modalities (e.g, WiFi, cellular, and satellite). Figure 1 shows our latest deployment of an instrumented buoy for a lake monitoring application. This buoys hosts a variety of sensor for

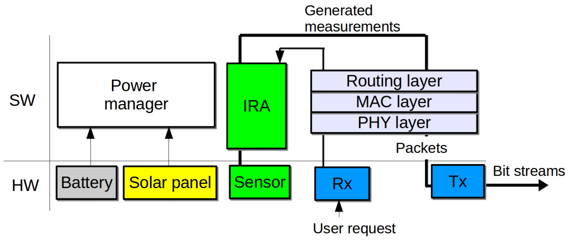

Figure 2: Interactive Context-Aware Power Management System Architecture.

monitoring lake processes, including temperature at twenty seven depths, dissolved oxygen, conductivity, pH/ORP, flourescence sensors (Chloraphyll a, Blue-green Algae, and Rhodamine WT) and voltage. These sensors are connected to an Android Cell phone via IOIO board. The phone runs the data acquisition program and sends data back to a data center over the cellular network. We use one Instapark 80W Monocrystalline solar panel as our green energy source (Ins, 2015). It has following power specifications: Maximum Power Voltage: 17.39V; Open Circuit Voltage: 21.97V; Maximum Power Current: 4.61A. Table 1 summarizes the sensing and communication and processing power consumption, which we use in our simulations.

4 INTERACTIVE-POWER MANAGEMENT

Our approach uses application-context (e.g., feedback from domain scientists or an automated system running user-specified rules) to optimally set sensor sampling rates. Figure 2 describes the proposed power management framework that runs at each sensor node. It consists of two major subsystems, namely, power manager (PM) and and the Interactive Resource Allocator (IRA) subsystem. The PM subsystem makes resource allocation decisions based on the current battery level and predicted harvesting level (ref. Eq (1)). The IRA subsystem then adapts the aforementioned sampling rate in an interactive manner (ref. Algorithm 2). We now describe the details of PF and IRA algorithms.

Each sensor node divides a time into K slots (Gorlatova et al., 2011). We denote $S = [s_1, \ldots, s_K]$ as a set of allocated energy to K time slots and s_i is the allocated energy to slot i. The embedded power manager allocates energy to each time slot based on the current batter level and predicted battery level (ref. Eq. (1)). $B(i)$ is battery level and $H(i)$ is the predicted harvest level at time slot i. We use B_{max} to denote total Battery capacity and B_{min} to denote minimum battery capac-

Algorithm 1: Advanced Progressive Filling (APF).

$avgHarvstEnergy = \sum_{i=1}^{K} H(i)/K$;
$s(1:K) := avgHarvestEnergy$;
for $i = K; i \geq 1; i = i-1$ **do**
  $[over, amount] \leftarrow check\_validity(s(i))$;
  if $over == TRUE$ **then**
    $s(i) = s(i) - amount$;
  end
end

`Function` $[over, amount] = check\_validity(s)$
$B_{current} =$ `current battery level`
for $i = 1; i \leq K; i = i+1$ **do**
  $B_{current} \leftarrow \min\{B(i) + Q(i) - s(i), B_{max}\}$;
  if $B_{current} < s(i+1)$ **then**
    return $[TRUE, s(i+1) - B_{current}]$;
  end
end
return $[FALSE, 0]$;

Algorithm 2: Interactive Resource Allocator.

$s \leftarrow$ `Algorithm 1`
for $i = 1; i \leq K; i = i+1$ **do**
  $s^{req} \leftarrow$ sampling rate given $s(i)$;
  if $s^{req} < s(i)$ **then**
    `// Support user request`
    $s(i) \leftarrow s^{req}$;
    $B_{saved} \leftarrow B_{saved} + \{s(i) - s^{req}\}$;
  else
    if $s^{req} < s(i) + B_{saved}$ **then**
      $s(i) \leftarrow s^{req}$;
      $B_{saved} = B_{saved} - \{s^{req} - s(i)\}$;
    else
      Aggressive : $s(i) \leftarrow s^{req}$;
      Conservative : $s(i) \leftarrow s(i)$;
      Hybrid : $s(i) \leftarrow s(i) + B_{saved}$;
    end
  end
end

ity. $U(\cdot)$ is utility function that calculates sampling rate given allocated energy. It is a non-negative, increasing, strictly concave function (Tutuncuoglu and Yener, 2012). The first constraint of Eq. (1) obeys the energy neutral operation in energy harvested wireless sensor network(Kansal et al., 2007).

$$\begin{aligned} &\max_{s_i} \sum_{i=1}^{K} U(s_i) \\ &s.t. B(i-1) + H(i-1) - s(i-1) \leq B(i) \\ &0 \leq s_i \leq B_{max},\ 0 \leq H(i),\ \ B_{min} \leq B(i) \leq B_{max} \end{aligned} \tag{1}$$

In order to solve Eq. (1), PM allocates constant energy over K time slots as described in Algorithm 1. The validity of this approach has been proved by (Gorlatova et al., 2011)(Tutuncuoglu and Yener, 2012). This reduces the computational complexity of PM to $O(n)$ compared to that of PF $O(n^2)$.

However, constant energy allocation do not consider a situation that system needs to consume more energy than harvested one. Interactive resource allocator (IRA) considere those scenario. We now describe the IRA subsystem. The sensor node virtually divides its battery into two parts, $B_{current}$ and B_{saved}. The IRA subsystem (ref. Algorithm 2) interacts with the application (user or automated system) and then calculates the energy required to meet the requested sampling rate. Intuitively, when the energy needed to satisfy the user request (s^{req}) is less than the energy allocated ($s(i)$) by the APF algorithm (system is currently oversampling), IRA turns down the current sampling rate and saves this extra energy to B_{saved} while achieving the necessary fidelity. However, when user requires sampling at higher rate than the current sampling rate (the system is currently under sampling), the sensor node augments $B_{current}$ with B_{saved} to support it. When ($s(i) + B_{saved} < s^{req}$ given $s(i) < s^{req}$), the system is under sampling because it does not have enough energy to support the requested sampling rate. In this case, we consider three policies (1) Aggressive: The ongoing event is so critical that the user sees benefit in capturing that even at the cost of reduced network lifetime. In this case, the IRA algorithm increases the sampling rate for the given slot to the requested rate. (2) Conservative: IRA algorithm decides to continue sampling at the current sampling rate at the cost of reduced fidelity. (3) Hybrid policy: The system selects the best sampling rate it can support in a greedy manner. This happens in the case where although the requested rate is not feasible due to energy constraints, but there is still benefit in increasing the sampling rate to the level that can be supported. A user monitors collected data and determines current optimal sampling rate that meets the science requirements. Sensor nodes receive the request and adjust their configuration based on onboard power management technique (described later).

5 MATHEMATICAL ANALYSIS

In this section, we theoretically compare the performance of interactive and non-interactive power management approaches in terms of user satisfaction. The interactive approach makes its decision based on battery level, predicted harvesting energy, and user request, while the non-interactive approach typically considers only the first two as its inputs. At a given slot i, when the allocated energy ($s(i)$) is larger than energy required to meet the user request (s^{req}), a sensor node can satisfy user request at that slot. However, in this case, the node is oversampling and wasting its energy.

$$z_i = \begin{cases} 1 & if \;\; s(i) \geq s^{req} \\ 0 & if \;\; s(i) < s^{req} \end{cases} \quad (2)$$

As shown in equation (2), z_i defines the condition of i's time slot. When $s(i)$ is larger than s^{req} the z_i has 1 which indicates that the system is oversampling and spending extra energy. Otherwise z_i has 0 as shown in equation (2).

Let us define the probability $p = Pr(s(i) \geq s^{req})$. The average number of slots in which a node spends oversamples and wastes energy is given by equation (3). Thus, in this case, the average number of time slots in which the non-interactive approach overspends energy in $K \cdot Pr\ (s_i \geq x_i)$.

$$E[Z_i] = K \cdot p = K \cdot Pr(s(i) \geq s^{req}) \quad (3)$$

The proposed interactive power manager (ref. Algorithm 2) saves energy when the energy needed to satisfy user request (s^{req}) is less than allocated energy ($s(i)$), and uses the saved energy (B_{saved}) as a boost when the energy needed to satisfy a user request is more than allocated energy. The interactive approach with hybrid policy fails to satisfy user requests only when the sum of allocated and saved energy is lower than the amount of user request, $s(i) + B_{saved} < s^{req}$. We describe this in equation (4).

$$z_i = \begin{cases} 1 & if \;\; s(i) + B_{saved} \geq s^{req} \\ 0 & if \;\; s(i) + B_{saved} < s^{req} \end{cases} \quad (4)$$

The $s(i) + B_{saved} \geq s^{req}$ includes both $s_i \geq x_i$ and $s(i) + B_{saved} \geq s^{req}$ situations. Thus, the average number of time slots that satisfy user request with interactive approach is $K \cdot \{Pr(s(i) \geq s^{req}) + Pr(s(i) + B_{saved} \geq s^{req})\}$. This result means that user-interactive power management always satisfies more user requests than the non-interactive mechanism because $Pr(s(i) + B_{saved} \geq s^{req}) \geq 0$. The interactive approach with conservative policy will show same performance with non-interactive one and aggressive policy always satisfies user satisfaction.

6 RESULTS

US climate Reference Network(USCRN), maintains a database of environmental data collected from various monitoring stations across the US. For our simulations, for solar energy prediction, we use data from USCRN database for Necedah, Wisconsin location since it is the closest location to our deployment. Our past research has shown that the state-of-the-art energy predictors such as Weather-Conditioned Moving Average, WCMA can be used to accurately predict the amount of harvesting energy (Piorno et al., 2009). Therefore, in this paper we use WCMA algorithm for solar energy prediction. To calculate accuracy, we use one week worth of sensor data (Wind speed data) from our deployment. We use Matlab to conduct simulations.

6.1 Study of Impact of Time Slot Length Variations on Energy Efficiency

In this study, we consider 24 hours duration and vary the time slot length from 1 (24 slots/day) hour to 24 hours (1 slot/day). We fix 1 sample per 10 min as default sampling rate. We consider user request pattern from 10% to 100%. In the case of 10% request pattern, among all time slots, 10% time slot support high request rate which requires 1 sample every 1 min. Remaining request pattern requires 1 sample every 5min. We use end point battery level as 11.1V. Thus, the capacity is (12-11.1)*55 = 49.5Wh. Table 2 shows percentage of energy consumed for each approach for different time slot lengths and request patterns. As expected (ref. Table 2), when we decrease request frequency, the overall energy consumption decreases. However, we observe an interesting patten when time slot length is varied. When time slot length is between 1 hour to 6 hours, the environmental conditions (for solar energy production) do not vary considerably and the overall energy consumption goes up as a function of slot length. However, for lengths greater than 6 hours the environmental conditions within a slot can vary significantly thereby changing the harvesting energy production (solar energy availability during day-night shifts). This results in lower energy consumption for 12 hours and 24 hours slot lengths as compared to slots of 1, 2, 3, and 4 hours duration.

6.2 Study of Impact of EPV Variations on Energy-efficiency

Our deployment uses Interstate DCM0055 Lead-Acid battery (Int,) with 55Ah capacity with Initial Battery Level (IBL) as 12V. The technical specification for this battery mentions that there are five different End Point Voltage (EPV) levels : 9.6V, 10.2V, 10.5V, 10.8V, 11.1V for this battery. When the battery level reaches the EPV, it stops working until the recharge process starts. We then calculate the available/ target battery capacity for each of the discharge levels as: (IBL - EPV) * battery capacity. For example, for 9.5V EPL, the target battery capacity is: (12 - 9.6)* 55 = 132 Wh. It can be seen that the energy efficiency decreases as the application request ratio increases since

Table 2: Impact of time slot length and request pattern variations on energy efficiency.

Request pattern	1 hr	2 hr	3 hr	4 hr	6 hr	12 hr	24 hr
10%	0.956276	0.834421	0.830564	1.293239	0.899995	0.468826	0.375603
20%	1.457325	1.494519	1.417344	1.342128	1.193348	1.186236	0.448982
30%	1.677017	1.690152	1.821041	1.929334	2.073806	1.251442	0.889197
40%	2.178127	2.179191	2.187712	2.173487	2.440535	1.512372	1.109292
50%	2.508317	2.790583	2.554353	2.662568	2.513921	1.512403	1.402832
60%	3.106887	2.961605	2.884691	3.200636	3.174275	1.903787	1.622956
70%	3.302188	3.279281	2.994695	3.542866	3.541096	2.36027	2.063197
80%	3.607844	3.474945	3.654829	3.983248	4.201438	2.555879	1.916398
90%	3.950051	3.695036	3.801447	4.080857	4.054915	2.686218	2.430062
100%	4.206684	4.086216	4.241561	4.374419	4.275124	2.882064	2.28323

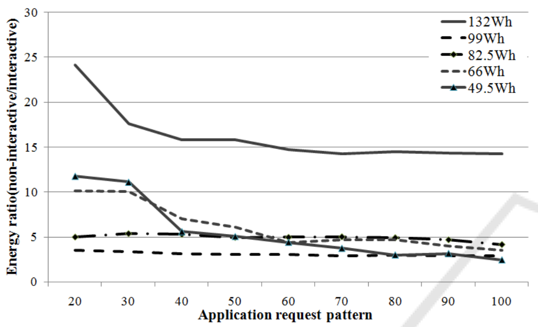

Figure 3: Impact of End Point Voltage variations on energy-efficiency.

in our case each request needs higher sampling rate (sampling every 1 minute). We can see that the proposed interactive approach is significantly more energy efficient than the non-interactive approach. This is because the later one allocates as much energy as it can in a fair manner, which leads to oversampling and wastage of energy. Figure. 3 also shows that higher discharging rate cannot use the total capacity, 55Ah because it draws high current. This situation is explained by Peukert's Equation (Doerffel and Sharkh, 2006).

6.3 Study of Impact of Harvesting Energy Variations on Energy Efficiency and Accuracy

In this paper we employ WCMA (Piorno et al., 2009) algorithm for solar energy prediction for the interactive and non-interactive approaches. Solar energy availability varies significantly as a function of geographic location and season. To understand its impact on the performance of our approach in this study we consider solar energy variations during the winter (2012/01/4 - 2012/01/10) season at three different geographic locations in the United States, namely, 1) Necedah, Wisconsin (44.0262, -90.0737), 2) Austin, Texas (30.25, -97.75), and 3) Santa Barbara, CA (34.425833, -119.714167). We set default sampling interval to be 10 minutes and high request sampling interval to be 1 minute.

Our results indicate that the proposed interactive approaches are orders of magnitude more energy efficient than the non-interactive approach. In particular, Table 3 shows the the percentage of remaining battery level after one week of operation. In case of non-interactive approach it is just 0.8152% for the Wisconsin winter case. The accuracy is expressed in terms of Root Mean Square Error (RMSE). Note that as shown Table 4 error of this approach is quite high (RMSE = 2.3057). We calculated that PF algorithm allocated energy to sample sensors every 17 seconds. This is counterintuitive because the approach samples data at very high frequency (default sampling rate for the interactive approach is every 10 minutes), but it still its error is higher than all the interactive approaches. A careful investigation shows that PF approach sets it Target Battery Level (TBL) to the battery end point voltage (9.6V). It will try to allocate maximum energy during each time slot in a fair manner. However, this includes the stored and harvesting energy. They assume an ideal solar prediction algorithm that always predicts the harvesting energy accurately. However, WCMA, the state-of-the-art solar energy prediction algorithm has a relative mean error of only 10%. When we plug-in this realistic solar energy prediction algorithm with the non-interactive algorithm, we see that during the one week of operation, the batter level goes below the end point level (target battery level) for approximately 11% of the slots. The system then stops operating thereby completely missing the sampling opportunities in those slots. In contrast, the interactive approaches avoid oversampling when not needed thereby saving the energy to allow higher sampling rates upon request. We also observe that the geographic locations did not have any major impact on the energy efficiency or the accuracy of the studied protocols.

Table 3: Percentage of remaining battery after 1 week.

	WI	CA	TX
Non-interactive	0.815	0.981	1.795
Interactive-conservative	99.92	99.92	99.94
Interactive-aggressive	99.83	99.83	99.86
Interactive-hybrid	99.89	99.89	99.91

Table 4: Impact of harvesting energy variations on system accuracy.

	WI	CA	TX
Non-interactive	2.305	2.498	2.132
Interactive-conservative	1.08	1.08	0.08
Interactive-aggressive	0.01	0.015	0.01
Interactive-hybrid	1.100	1.100	1.100

7 CONCLUSION

The state-of-the-art energy allocation algorithm that takes into account current battery level and harvesting energy strives to fairly allocate as much energy as possible along the time dimension. This approach by not considering application-context leads to very high and uniform sampling rates. However, sampling the environment at fixed predefined intervals is neither possible (need to accommodate system failures) nor desirable (sampling rate might not capture an important event with desired fidelity). To that end, in this paper we propose a novel interactive power management technique that adapts sampling rate as a function of both application-level context (e.g., user request) and system-level context (e.g harvesting energy availability). Our simulations use sensor data and system specifications (battery and solar panel specs, sensing and communication costs) for a real sensor network deployment. Existing interactive algorithm considers an ideal solar energy prediction algorithm that makes no prediction errors. However, by plugging-in a realistic solar energy prediction algorithm, we show that the existing approach often leads to draining the battery below the end point voltage thereby resulting in lower accuracy while spending high energy (due to high sampling rate). Our results show that the proposed approach saves significant amounts of energy compared by avoiding oversampling when application does not need it and uses this saved energy to support sampling at high rates to capture event with necessary fidelity when needed. The computational complexity of our approach is lower ($O(n)$) than the state-of-the-art non-interactive energy allocation algorithm ($O(n^2)$).

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