Energy Budget Analysis of SWaP-Constrained UAV-Deployable Water-Level Sensors with Varying Sampling Intervals and Idle Currents

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ABSTRACT

Reliable water-level monitoring is essential for flood prediction and early warning, particularly in undersampled or ungauged regions. Low-cost, unmanned aerial vehicle (UAV) deployable sensor platforms are proposed as a promising approach for rapidly instrumenting these environments prone to rising water. Such platforms must operate under strict size, weight, and power (SWaP) constraints, where limited battery capacity and variable solar input restrict long-term deployment. Prior work has demonstrated the feasibility of compact water-level sensors, but integrating solar harvesting without increasing system size or compromising UAV-deployable form factors and mounting constraints remains a key challenge. More broadly, edge-based cyber-physical systems face the challenge of extending battery life under tight SWaP constraints, where adaptive or selective sampling serves as a key control parameter. However, for UAV-deployable water-level sensors operating in the solar conditions relative to the southeastern United States, the quantitative relationship between available solar power, idle current, and sampling rate, and how these jointly determine net energy balance, remains poorly characterized. Here, we present an energy budget analysis of the team's UAV-deployable water-level sensor equipped with solar charging. Using a simulation framework informed by field deployment data collected near Charleston, South Carolina, USA, we evaluate our SWaP-Constrained UAV-deployable Water-Level Sensor (SCUWLS) performance across a range of idle currents and sampling intervals. We show, through modeling, that reducing the idle current to 1 mA while maintaining a 29 mA draw during sampling enables near energy-neutral operation with approximately 55 mW of daily harvested solar energy, while sustaining sampling rates of approximately one sample per minute. At lower sampling rates, the SCUWLS exhibits a net positive energy balance, indicating the potential for extended or continuous operation. These results demonstrate that idle current is the dominant factor governing long-term energy sustainability and provides a basis for designing energy-aware sampling strategies for persistent environmental monitoring in difficult-to-access locations.

Keywords: UAV sensors; water level monitoring; energy harvesting; solar sensing; energy neutrality; SWaP constrained systems; adaptive sampling

1. INTRODUCTION

Flooding is among the most dangerous and costly natural hazards worldwide, causing fatalities, displacement, and substantial damage to property and infrastructure every year.[1] Reliable monitoring of water stage, the vertical height of the water surface measured from a fixed reference point, is central to infrastructure management because it gives the earliest quantifiable indication that a flood is developing[2] or if a dam is failing.[3] With stage data from well-placed sensors, threshold-based alerts can be triggered early enough for meaningful evacuation and

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emergency response, reducing casualties and property loss.[4] Without stage data, even short gaps in coverage can be fatal. The July 4th, 2025, flash flood in Kerr County, Texas, illustrates the need for early warning.[5] The South Fork Guadalupe River watershed in Texas had no upstream gauges, and the river rose approximately 11 m within five hours. The absence of any upstream sensing contributed to more than 130 deaths across the region. The density and reliability of stage monitoring networks are direct determinants of how much warning time downstream communities receive.

In practice, most rivers and headwater catchments around the world remain ungauged.[6] Conventional stage sensors, including United States Geological Survey (USGS) stilling wells, bubble gauges, and radar-based rapid-deployment gauges perform well where installed, but the material and installation costs make dense networks financially impractical.[3] Small tributary channels and urban drainages, precisely where flash floods tend to develop, are routinely left without any instrumentation.[7] This has motivated a growing line of work on low-cost, accessible water-level sensing.[8] For example, Bresnahan et al. built an open-source, Do-it-yourself (DIY) ultrasonic water-level sensor intended for citizen-science use in coastal and inland flood-prone areas, showing that sub-centimeter accuracy is achievable at a small fraction of the cost of a commercial gauge.[9] The LevelWAN system takes a similar approach, pairing a low-power ultrasonic transducer with LoRaWAN (Long Range Wide Area Network) telemetry for near-continuous water-level records in stream and sewer environments.[10] Internet of Things (IoT) platforms with automated alert thresholds have also been demonstrated at scale, further lowering the barrier for non-specialist operators.[11] These efforts collectively show that open, low-cost designs can extend monitoring coverage into under-sampled basins and put useful instrumentation in the hands of citizen scientists, municipalities, and field engineers.

The sensor platform used in this work was originally introduced by Smith et al.[12] and targets these underserved flood-prone deployment contexts. The package consists of an HC-SR04 ultrasonic sensor in a compact, size, weight, and power constrained (SWaP) enclosure that attaches to the underside of a bridge or culvert via permanent magnet, allowing a UAV to deliver and retrieve the unit without manual access to the structure.[13] The ultrasonic sensor is suitable to detect stage rise at upstream tributary locations well before hazardous conditions develop at the downstream site, giving actionable lead time for evacuation.[5]

The same SWaP constraints that make UAV deployment feasible; however, also cap the available energy budget. Hence, extending battery life without enlarging the package requires smarter power management. The sensor spends most of its deployed time in sleep mode between measurement cycles, and the idle current during this period accounts for the bulk of total energy consumption. Reducing idle current is the most direct path to longer deployment. In parallel, adaptive sampling offers a software-level approach: rather than a fixed measurement interval, the sensor can increase its sampling rate when the stage is rising rapidly and slow down during stable conditions. The sampling rate-based event-driven adaptation is well established as a practical way to preserve data quality during flood events while conserving energy otherwise.[14] Remaining battery capacity provides a second control input, allowing the sampling rate to be progressively reduced as stored energy declines, thereby extending operation until retrieval. This paper identifies an idle current threshold that enables steady-state battery operation and establishes the relationship between sampling interval and remaining battery energy, providing a foundation for the development of energy-aware control strategies.

2. METHODOLOGY

This section describes the design, field deployment, and power consumption analysis methodology.

2.1 Physical design of the sensor

The sensor node is designed as a compact, size, weight, and power-constrained package for deployment beneath bridges or culverts. Its chassis is 3D printed to provide a lightweight and compact structure that integrates the sensing, power, and electronic elements within a single enclosure, as shown in Figure 1. Water level is measured using an HC-SR04 ultrasonic sensor, which determines the distance from the sensor to the water surface through ultrasonic ranging. The sensor is powered by a 7.4 V, 1500 mAh lithium polymer battery with a total energy capacity of 11.1 Wh, which supplies energy to the electronics. To support extended field operation, nine 184 mW solar panels are incorporated to recharge the battery during the day. The electronics and battery are enclosed within a clear PVC (Polyvinyl Chloride) housing sealed with an O-ring to provide waterproofing

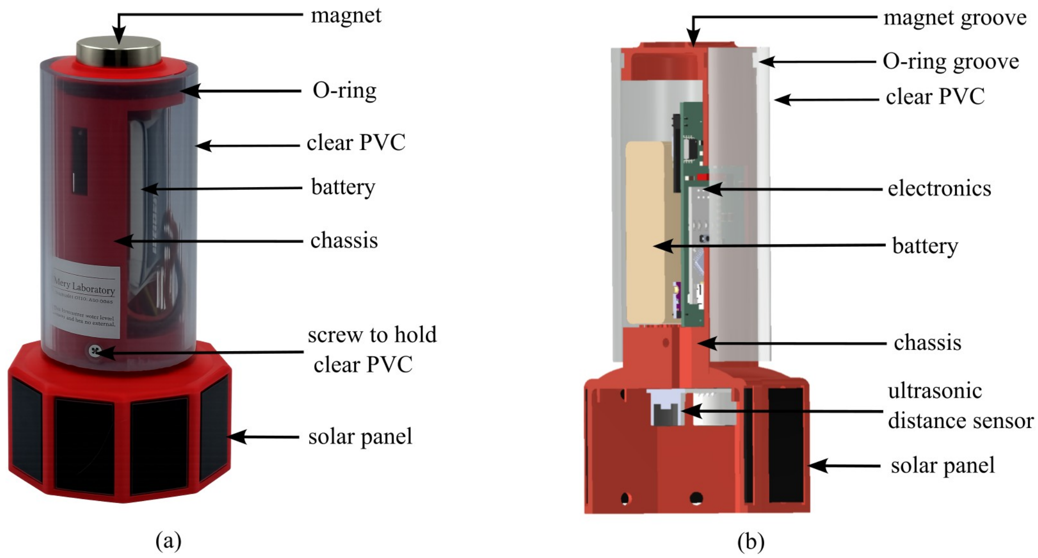

Figure 1. The SCUWLS package, showing: (a) the fully assembled package, and (b) the cross-section CAD view.

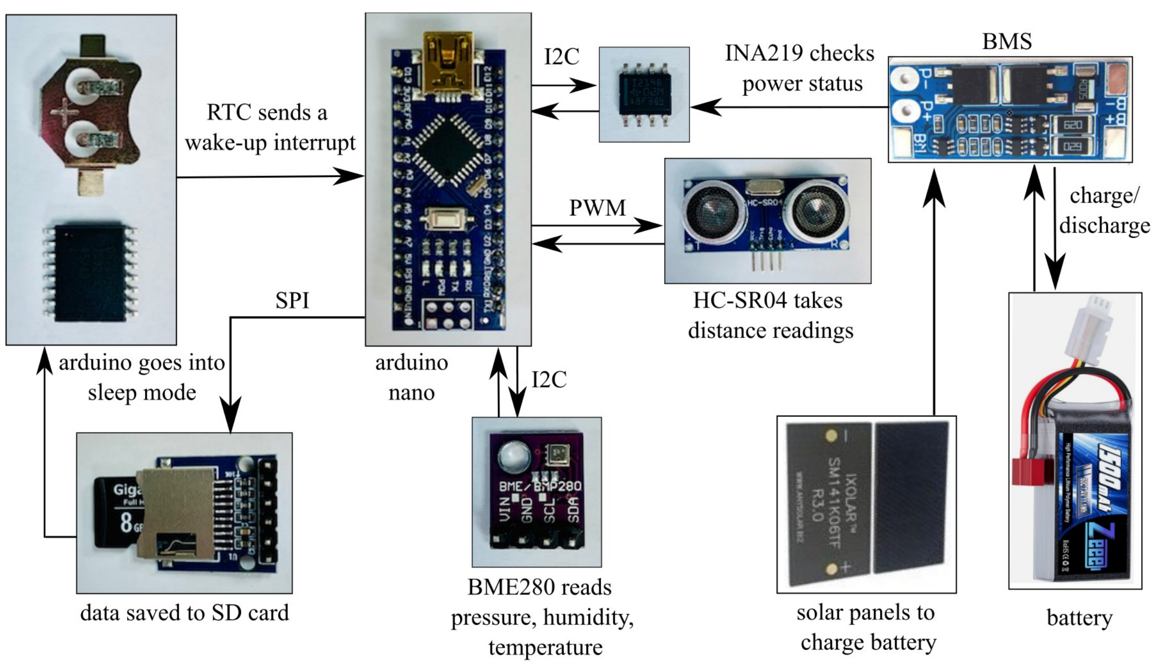

Figure 2. The embedded hardware and operation flow of the system.

and environmental protection. For mounting beneath steel bridge or culvert structures using UAVs, there is a design variation that utilizes an electro-permanent magnet for controllable attachment and retrieval from steel structures.[13] The hardware and design files for this sensor are open-source and available through a public repository.[15]

Table 1. present system's power and operational specification

current consumption during sampling	29 mA
current consumption during idle	9 mA
time to record one sample	3 s
battery capacity	1500 mAh
battery operational voltage range	8.4 – 6.6 V (BMS cuts down power after 6.6 V)
sampling interval	dynamic with the following hardcoded conditions- 30 min for $8.0\,\mathrm{V} \leq$ battery voltage $\leq 8.4\,\mathrm{V}$ 60 min for $7.4\,\mathrm{V} \leq$ battery voltage $< 8.0\,\mathrm{V}$ 120 min for battery voltage $< 7.4\,\mathrm{V}$
operation duration without solar power	7 – 8 days
operation duration with solar power	12 – 20 days

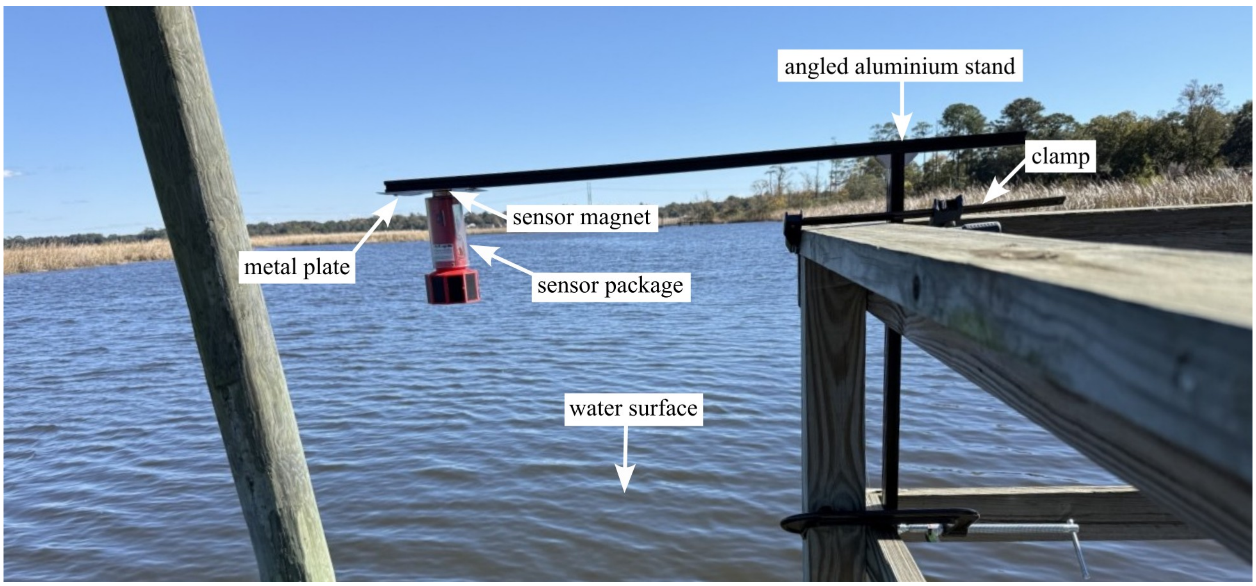

Figure 3. Deployed sensor at a dock at the intersection of Turkey Creek and Goose Creek in Hanahan, SC.

2.2 Embedded system and specifications

As shown in Figure 2, the embedded system is centered on an Arduino Nano, which serves as the main controller for sensing, data logging, and power management operations. A DS3231 RTC chip is used to support low-power operation by placing the controller in sleep mode between measurements and issuing a wake-up interrupt before each sampling event. After waking, the Arduino collects sensor data and stores the recorded measurements on an onboard SD card for local data retention. All electronic components are integrated on a custom printed circuit board (PCB), which provides a compact and organized implementation suitable for field deployment. The design also includes a socket for an nRF24 radio module, enabling wireless transmission of measurements to a remote base station. Power regulation is handled by the battery management system (BMS), which manages power flow between the solar panels, the battery, and the embedded electronics, allowing daytime charging while supplying the system load. In addition, an INA219 power-monitoring module measures the electrical state of the system and provides information related to the remaining battery reserve. The system is programmed to dynamically operate on three distinct sampling intervals of 30 min, 60 min, and 120 min based on battery voltage. The system's power and operational specifications are shown in Table 1.

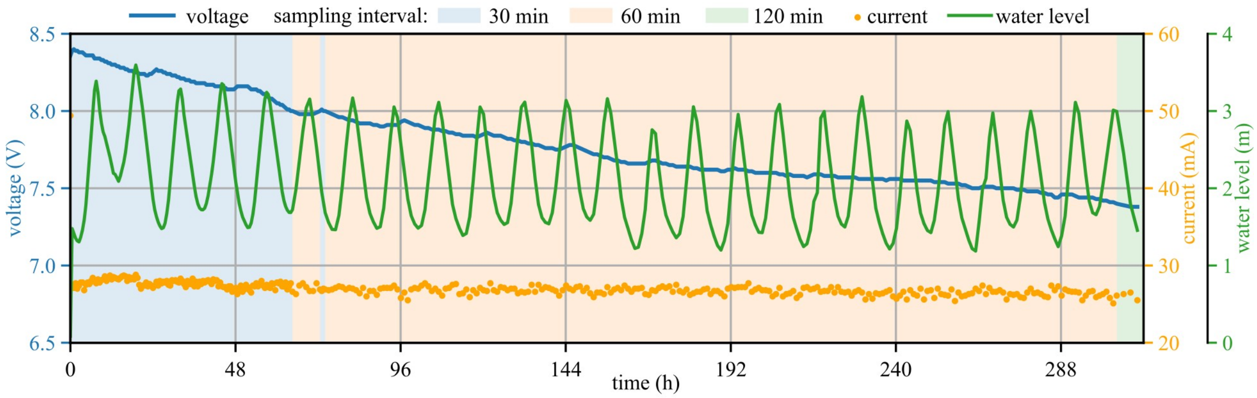

Figure 4. Power consumption and water level data gathered from the field deployment over a duration of 312 h showing three distinct sampling intervals of 30, 60, and 120 min based on battery voltage.

2.3 Field deployment and data collection

The sensor was field-deployed on a dock located at the intersection of Turkey Creek and Goose Creek in Hanahan, South Carolina, (North-west of Charleston South Carolina) where the water surface is influenced by periodic tidal variation. As shown in Figure 3, an angled aluminum stand was used to position the sensor directly above the water surface. A metal plate was attached to the end of the stand to provide a steel mounting surface for the sensor magnet. The unit remained deployed for 20 days and stored measurements locally on the onboard SD card. The recorded data is summarized in Figure 4, showing stable long-term operation under field conditions. The battery voltage gradually decreased over time, from about 8.4 V at deployment to approximately 7.4 V near the end of the plotted interval, while the current draw remained relatively steady. The shaded regions indicate that the adaptive sampling strategy changed among 30, 60, and 120 min intervals according to battery voltage. The measured water level exhibits a clear repeating oscillatory pattern, consistent with the expected tidal behavior at the site, demonstrating that the system successfully captured periodic water-level changes throughout deployment. The plot shown in Figure 4 is shown up to 320 hrs of operation, as after that the sampling interval became too large to capture periodic changes properly.

2.4 Simulation model parameters

The simulation model parameters were selected from the field deployment data. The measured water-level response showed a periodic tidal pattern with an approximate 12 h cycle, and the water level varied from about 1.5 m to 3.0 m on average. These observations were used to define the simulated water-level input as a repeating 12 h oscillation between 1.5 m and 3.0 m. Field measurements also indicated that the solar panels supplied approximately 55 mW during daytime conditions. Accordingly, the simulation included a daytime solar-power input of 55 mW applied for 12 h each day and zero solar input during nighttime, represented by the square-wave profile shown in Figure 5. As listed in Table 1, the sensor consumes about 29 mA while taking a sample and saving the measurement to the onboard SD card. For wireless transmission, the system uses an nRF24 radio module, which consumes approximately 12 mA in steady-state operation. Therefore, the total active current used in the simulation was assumed to be 41 mA (29 mA sensing + 12 mA radio). Using these parameters, a simplified operating environment was constructed to evaluate long-term sensor performance. The simulation was then used to examine the remaining battery energy under different idle-current levels, sampling intervals, and operation durations. The simulation results are discussed in Section 3.

3. RESULTS

Because the sensor wakes only to acquire and store a measurement and then returns to sleep, it spends most of its operating time in a low-power idle state. However, even during sleep, the connected peripheral hardware continues to draw power, resulting in a nonzero idle current. As listed in Table 1, the present sensor configuration has an idle current of 9 mA. Therefore, reducing idle current is the most direct way to improve the battery energy

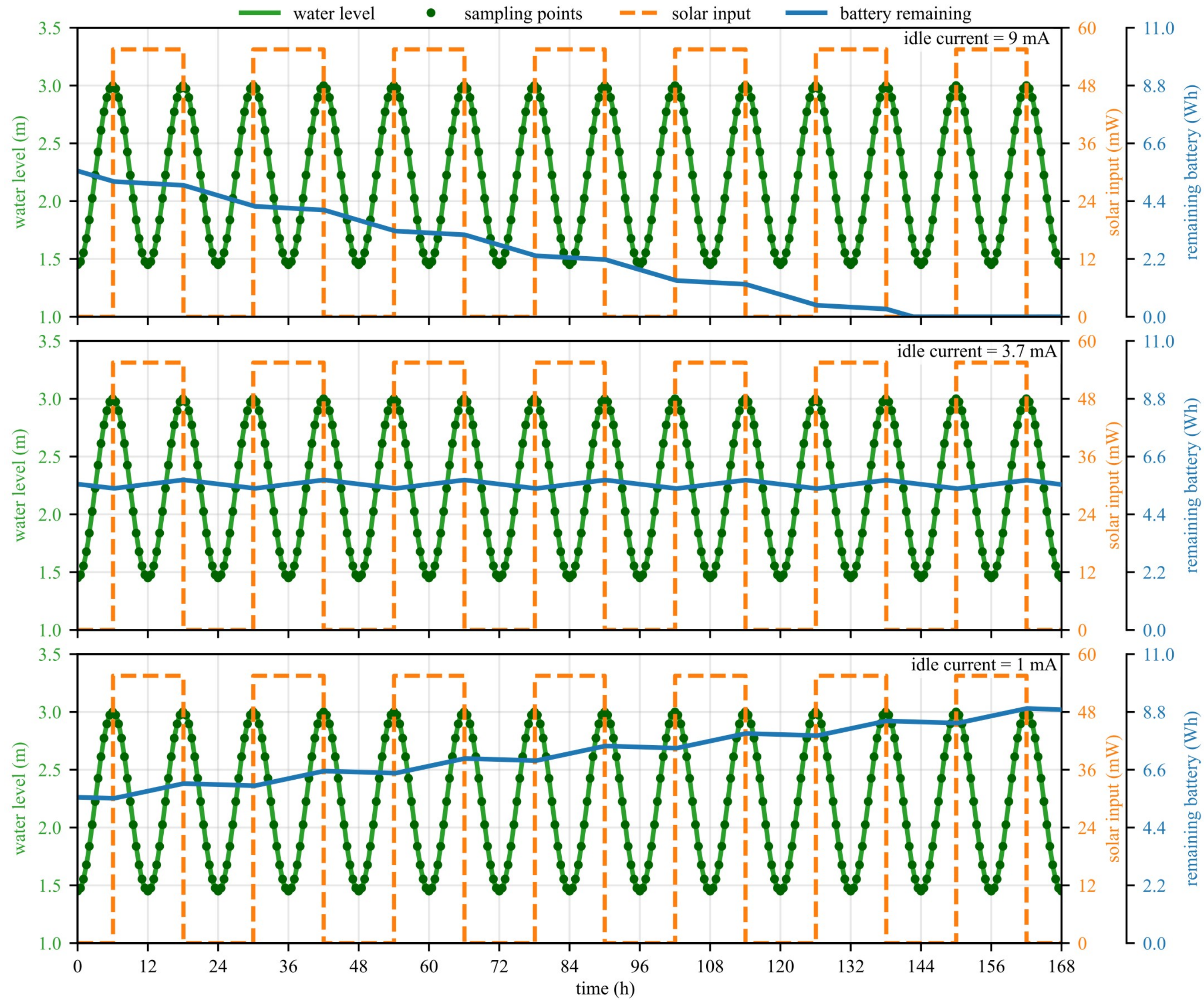

Figure 5. Simulation of power consumption over a one-week period (168 h) with a fixed 30 min sampling interval, for three idle-current levels of 9 mA, 3.7 mA, and 1 mA, showing decreasing, near-steady, and increasing trends in remaining battery capacity, respectively.

reserve. To examine the idle current's effect, the sensor operation was simulated over a one-week period (168 h) using a fixed 30 min sampling interval, which corresponds to the shortest interval used during field data collection. The initial battery energy was assumed to be half of full capacity, or 5.55 Wh. The simulation results are shown in Figure 5. For the present idle current of 9 mA, the battery energy decreases continuously and is fully depleted after approximately 144 h of operation. When the idle current is reduced to 3.7 mA, the battery remains close to its initial level, indicating near-steady-state operation. When the idle current is further reduced to 1 mA, the remaining battery energy increases throughout the simulation and reaches about 8.8 Wh by the end of the one-week period. These results show that idle current has a dominant effect on long-term energy sustainability.

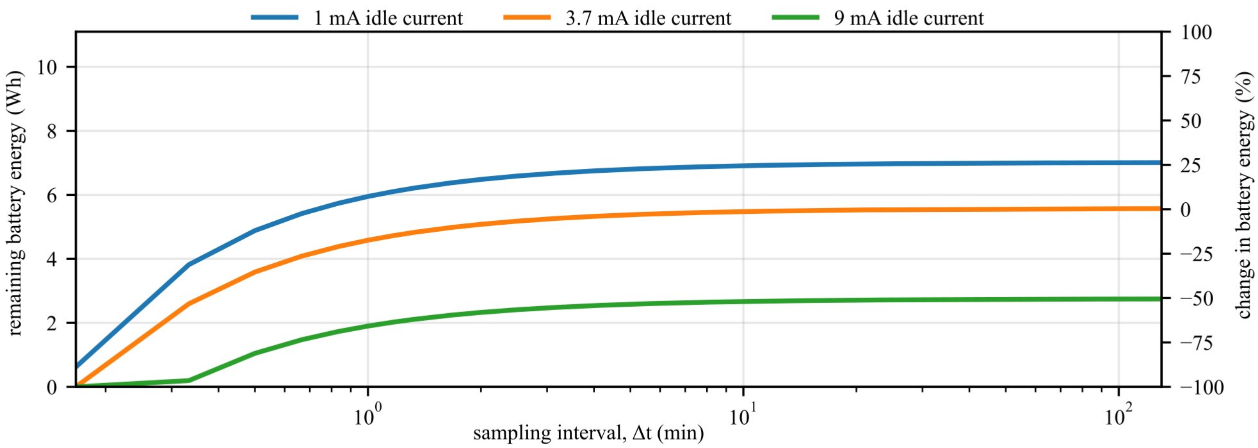

Figure 6. Simulated remaining battery energy over three days of operation period as a function of sampling interval, where the x-axis is plotted on a logarithmic scale, and the y-axis represents remaining battery capacity under three different idle current load of 1 mA, 3.7 mA, and 9 mA.

Figure 6 shows the simulated remaining battery energy after three days of operation as a function of sampling interval for three idle-current levels. In all cases, increasing the sampling interval improves the remaining battery reserve because the sensor wakes less frequently and therefore spends less time in its higher-power active state. The curves rise rapidly at short sampling intervals and then gradually approach a plateau, indicating that the largest energy benefit is obtained when increasing the interval from the high-frequency sampling range. This result is useful for energy controller design because it provides a direct mapping between energy reserve and sampling interval. A controller can use the measured battery state to adjust the sampling interval dynamically, increasing it when the battery reserve becomes low and decreasing it when sufficient energy is available, thereby maintaining near-steady energy operation over long deployments. The 1 mA idle-current case is particularly significant because the blue curve shows that the system can operate at a sampling interval of about 1 min while still maintaining a battery level slightly above the zero-percentage-change condition. In other words, at this operating point, the system supports near-continuous high-rate monitoring without net battery depletion over the simulated period. This demonstrates that lowering the idle current substantially expands the feasible control range and allows the sensor to respond to rapidly changing water conditions while maintaining energy reserve.

4. CONCLUSION

This study presented the design, field deployment, and energy analysis of a SWaP-constrained UAV-deployable water-level system (SCUWLS) for long-term monitoring in difficult-to-access locations. The system integrates ultrasonic sensing, onboard logging, solar charging, and battery-aware operation in a compact package suitable for deployment beneath bridge or culvert structures. Field deployment at Turkey Creek and Goose Creek demonstrated successful operation under real tidal conditions. The simulation results quantified the dominant role of idle current in long-term energy sustainability. Reducing the idle current to 3.7 mA produced near-steady-state behavior, while reducing it further to 1 mA increased the remaining battery energy to about 8.8 Wh after one week of operation.

The sampling-interval study showed that, at 1 mA idle current, the system could operate at approximately 1 min sampling intervals while still maintaining battery energy slightly above the zero-change condition. Demonstrated results show that reducing idle current not only improves endurance but also enables substantially faster data collection without net battery depletion. The relationship identified between battery reserve, idle current, and sampling interval provides a practical basis for controller design. Rather than relying only on fixed voltage thresholds, a future controller can use battery-state information from the INA219 and the simulated energy-response curves to dynamically select the sampling interval that maintains energy balance. In this way, the sensor can sample more frequently when energy is abundant and automatically reduce sampling frequency when reserve energy becomes limited. Such a strategy would improve long-term autonomy, preserve battery reserve, and allow higher temporal resolution during critical water-level events.

5. ACKNOWLEDGMENTS

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