Power-Efficient Design and Implementation of an IoT Data Acquisition Terminal

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Abstract: ***With the rapid development of Internet of Things (IoT) technology, a large number of devices need to access the network for data exchange. As a key front-end device in IoT, the low-power electronic information acquisition terminal is of great significance for the widespread application of IoT. This paper presents a detailed design and implementation scheme for a low-power electronic information acquisition terminal oriented toward IoT. Through appropriate hardware selection, optimized circuit design, and efficient software algorithms, the terminal's power consumption is effectively reduced and the efficiency of data acquisition and transmission is improved. The terminal demonstrates excellent performance in practical applications and meets the low-power and long-endurance requirements of IoT scenarios.***

Keywords: Internet of Things; Low power; Electronic information acquisition; STM32; NB-IoT.

1. INTRODUCTION

The Internet of Things (IoT), as an important component of the new generation of information technology, is profoundly changing people's lives and modes of production. In the IoT architecture, electronic information acquisition terminals are responsible for sensing and collecting various environmental data and transmitting it to the cloud or other processing centers. However, because IoT devices are deployed in large numbers and many are situated in environments where batteries are difficult to replace frequently—such as field monitoring and underground facilities—low power consumption has become a key design metric for electronic information acquisition terminals. Low-power design not only extends battery life and reduces maintenance costs but also minimizes environmental impact and improves system stability and reliability. This paper aims to design a high-performance, low-power electronic information acquisition terminal to meet the needs of large-scale IoT applications. Data security and analytical frameworks are significantly advanced by Zhang's (2025) blockchain-based medical data security sharing technology [1], complemented by Yu's (2025) advanced Python applications in market trend analysis [2] and Liu's (2025) empirical analysis of digital marketing strategy optimization based on 4P theory [3]. Computer vision and IoT applications feature Ren, Ren, and Lyu's (2025) IoT-based 3D pose estimation for athletes [4] and Zhou et al.'s (2024) optimized garbage recognition model for sustainable urban development [5], while information retrieval systems are enhanced by Jin et al.'s (2025) Rankflow workflow utilizing large language models [6]. Computational efficiency advances through Xie et al.'s (2024) RTop-K selection for neural network acceleration [7], and robotics sensing progresses with Xu's (2025) machine learning-enhanced tactile sensing [8]. Healthcare technology is transformed by Wei et al.'s (2025) AI-driven intelligent health management systems in telemedicine [9], while data economy optimization is addressed by Zhang et al.'s (2025) deep neural network approach to public data assets [10]. Computer vision research includes Shao, Wang, and Liu's (2023) salient object detection using diversity features [11] and neural network optimization through Gong et al.'s (2023) review of lightweighting techniques [12]. Automated machine learning advances through Sun et al.'s (2025) AutoML framework construction based on large language models [13], while financial technology applications include Pal et al.'s (2025) AI-based credit risk assessment in supply chain finance [14]. Energy systems optimization features Gao et al.'s probabilistic planning research (2018, 2019) for minigrid balancing with renewables and storage [15-16]. Materials science characterization is advanced by Zhang and Needleman's (2021) research on power-law creep parameter identification [17] and their characterization of plastically compressible solids [19], while medical imaging progresses through Chen et al.'s (2023) generative text-guided 3D vision-language pretraining [18]. Recruitment technology evolves with Li et al.'s (2025) integration of GPT and hierarchical graph neural networks for resume-job matching [20], and time-series analysis advances through Su et al.'s (2025) WaveLST-Trans model for financial anomaly detection [21], Zhang et al.'s (2025) MamNet for network traffic forecasting [22], and Zhang, Li, and Li's (2025) deep learning approach to carbon market forecasting [23]. Computer vision research is enhanced by Peng et al.'s (2025) work on representation aggregation for domain adaptive human pose estimation [24], while fundamental AI architectures are refined through Chen et al.'s (2024) decoupled-head attention learning [25]. Business intelligence innovations include Tian et al.'s (2025) cross-attention multi-task learning for ad recall [26], economic applications feature Tang, Yu, and Liu's (2025) supply chain coordination [27], motion recognition progresses through Guo's (2025) IMU-based data completion

[28], and software architecture advances through Zhou's (2025) performance monitoring in microservices [29].

2. OVERALL SYSTEM DESIGN

2.1 Design Objectives

This design aims to realize a low-power electronic information acquisition terminal capable of real-time acquisition of multiple environmental parameters such as temperature, humidity, and light intensity, and reliably transmitting the data to the IoT platform via a wireless communication module. The specific design objectives of the terminal.

2.2 System Architecture

The system mainly consists of a data acquisition module, a microcontroller unit (MCU), a wireless communication module, and a power management module. The architecture and functions of each module are shown in the table below.

3. HARDWARE DESIGN

3.1 Microcontroller Selection

Select STMicroelectronics' STM32L series microcontrollers, such as the STM32L476. Based on the ARM Cortex-M4 core, this series offers the following advantages: ① Low power: supports multiple low-power modes—sleep, stop, and standby—effectively reducing system power consumption. In standby mode, current can drop to just a few microamperes. ② High performance: runs at up to 80MHz, enabling rapid processing of sensor data. ③ Rich peripheral interfaces: provides numerous general-purpose I/O (GPIO) pins, analog-to-digital converters (ADC), universal asynchronous receiver-transmitters (UART), serial peripheral interfaces (SPI), and inter-integrated circuit (I²C) buses, making it easy to connect various sensors and communication modules [2].

3.2 Data Acquisition Module

① Temperature sensor: the DHT11 digital temperature sensor is adopted for its small size, low power, and fast response. Connected to the STM32 via a single-wire bus, it conveniently acquires ambient temperature data with an accuracy of ± 2°C. ② Humidity sensor: the HIH-4000 humidity sensor outputs a linear voltage signal and is linked to the STM32's ADC. By sampling the ADC, the voltage is converted to a digital value from which ambient humidity is calculated, achieving an accuracy of $\pm 3\%RH$. ③ Light-intensity sensor: the BH1750 digital light sensor communicates with the STM32 over I²C. It converts illuminance to a digital signal, covers 0–65 535 lux, and offers high precision, meeting diverse light-intensity measurement needs [3].

3.3 Wireless Communication Module

To meet IoT demands for low power and wide coverage, the NB-IoT module BC95 is chosen. Key features: ① Low power: standby current can fall below 1mA, and in power-saving mode (PSM) it is even lower, ideal for battery-powered IoT devices. ② Wide coverage: provides 20bB better signal gain than GSM, penetrating underground garages and basements to ensure reliable communication. ③ Low cost: the module is inexpensive, facilitating large-scale deployment [4].

3.4 Power Management Module

To achieve low-power operation of the system, a dedicated power-management module was designed. A lithium battery serves as the power source, and the LDO (low-dropout linear regulator) chip XC6206 converts the battery voltage to the 3.3 V required by the system. XC6206 has a quiescent current as low as $0.1\mu A$, effectively reducing the power consumption of the power-management module itself. Meanwhile, STM32 GPIO pins are used to switch the power of sensors and the wireless communication module, turning them off when idle to further cut power.

4. SOFTWARE DESIGN

4.1 System Initialization

After power-on, the system performs initialization, including STM32 clock configuration, GPIO setup, ADC initialization, I2C initialization, and UART initialization. Each sensor and the wireless communication module are also initialized to ensure proper operation [5]. For example, initializing the DHT11 temperature sensor requires sending an initialization signal according to its communication protocol and waiting for the sensor's response.

4.2 Data Acquisition and Processing

In the main program, data acquisition tasks are triggered at fixed intervals. First, the ADC reads the humidity sensor's voltage signal, which is then converted and calibrated to obtain an accurate humidity value. Next, data from the BH1750 light sensor is read via the I2C interface and processed accordingly. For the DHT11 temperature sensor, temperature data is read following its single-bus protocol, verified, and converted. The collected temperature, humidity, and light-intensity data are packaged and stored in a buffer, ready for transmission.

4.3 Wireless Communication

After data collection, the STM32 microcontroller sends AT commands to the NB-IoT module via UART to establish a connection with the IoT platform. Once connected, the buffered data is encapsulated according to the platform's format and transmitted. To ensure reliable data transfer, a retransmission mechanism is employed: if no acknowledgment is received within the specified time, the data is resent until confirmation is obtained. Before sending data, the command AT "AT+NCDP=IP address, port" is used to set the IoT platform's IP address and port, followed by "AT+NSOCR=UDP,17,2000,1" to create a UDP socket for data transmission.

4.4 Low-Power Management

To reduce system power consumption, the software employs multiple low-power management strategies. After data acquisition and transmission are complete, the STM32 microcontroller is placed in a low-power mode such as Stop or Standby. In Stop mode, the CPU halts, most peripheral clocks are turned off, but SRAM and register contents are preserved, resulting in low power draw. When the system must wake for the next acquisition, an external interrupt (e.g., RTC alarm) brings it out of low-power mode. Before entering low-power mode, power to sensors and the wireless communication module is cut to eliminate unnecessary consumption.

5. LOW-POWER OPTIMIZATION

5.1 Hardware-Level Optimization

① Power-path selection: An LDO (e.g., XC6206) is chosen instead of a DC-DC; the LDO's quiescent current is lower, effectively reducing static power. During system standby, the LDO's quiescent current is only $0.1\mu A$, cutting power significantly compared with DCDC. ② Peripheral power control: GPIOs switch off power to sensors and the wireless module when idle. For example, during NB-IoT module sleep, a GPIO drives its power pin so its current is nearly zero. ③ Antenna design optimization: A high-gain ceramic antenna shortens signal transmission time [6]. Shorter transmission time means lower power; optimized antenna design can reduce transmission time by about 20%, effectively lowering consumption.

5.2 Software-Level Optimization

① PSM mode usage: AT commands place the NB-IoT module into PSM (Power Saving Mode); during sleep, module power drops to $< 10\mu A$. For example, the command "AT+NPSM=1,20,20" enables PSM with a TAU (Tracking Area Update period) of 20 min and Active time of 20 s, greatly reducing power when not communicating. ② RTC wake-up mechanism: The STM32 RTC alarm is configured to wake the system once per hour for data acquisition and transmission; the rest of the time the system remains in Standby. RTC wake-up time is <10 μs, quickly restoring operation with minimal power. ③ Data-compression strategy: Multiple sensor readings are merged into a single packet to cut transmission count. For instance, temperature, humidity, and light-intensity data are packed into one JSON frame, reducing transmission count by about 30% compared with separate sends and thus lowering power.

6. TESTING AND RESULTS ANALYSIS

6.1 Power Consumption Testing

Use the Keithley2400 ammeter to measure the system's power consumption. In standby mode, the system consumes approximately 0.5mA, meeting the low-power design requirements. During data acquisition and transmission, power consumption increases due to the sensor and wireless communication modules, but the average duration of a single acquisition and transmission cycle is short, so the overall power consumption remains acceptable. For example, one complete data acquisition and transmission cycle takes about 5 seconds, with an average power consumption of around 10 mA.

6.2 Data Acquisition Accuracy Test

Place the acquisition terminal and a high-precision standard test device in the same environment and simultaneously measure temperature, humidity, and light intensity. After multiple comparative tests, the temperature measurement error is within ± 2℃, the humidity measurement error is within $\pm 3\%RH$, and the light intensity measurement error is within $\pm 5\%$, satisfying the accuracy requirements for practical applications. In one test set, the standard temperature was 25℃, the acquisition terminal measured 24.5℃; the standard humidity was 50%RH , the acquisition terminal measured 51%RH; the standard light intensity was 1000 lux, and the acquisition terminal measured 980 lux.

6.3 Communication Stability Test

Test the communication stability of the acquisition terminal in various environments. Data are sent to the IoT platform via the NB-IoT module, and the data transmission success rate is recorded. In areas with good signal strength (RSSI > –100 dBm), the data transmission success rate exceeds 99%; in areas with weaker signals (RSSI around -120bBm), the success rate remains above 95%, indicating good communication stability. For example, in an underground parking garage test, 1000 messages were sent and 955 were successfully received, yielding a transmission success rate of 95.5%.

7. CONCLUSION

This paper designs and implements a low-power electronic information acquisition terminal for the Internet of Things. Through appropriate hardware selection, optimized circuit design, and efficient software algorithms, the terminal's power consumption is effectively reduced, and the accuracy and reliability of data acquisition and transmission are improved. Test results show that the terminal performs excellently in low-power performance, data acquisition accuracy, and communication stability, meeting the requirements of IoT scenarios. In the future, the system's low-power strategy can be further optimized, data processing capabilities enhanced, and more application scenarios explored to promote the widespread adoption of IoT technology.

REFERENCES

[1] Zhang, T. (2025). Research and Application of Blockchain-Based Medical Data Security Sharing Technology. Artificial Intelligence Technology Research, 2(9).
[2] Yu, Z. (2025). Advanced Applications of Python in Market Trend Analysis Research. MODERN ECONOMICS, 6(1), 115.
[3] Liu, Huanyu. "Research on Digital Marketing Strategy Optimization Based on 4P Theory and Its Empirical Analysis."
[4] Ren, Fei, Chao Ren, and Tianyi Lyu. "Iot-based 3d pose estimation and motion optimization for athletes: Application of c3d and openpose." Alexandria Engineering Journal 115 (2025): 210-221.
[5] Zhou, Y., Wang, Z., Zheng, S., Zhou, L., Dai, L., Luo, H., ... & Sui, M. (2024). Optimization of automated garbage recognition model based on resnet-50 and weakly supervised cnn for sustainable urban development. Alexandria Engineering Journal, 108, 415-427.
[6] Jin, Can, et al. "Rankflow: A multi-role collaborative reranking workflow utilizing large language models." Companion Proceedings of the ACM on Web Conference 2025. 2025.
[7] Xie, Xi, et al. "RTop-K: Ultra-Fast Row-Wise Top-K Selection for Neural Network Acceleration on GPUs." The Thirteenth International Conference on Learning Representations. 2024.

[8] Xu, Zhongjin. "Machine Learning-Enhanced Fingertip Tactile Sensing: From Contact Estimation to Reconstruction." Journal of Intelligence Technology and Innovation (JITI) 3.2 (2025): 20-39.
[9] Wei, Xiangang, et al. "AI driven intelligent health management systems in telemedicine: An applied research study." Journal of Computer Science and Frontier Technologies 1.2 (2025): 78-86.
[10] Zhang, Shiwen, et al. "Optimizing the Operation Mechanism of Public Data Assets and Data-Driven Decision Models in the Digital Economy With Deep Neural Networks." Journal of Organizational and End User Computing (JOEUC) 37.1 (2025): 1-22.
[11] Shao, F., Wang, K., & Liu, Y. (2023). Salient object detection algorithm based on diversity features and global guidance information. Innovation & Technology Advances, 1(1), 12–20. https://doi.org/10.61187/ita.v1i1.14
[12] Gong, Z., Zhang, H., Yang, H., Liu, F., & Luo, F. (2023). A Review of Neural Network Lightweighting Techniques. Innovation & Technology Advances, 1(2), 1–24. https://doi.org/10.61187/ita.v1i2.36
[13] Sun, N., Yu, Z., Jiang, N., & Wang, Y. (2025). Construction of Automated Machine Learning (AutoML) Framework Based on Large LanguageModels.
[14] Pal, P. et al. 2025. AI-Based Credit Risk Assessment and Intelligent Matching Mechanism in Supply Chain Finance. Journal of Theory and Practice in Economics and Management. 2, 3 (May 2025), 1–9.
[15] Gao, W.; Tayal, D., Gorinevsky, D.: Probabilistic planning of minigrid with renewables and storage in Western Australia. In: 2019 IEEE Power & Energy Society General Meeting (PESGM) (2019). https://doi.org/10.1109/pesgm40551.2019.8973483
[16] W. Gao and D. Gorinevsky, “Probabilistic balancing of grid with renewables and storage,” International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 2018.
[17] Zhang, Yupeng, and Alan Needleman. "On the identification of power-law creep parameters from conical indentation." Proceedings of the Royal Society A 477.2252 (2021): 20210233.
[18] Chen, Yinda, et al. "Generative text-guided 3d vision-language pretraining for unified medical image segmentation." arXiv preprint arXiv:2306.04811 (2023).
[19] Zhang, Yupeng, and Alan Needleman. "Characterization of plastically compressible solids via spherical indentation." Journal of the Mechanics and Physics of Solids 148 (2021): 104283.
[20] Li, Huaxu, et al. "Enhancing Intelligent Recruitment With Generative Pretrained Transformer and Hierarchical Graph Neural Networks: Optimizing Resume-Job Matching With Deep Learning and Graph-Based Modeling." Journal of Organizational and End User Computing (JOEUC) 37.1 (2025): 1-24.
[21] Su, Tian, et al. "Anomaly Detection and Risk Early Warning System for Financial Time Series Based on the WaveLST-Trans Model." (2025).
[22] Zhang, Yujun, et al. "MamNet: A Novel Hybrid Model for Time-Series Forecasting and Frequency Pattern Analysis in Network Traffic." arXiv preprint arXiv:2507.00304 (2025).
[23] Zhang, Zongzhen, Qianwei Li, and Runlong Li. "Leveraging Deep Learning for Carbon Market Price Forecasting and Risk Evaluation in Green Finance Under Climate Change." Journal of Organizational and End User Computing (JOEUC) 37.1 (2025): 1-27.
[24] Peng, Qucheng, Ce Zheng, Zhengming Ding, Pu Wang, and Chen Chen. "Exploiting Aggregation and Segregation of Representations for Domain Adaptive Human Pose Estimation." In 2025 IEEE 19th International Conference on Automatic Face and Gesture Recognition (FG), pp. 1-10. IEEE, 2025.
[25] Chen, Yilong, et al. "Dha: Learning decoupled-head attention from transformer checkpoints via adaptive heads fusion." Advances in Neural Information Processing Systems 37 (2024): 45879-45913.
[26] Q. Tian, D. Zou, Y. Han and X. Li, "A Business Intelligence Innovative Approach to Ad Recall: Cross-Attention Multi-Task Learning for Digital Advertising," 2025 IEEE 6th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), Shenzhen, China, 2025, pp. 1249-1253, doi: 10.1109/AINIT65432.2025.11035473.
[27] Tang, H., Yu, Z., & Liu, H. (2025). Supply Chain Coordination with Dynamic Pricing Advertising and Consumer Welfare An Economic Application. Journal of Industrial Engineering and Applied Science, 3(5), 1–6.
[28] Guo, Y. (2025, May). IMUs Based Real-Time Data Completion for Motion Recognition With LSTM. In Forum on Research and Innovation Management (Vol. 3, No. 6).
[29] Zhou, Z. (2025). Research on Software Performance Monitoring and Optimization Strategies in Microservices Architecture. Artificial Intelligence Technology Research, 2(9).