Research on Remote Data Acquisition Model of Power Batteries in the Internet of Vehicles Environment

Dan Zou
College of Mechanical and Electrical Engineering, Yunnan Opening University, Kunming, Yunnan, China

Abstract: As the primary power source for new energy vehicles, the performance of power batteries is one of the key factors determining vehicle stability, safety, and driving range. The intervention of remote data acquisition and intelligent monitoring technologies enables timely and efficient monitoring of the operational status of power battery packs, analysis of critical battery pack data, assistance to the vehicle control system in reasonably selecting control strategies, and early warning and analysis of safety hazards and faults in power battery packs, providing a more robust guarantee for the safety of electric vehicles. This paper conducts an in-depth study on the remote data acquisition model of power batteries in the Internet of Vehicles (IoV) environment, aiming to construct an efficient and reliable acquisition system. Experimental verification shows that the constructed model can accurately and timely collect and transmit battery data, providing strong support for battery health management and fault early warning.

Keywords: Power Battery; Remote Data Acquisition; Internet of Vehicles (IoV); Sensor; On-Board Terminal

1. Introduction

With the transformation of the global energy structure and the growing awareness of environmental protection, electric vehicles (EVs), as a clean-energy transportation solution, have emerged as a major trend in the automotive industry. The power battery, a core component of new energy vehicles, directly impacts the operational performance and user experience of the vehicle through its performance and safety. Key parameters of power batteries include voltage, current, temperature, and State of Charge (SOC). By analyzing these parameters, the Battery Management System (BMS) can perform functions such as charge/discharge control, cell balancing, and fault diagnosis, thereby optimizing battery usage efficiency and extending battery lifespan.

However, traditional data acquisition methods for power batteries face limitations such as insufficient real-time data collection, restricted data coverage, poor flexibility, and limited analytical capabilities. These shortcomings hinder their ability to meet the demands of large-scale EV deployment and refined battery management.

Compared with traditional methods, remote data acquisition enables real-time monitoring of battery status and critical parameters, provides timely warnings for faults and abnormalities, and significantly reduces the occurrence of safety incidents. Simultaneously, the remote data acquisition system for power batteries streamlines battery monitoring and management. Data servers can analyze, store, and upload collected data to centralized monitoring centers, achieving unified management of multiple electric vehicles (EVs). This remote monitoring capability eliminates geographical constraints, allowing continuous battery status tracking regardless of the vehicle's location. For large-scale EV fleet operators, remote monitoring and management substantially enhance operational efficiency and reduce administrative costs [1-3].

The key technologies of the remote data acquisition model for power batteries include data acquisition, data transmission, data processing and storage technologies, as well as data visualization and user interfaces [4]. Among these, the development of the model prioritizes the following trends:

- High-precision data acquisition and processing
- Enhanced system real-time performance and reliability

- Intelligent data analysis and decision-making
- Integration with multi-energy systems

2. System Architecture and Key Technologies

The remote data acquisition system for power batteries is generally built upon the Internet of Vehicles (IoV) architecture. It enables connectivity between vehicles and various terminal devices/service platforms (V2X, Vehicle to Everything) through wireless communication technologies, facilitating real-time data exchange and processing to enhance vehicle intelligent capabilities and improve the operational efficiency of transportation systems.

The remote data acquisition model consists of three layers:

- Data Acquisition Layer
- Data Transmission Layer
- Data Storage and Processing Layer

The detailed structure is shown in Figure 1.

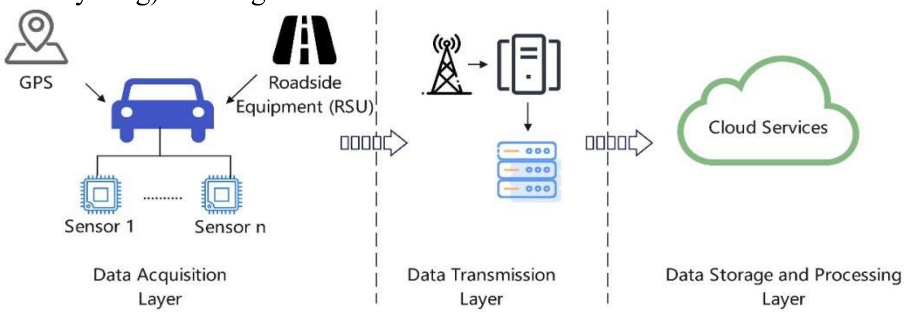


Figure 1. Architecture of the Remote Data Acquisition Model for Power Batteries

2.1 Data Acquisition Layer

The data acquisition layer comprises sensor modules, vehicle terminals, and other components. The sensor module is a critical component for obtaining battery parameters, and its performance directly impacts the accuracy and reliability of data. The sensor module primarily collects parameters such as individual cell voltage, temperature, and bus current. This data is transmitted to the vehicle terminal via the vehicle CAN bus through individual module ECUs (Electronic Control Units) and is used to calculate battery charge/discharge capacity, evaluate battery performance, and enable precise charge/discharge control.

The vehicle terminal, serving as the core of the data acquisition layer, performs functions including information collection, data processing, and communication with upper-level systems. It can be integrated into a T-Box or vehicle control unit (e.g., a gateway) [5].

The sampling frequency of the data acquisition layer determines the system's real-time performance in obtaining battery data, Typical sampling frequencies range from 10Hz (for temperature) to 1kHz (for voltage/current), with accuracies of ±0.5% for voltage and ±1℃ for temperature， while the sampling accuracy governs data precision. Both are critical factors influencing the overall performance of the power battery remote data acquisition system. In practical applications, sampling frequency and accuracy must be optimized based on specific requirements to balance data quality with system cost and resource consumption.

2.2 Data Transmission Layer

The data transmission layer is responsible for reliably and efficiently transmitting collected battery data to data processing centers or cloud servers. Remote data transmission technologies include CAN bus and IoT integration, cellular networks (4G/5G), Dedicated Short-Range Communication (DSRC), Vehicle-to-Vehicle (V2V) communication, Vehicular Ad-hoc Networks (VANETs) with multi-hop communication, and satellite communication. These methods have distinct advantages and limitations, making them suitable for different scenarios.

2.2.1 CAN bus and IoT integration:

CAN bus enables reliable in-vehicle data transmission. Battery internal data (e.g., voltage, temperature) is transmitted via the CAN bus to the vehicle terminal, which then integrates IoT modules for remote transmission. This hybrid approach is widely used in applications such as Battery Management System (BMS) remote monitoring and smart charging management.

2.2.2 Cellular networks (4G/5G):

Cellular networks support long-distance wireless transmission of power battery data, offering wide-area coverage and high bandwidth for real-time data uploads and cloud interactions. 5G technology, with its ultra-low latency (millisecond-level) and high reliability, is particularly suited for high-real-time scenarios [6].

2.2.3 Specialized technologies:

DSRC and V2V: Based on the IEEE 802.11p protocol, these enable direct vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication with latencies as low as 20 ms.

VANETs and Multi-hop Communication: Data is relayed through multi-hop vehicle networks, combined with satellite communication for global coverage in areas without cellular base stations.

Reliability and stability of data transmission are critical to ensuring the robust operation of remote data acquisition systems. By comprehensively applying technologies such as data encryption, error-correcting coding, adaptive transmission, and multi-path transmission, the stability of data transmission in power battery remote acquisition systems can be significantly improved. This ensures that battery data is transmitted accurately and reliably to its destination, laying a solid foundation for subsequent data processing and analysis.

The purpose of data encryption is to prevent data theft or tampering, ensuring the security and stability of data transmission. Common encryption protocols include Secure Sockets Layer (SSL) and Transport Layer Security (TLS), which encrypt plaintext data into ciphertext for transmission. This protects the privacy of battery data, ensures data integrity, and avoids erroneous decisions and potential risks caused by data tampering.

Error-correcting coding (ECC) technology is employed for error control and correction in data transmission. By adding redundant information to the original data, the receiver can verify and correct errors in the received data using this redundancy. Common error-correcting coding methods include the Cyclic Redundancy Check (CRC) and Hamming codes.

Adaptive transmission and multi-path transmission technologies are critical for enhancing the stability of data transmission. Adaptive Transmission dynamically optimizes data transmission strategies by monitoring real-time network parameters such as signal strength, latency, and packet loss rate. It adapts modulation schemes, data rates, or error correction mechanisms to maintain stable performance across varying network conditions (e.g., transitioning from 4G to 5G or Wi-Fi).

By leveraging multiple parallel communication links (e.g., cellular + DSRC + satellite), Multi-Path Transmission ensures continuous data flow. If one path fails or degrades, traffic is automatically rerouted through alternative links, achieving 99.99% transmission continuity in dynamic environments like vehicular networks.

2.3 Data Processing and Storage Layer

The data processing and storage layer is designed to preprocess and store power battery data.

2.3.1 Data Preprocessing

In remote power battery data acquisition systems, raw data often contains various noise and outliers due to factors such as sensor errors and electromagnetic interference. Additionally, data formats and ranges may vary. To improve data quality and provide a reliable foundation for subsequent analysis and decision-making, raw data must undergo preprocessing. Common preprocessing methods include data cleaning, noise reduction, and normalization.

The purpose of data cleaning is to identify anomalies and either remove or correct outliers. A commonly used data cleaning method is the Z-Score method. The Z-Score is a statistical technique that evaluates how far a data point deviates from the mean, standardized by the standard deviation. The calculation formula is shown in Equation (1).

$$Z = \frac{X-\mu}{\sigma} \quad (1)$$

In the formula, X denotes the original data value, μ denotes the mean of the data, and σ denotes the standard deviation.

Noise reduction smooths the data and eliminates noise interference. Common denoising methods include filtering algorithms such as the mean filter, median filter, and Kalman filter.

Data normalization is a critical technique in data preprocessing. It transforms data into a specific range or distribution to eliminate the impact of varying scales or units on data analysis, enabling comparison and analysis of different parameters on a unified scale. This enhances the accuracy and stability of data analysis algorithms. A commonly used normalization method is Min-Max Normalization, which linearly maps data to a predefined interval (e.g., [0, 1]). The calculation formula is shown in Equation (2):

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

In the formula, Y is the normalized data, X is the original data, X_{min} is the minimum value in the original dataset, and X_{max} is the maximum value in the original dataset.

2.3.2 Data storage

Data storage is a critical component for long-term data preservation and subsequent analysis. Common data storage methods include database storage and cloud storage.

In power battery data management, relational databases such as MySQL and Oracle excel at organizing and managing structured data. Parameters like voltage, current, temperature, and timestamps can be stored in predefined table structures. When analyzing historical battery data, users can query voltage values within specific time periods using SQL statements and calculate statistical metrics (e.g., mean, maximum, minimum) to support battery performance evaluation.

In addition to structured sensor data, power battery data acquisition may involve unstructured data such as logs or fault descriptions. Non-relational databases like MongoDB and Redis efficiently store such data, offering horizontal scalability and high-concurrency read/write performance. In distributed storage environments, these databases use sharding to distribute data across multiple nodes, enabling linear scalability of storage capacity to meet the growing demands of power battery data volumes.

Cloud storage, a storage method emerging with the development of cloud computing in recent years, provides elastic storage resources that dynamically adjust storage capacity based on data volume, eliminating the need for users to manage complex hardware deployment and maintenance. Additionally, cloud storage offers high availability and data backup capabilities, typically replicating data across multiple geographic locations to ensure security and reliability.

In multi-vehicle, large-scale power battery data acquisition scenarios, cloud storage enables centralized storage of battery data from all vehicles, facilitating unified management and analysis for automakers and research institutions.

3. System Sensor Selection

Sensors are critical components for data acquisition. The primary parameters for monitoring the status, managing the operational processes, and analyzing faults of power battery packs include voltage, current, and temperature. Below is a selection analysis of these three types of sensors.

3.1 Voltage Sensor Selection Analysis

The voltage of a single cell in a new energy power battery ranges from 3–4V, while the entire battery pack typically operates within 300–800V. Voltage sensors must meet the required voltage range and provide robust isolation to prevent high-voltage damage to the system. Additionally, due to the wide operating temperature variations in new energy vehicles, sensors must exhibit high temperature stability.

Key Parameters for Voltage Sensors:

- Cell Voltage Measurement Range: 2.5V–4.5V (covers overcharge and overdischarge limits)
- Isolation Withstand Voltage: ≥2× system maximum voltage
- Accuracy: ≤±0.5% FS (Full Scale)
- Response Time: ≤10ms

A comparison of sensor selection options is shown in Table 1.

3.2 Current Sensor Selection Analysis

Current measurement is critical for calculating battery states such as State of Charge (SOC) and State of Health (SOH). The operating current range of pure electric vehicles typically spans from tens to hundreds of amperes. When selecting a sensor, factors such as measurement range, response time, bandwidth, and sampling rate must be considered, especially for capturing rapid current variations under dynamic operating conditions.

Key Parameters for Current Sensors:

- Measurement Range: ±500A (bidirectional charge/discharge measurement)
- Bandwidth: ≥10kHz (to capture transient currents)
- Accuracy: ≤±1% FS (essential for high-precision SOC/SOH estimation)
- Temperature Drift: ≤±0.1%/°C (stable

performance across wide temperature ranges)
A comparison of sensor selection options is shown in Table 2.

3.3 Temperature Sensor Selection Analysis

The temperature of power battery packs directly impacts their performance and safety. Common temperature sensors include NTC thermistors, RTDs (Resistance Temperature Detectors), and digital sensors. Key parameters for sensor selection include temperature range, accuracy, response time, reliability, and the need for multi-point measurements within the battery pack, which necessitates compact sensor sizes and flexible installation methods.

Key Parameters for Temperature Sensors:

- Temperature Range: -40℃ ~ +125℃ (covers extreme operating conditions)
- Response Time: ≤5s (rapid detection of thermal runaway)
- Multi-Point Monitoring: 2–4 measurement points per module (for cell balancing)
- Long-Term Stability: ≤±1℃/year

A comparison of sensor selection options is shown in Table 3.

Table 1. Voltage Sensor Selection Comparison

Type	Principle	Advantages	Disadvantages	Model
Isolation Amplifier	Resistive Divider + Isolation Amplifier	Low cost, simple structure	Significant temperature drift, poor long-term stability	TI AMC1301
Hall Sensor	Hall Effect	Non-contact, strong EMI immunity	High cost, zero-point drift	LEM LV25-P
Fiber Optic Sensor	Electro-Optic Modulation	Ultra-high isolation, EMI-resistant	Expensive, complex system integration	Customized

Based on practical operational requirements, closed-loop Hall sensors are selected as the system voltage sensors.

Table 2. Current Sensor Selection Comparison

Type	Principle	Advantages	Disadvantages	Model
Shunt Resistor	Ohm's Law (I=V/R)	Low cost, fast response	Severe self-heating, complex thermal compensation	Vishay WSLP Series
Open-Loop Hall	Hall Element + Magnetic Core	Non-contact, moderate cost	Magnetic hysteresis, limited accuracy	Allegro ACS758
Fluxgate Sensor	Fluxgate Principle	Ultra-high accuracy (±0.1%), low drift	High cost, large size	LEM ITN Series

Considering the system's operational requirements and the need for accurate SOC estimation in power battery packs, fluxgate sensors are selected for current data acquisition.

Table 3. Temperature Sensor Selection Comparison

Type	Principle	Advantages	Disadvantages	Model
NTC Thermistor	Negative Temperature Coefficient	Ultra-low cost, high sensitivity	Nonlinear output, requires calibration	Murata NXFT Series
PT100/1000	Platinum Resistance	High linearity, accuracy (±0.3℃)	Higher cost, 3-wire compensation needed	TE Connectivity PTF
Digital Sensor	Integrated ADC + Digital I/F	Digital output, strong noise immunity	Higher per-unit cost, limited bandwidth	Maxim DS18B20

The system selects NTC thermistors for temperature data acquisition.

3.4 Key Considerations for System Integration

When selecting sensors, in addition to primary parameters such as measurement range, accuracy, and response time, system integration requirements must be thoroughly evaluated. These include size and installation methods, power consumption, communication interface types, EMC/EMI resistance, and safety ratings.

Due to the limited internal space of the battery pack, selected sensors must adopt surface-mount or modular integrated designs, with installation methods suitable for the battery module structure. The operating and standby power consumption of sensors directly affect the overall energy consumption of the system. During system design, priority should be given to low-power sensor modules, along with strategies such as sleep modes and dynamic adjustment of sampling rates to reduce power consumption. Aligned with the operational characteristics of onboard systems, communication interfaces should prioritize high real-time performance protocols like CAN FD or SENT. For EMC design, sensors must comply with the ISO 11452-2 automotive electronic anti-interference standard.

4. System Vehicle Terminal Construction

The vehicle terminal hardware adopts an embedded system, which is installed within the T-Box or gateway. The detailed structure is shown in Figure 2.

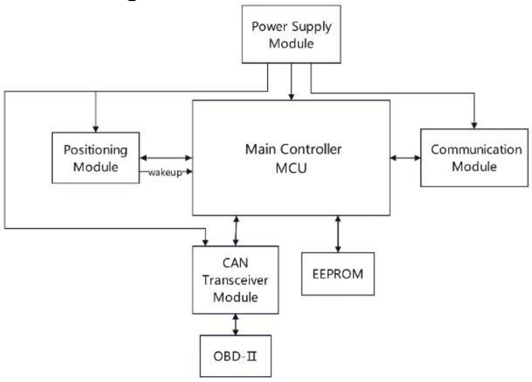


Figure 2. Vehicle Terminal Hardware System Architecture

The hardware system consists of a main controller MCU, communication module, positioning module, power supply module, and Electrically Erasable Programmable Read-Only Memory (EEPROM). After receiving sensor-collected data from vehicle components, the control units exchange information with the vehicle terminal via the CAN bus. The CAN transceiver performs signal conversion between data and differential voltage levels.

The communication module receives commands through a serial port and transmits the vehicle's location data to the MCU. The MCU communicates remotely with the cloud via the communication module, transmitting real-time vehicle status information to the monitoring platform and receiving command signals from the cloud. The power supply module provides a stable operating voltage for the hardware system [7].

4.1 Main Controller

The main controller MCU is the core of the embedded system, selected as the STM32F103RBT6 chip. The STM32F103RBT6 is a 32-bit microcontroller based on the ARM Cortex-M3 core, manufactured by STMicroelectronics. Key specifications include:

- Clock Speed: 72 MHz
- Memory: 128 KB Flash, 20 KB SRAM
- Analog-to-Digital Converters (ADCs): Two 12-bit ADCs
- Timers: Three general-purpose 16-bit timers, one PWM timer
- Communication Interfaces: Two I²C, SPI, USART, USB, and one CAN interface
- Operating Temperature: -40°C to +85°C
- Power Modes: Supports multiple power-saving modes for low-power applications.

The minimum system circuit for the vehicle terminal is shown in Figure 3.

4.2 Power Supply Module

The power supply module provides a stable 3.3V voltage to the main control circuit, utilizing the linear voltage regulator ME6211C33M5G. This chip delivers 3.3V output voltage with a 500mA current capacity and operates within a temperature range of -40°C to +150°C, meeting the system design requirements. The hardware circuit of the power supply module is shown in Figure 4, with the 5V input power supplied by the vehicle power source.

4.3 CAN Transceiver Module

The CAN transceiver module primarily performs the conversion between data and differential voltage signals. The circuit is shown in Figure 5. The TD301DCANHE chip is selected for the communication module. This chip operates on a 3.3V power supply, with a 120Ω termination resistor connected between the CANH and CANL pins [8,9].

4.4 Communication Module

Communication modules are categorized by functionality into cellular modules (e.g., 2G/3G/4G/5G/NB-IoT) and non-cellular modules (e.g., Wi-Fi, Bluetooth, LoRa). By transmission rate, they can be classified as:

- High-rate modules (e.g., 5G and 4G),
- Medium-rate modules (e.g., 3G and eMTC),
- Low-rate modules (e.g., 2G and NB-IoT).

Considering both transmission range and rate requirements, the high-rate cellular module

EC20 is selected [10].

The EC20 module adopts LTE 3GPP Rel.11 technology, operates on a 3.3V power supply (compatible with the system's power design), and supports 4G communication with a maximum downlink rate of 150 Mbps and uplink rate of 50 Mbps, meeting data transmission demands.

The EC20 module parameters are listed in Table 4.

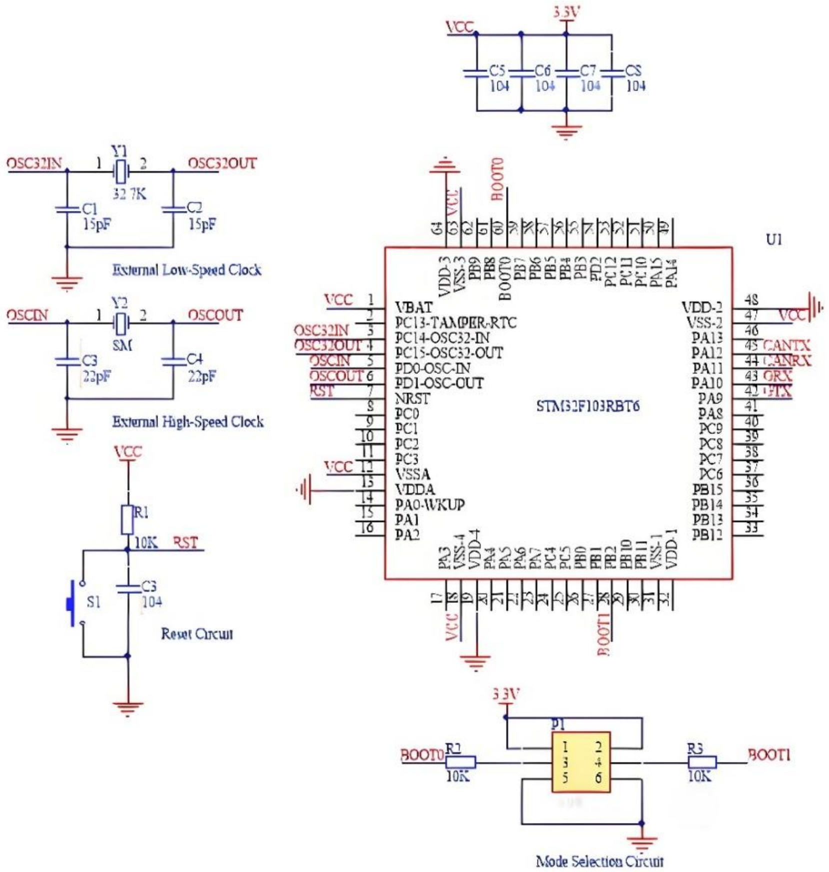


Figure 3. Minimum System Circuit Diagram

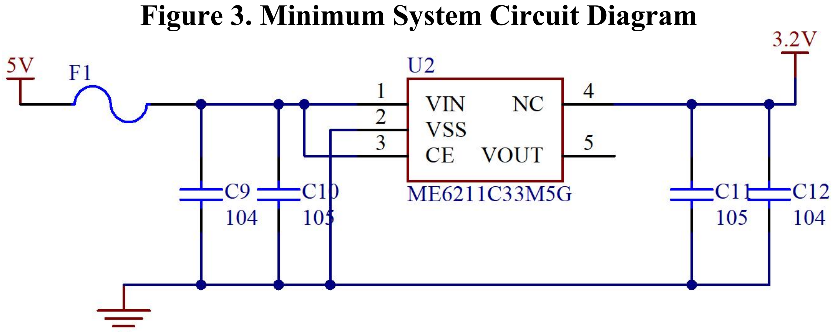


Figure 4. Power Supply Module

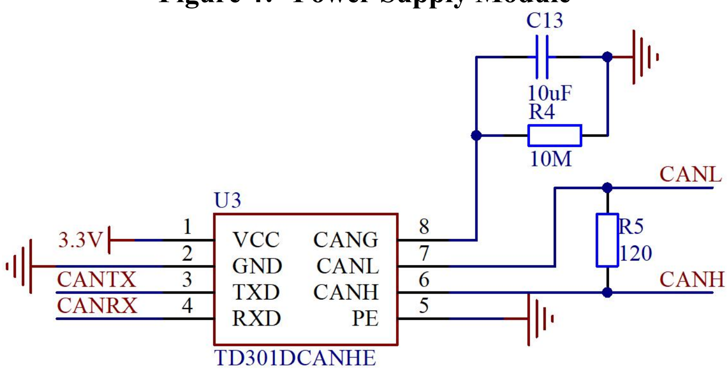


Figure 5. CAN Transceiver Module

Table 4. EC20 Parameter Table

Parameter	Specification
Operating Voltage	3.3V
Frequency Bands	TDD-LTE: B38/B39/B40/B41 FDD-LTE: B1/B3/B8 WCDMA: B1/B8 TD-SCDMA: B34/B39 GSM: 900/1800 MHz
Transmission Rate	EDGE: Max 236.8 Kbps (DL/UL) GPRS: Max 85.6 Kbps (DL/UL)
Interfaces	UART: Supports RTS/CTS hardware flow control (Baud rate up to 230,400 bps) USB: USB 2.0 protocol (Max 480 Mbps)
Protocols	TCP/UDP/PPP/FTP/HTTP

Note: Since the EC20 module operates at 1.8V when using the UART interface, a level conversion circuit is required. Therefore, in the system design, the USB interface is directly connected to the main controller.

4.5 Positioning Module

The positioning module provides vehicle location information to the main controller. The UM220 dual-system chip from Unicore Communications is selected. This chip supports both GPS and BeiDou positioning systems, operates at 3.0–3.6V (compatible with the system power supply), and its detailed parameters are listed in Table 5.

The circuit design of the positioning module is shown in Figure 6. TXD2 and RXD2 are used as data output interfaces connected to the main controller's serial port. D2 is a germanium diode with a forward voltage drop of 0.3V, serving as a voltage matching component between the VBAT pin and the 3.3V power supply module.

Table 5. UM220 Parameters

Operating Voltage	3.0–3.6V
Frequency	1559–1577 MHz
Operating Temperature	-40°C to +85°C
Interfaces	3 UART ports, LVTTL level, baud rate 1200–230,400 bps
Positioning Accuracy	3m
Velocity Accuracy	0.1 m/s

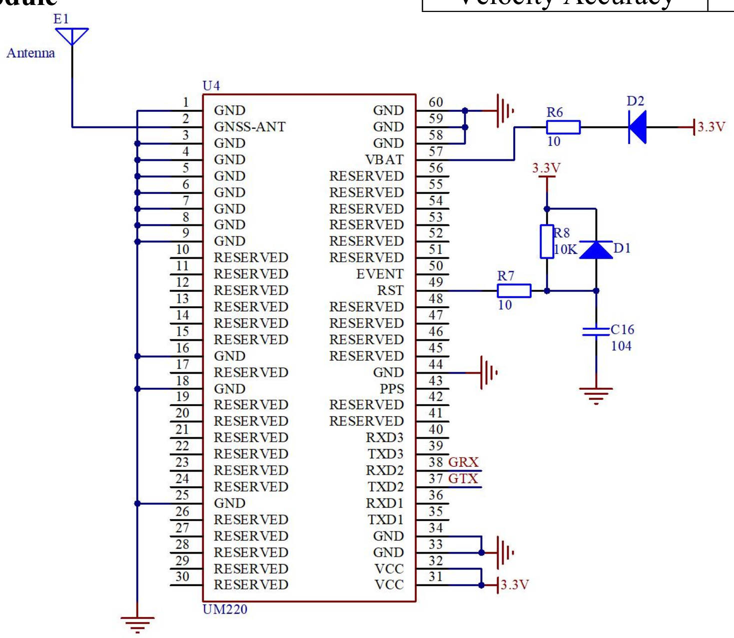


Figure 6. Positioning Module Circuit

5. System Key Technologies

5.1 CAN Bus Technology

The main control unit of the remote diagnostic system collects status data from vehicle components via the CAN bus. The CAN transmission protocol is a multi-master serial communication bus characterized by high bit rate and high resistance to electromagnetic interference. The international CAN standards primarily include *ISO 11898* (for high-speed applications) and *ISO 11519* (for low-speed fault-tolerant applications).

The CAN bus network architecture includes closed-loop and open-loop structures. The closed-loop structure is suitable for high-speed, short-distance CAN networks, while the open-loop structure is used for low-speed, long-distance transmission. Terminal nodes on the bus are integrated into vehicle control units, with hardware components including CAN controllers and CAN transceivers.

CAN employs twisted-pair cables for differential signal transmission, where information is conveyed through the voltage difference between two lines (CAN_H and CAN_L). This design provides strong noise immunity and effectively suppresses external electromagnetic interference (EMI). The CAN bus excels in real-time performance, where its arbitration mechanism and frame priority design ensure low latency and predictability. It supports a multi-master system, allowing multiple nodes to simultaneously send and receive data without a master-slave hierarchy. However, only one node can transmit data at any given time. Utilizing a non-destructive arbitration mechanism, the bus determines which node retains transmission rights by comparing the priority of message identifiers (IDs), ensuring the highest-priority message is transmitted without interruption [11].

5.2 Fault Diagnosis Protocol

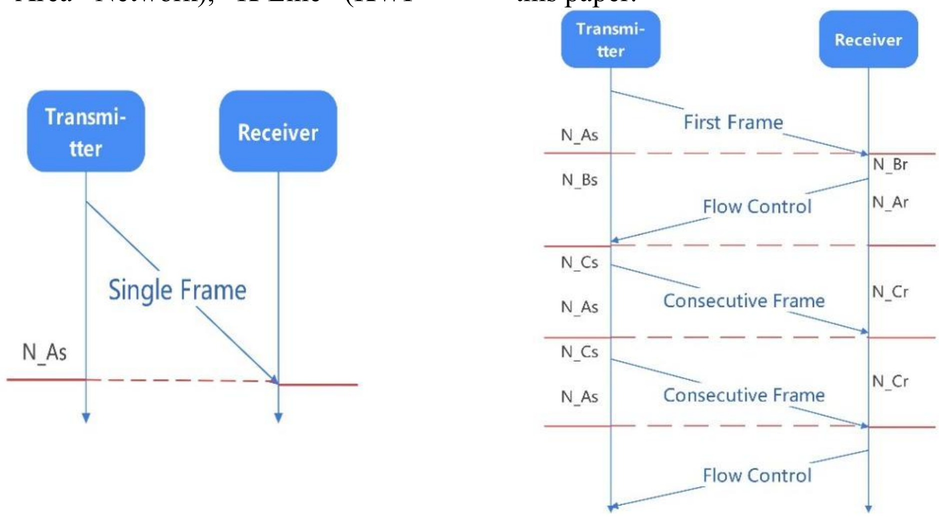
The vehicle fault diagnosis protocol is a standardized communication protocol used for data transmission between vehicle Electronic Control Units (ECUs) and external diagnostic equipment. It enables maintenance technicians to read vehicle fault codes, facilitating effective fault diagnosis and repair.

Common fault diagnosis protocols include OBD-II (On-Board Diagnostics II), CAN (Controller Area Network), K-Line (KWP 2000), J1850, ISO 9141, ISO 14230, J1939, UDS (Unified Diagnostic Services, ISO14229), ISO15765 (UDS on CAN), etc. Among them, UDS ISO14229 and ISO15765 are the most critical protocols in applications.

The Unified Diagnostic Services (UDS) are defined in the international standard ISO 14229-1. The UDS standard is a collection of services that specify not only the usage and format of these services but also standardized data definitions. Its scope covers functional units such as data transmission, diagnostic and communication management, input/output control, transmission and storage of data, remote activation of routines, and upload/download operations [12,13].

The ISO 15765 protocol is divided into four parts. ISO 15765-1 defines the physical layer and data link layer, while ISO 15765-2, on the other hand, specifies the network layer functions, including timeout control mechanisms, and enables the mutual conversion between SDU (Service Data Unit) and PDU (Protocol Data Unit)—namely, packet disassembling and assembling. To achieve this, ISO 15765-2 defines four types of frames: Single Frame (SF), First Frame (FF), Consecutive Frame (CF), and Flow Control Frame (FC). Meanwhile, it establishes two communication modes: single-frame and multi-frame communication, as illustrated in Figure 7.

ISO 15765-3 specifies the specific services of the application layer, while ISO 15765-4 outlines the requirements for relevant emission systems. Details are not elaborated further in this paper.



(a) Single Frame (b) Multi-frame

Figure 7. Data Frame Transmission Process

5.3 Server Architecture

Taking into account the characteristics and requirements of the vehicle-mounted terminal in the remote diagnosis system, the system design employs a B/S architecture (Browser/Server model). In this architecture, the core business logic processing is centralized on the server side, with the server undertaking most of the system's functional operations. This approach not only alleviates the workload on the vehicle-mounted client but also reduces hardware costs and ensures compatibility with diverse operating systems. Clients can interact with the server via a browser alone, enabling seamless data exchange while facilitating remote maintenance and upgrades—thereby minimizing the complexity and cost of system upkeep.

The B/S architecture comprises three primary tiers: the presentation layer, the logic layer, and the data layer. These three tiers collaborate synergistically to form the fundamental framework of the B/S architecture, as illustrated in Figure 8.

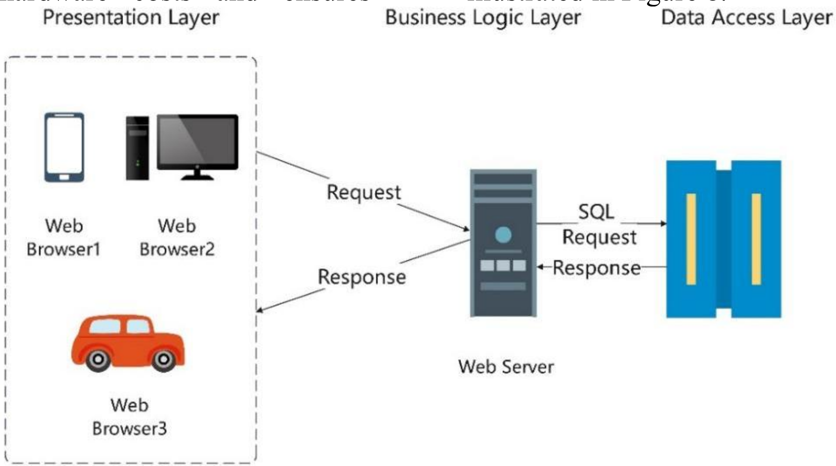


Figure 8. Server Architecture

In the design of the remote diagnosis system, the presentation layer corresponds to vehicle-mounted clients, mobile phones, tablets, diagnostic clients, etc., which communicate with users through human-machine interaction interfaces. These terminals can establish communications with cloud servers via HTTP or HTTPS protocols to send diagnostic requests or receive data and commands from the servers. A simple interaction interface enables coverage of a wide range of users with diverse needs [14]. The logic layer and data layer correspond to cloud diagnostic servers, where vehicle data and customer request information transmitted via remote networks are stored and processed to analyze vehicle operating status and perform diagnostics. Meanwhile, with the introduction of big data technology, the remote diagnostic capabilities of automotive systems based on the B/S architecture have been further enhanced. Through analysis of massive data in the cloud, potential patterns and relationships can be mined to optimize diagnostic models and improve the system's adaptive capabilities.

6. Conclusion

This paper delves into the construction methodology of a remote data acquisition model for power batteries within the vehicle networking ecosystem. It conducts a comprehensive exploration of the data acquisition system's architectural design, pivotal supporting technologies, sensor selection strategies, and the implementation of vehicle-mounted terminal hardware and software. By establishing a hierarchical data acquisition framework and meticulously optimizing the selection of high-precision sensors and low-power communication technologies, the model enables the real-time collection and reliable transmission of multi-dimensional state parameters of power batteries. Moreover, the modular design of the vehicle-mounted terminal significantly enhances the real-time performance of data processing and local analysis capabilities, laying a solid data foundation for battery health management, fault pre-warning, and energy efficiency optimization in vehicle networking scenarios. Rigorous experimental validations demonstrate that the proposed model has achieved the anticipated targets in terms of data integrity, transmission efficiency, and system stability.

Building upon the existing model, to address the data acquisition demands under complex and dynamic operating conditions, it is imperative to conduct in-depth research on multi-source heterogeneous data fusion algorithms and lightweight deep learning models. These efforts aim to elevate the accuracy of data feature extraction and the efficiency of edge computing. Additionally, exploring how to optimize the synergy between the battery management system and vehicle energy management strategies through data-driven approaches emerges as a crucial avenue for future investigation.

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