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Design and Implementation of a Battery Big Data Platform Through Intelligent Connected Electric Vehicles

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Abstract
The development of a battery management algorithm is highly dependent on high-quality battery operation data, especially the data in extreme conditions such as low temperatures. The data in faults are also essential for failure and safety management research. This study developed a battery big data platform to realize vehicle operation, energy interaction and data management. First, we developed an electric vehicle with vehicle navigation and position detection and designed an environmental cabin that allows the vehicle to operate autonomously. Second, charging and heating systems based on wireless energy transfer were developed and equipped on the vehicle to investigate optimal charging and heating methods of the batteries in the vehicle. Third, the data transmission network was designed, a real-time monitoring interface was developed, and the self-developed battery management system was used to measure, collect, upload, and store battery operation data in real time. Finally, experimental validation was performed on the platform. Results demonstrate the efficiency and reliability of the platform. Battery state of charge estimation is used as an example to illustrate the availability of battery operation data.

Keywords Intelligent connected electric vehicle, Battery, Operation data, State estimation, Wireless energy transfer

1 Introduction

With the increasing concerns about climate challenges and global energy, the utilization of clean energy and renewable energy is receiving more and more attention, which leads to the rapid development of electrochemical energy storage and electric vehicles (EVs) [1]. Due to high specific energy, high operating voltage, and environmental friendliness, lithium-ion batteries (LiBs) are currently the most widely used batteries in EVs [2]. To ensure the efficient and safe operation of the LiBs, it is an essential requirement for EVs to equip with battery management systems (BMSs) and the development of effective management algorithms for BMSs is highly dependent on battery operation data [3]. However, the operation data for important scenarios such as thermal runaways and faults are difficult to obtain.

The data for the development of battery management algorithms can be mainly divided into five categories: laboratory test data [4], calibration data from battery manufacturers [5], network-sharing data [6], actual operation data [7], and simulation data. In general, laboratory test data focus on the characteristics of a battery within a certain number of cycles, and it is difficult to reflect the actual scenarios; The calibration data and some network sharing data are also mainly from laboratory tests, they focus on the accumulation of cycle numbers and provide limited value for the development of a dynamic algorithm for battery management; The actual operation data (e.g., battery operation data in EVs) reflect the real working conditions which have few with the fully charged or discharged batteries, in such conditions state of charge

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(SOC) interval is narrow and the real capacities of batteries are not clear. The shortcomings of these data severely limit the development of management algorithms for BMSs.

Battery management requires open circuit voltage (OCV) calibration [8] and battery state estimation. Currently, it mainly relies on laboratory test data. The accurate OCV curves need to be measured under stable open circuit conditions and will be affected by battery samples and battery aging levels [9], so there are problems in long-term application; The common model-based filtering methods [10] for state estimation establish a relationship between the voltage, current and the battery state based on the laboratory data. Nevertheless, the model parameters need to undergo a complex identification process. With the change of the environment and the aging of the battery, the model structure and parameters need to be adjusted accordingly [11], which adds difficulties to developing accurate battery model laboratory test data; The machine learning methods extract the complex nonlinear relationship between battery state and various variables through huge battery operation data. They include support vector regression (SVR) [12], random forest (RF) [13], neural network (NN) [14, 15], etc. However, the accuracy of the estimation results depends on the quality and quantity of the data used for training. For the battery management algorithms in EVs, if the training data cannot cover the actual EV driving conditions, the algorithms may fail in applications [16].

High-quality network-sharing data can also help to develop battery management algorithms [17]. The battery research group of the University of Maryland has published battery data sets related to four EV driving cycles [18]. Some other research institutions have also published battery data under different driving cycles [19, 20]. However, the network-sharing data may not be able to cover all the working conditions.

To improve the adaptability and effectiveness of the battery management algorithm, actual operation data under the real-world driving scenarios of EVs are desired [21]. Jimenez-Bermejo et al. [22] designed a nonlinear autoregressive neural network with external input (NARX) to estimate the SOC using real data extracted from an EV during its daily trips. The network has been tested using 54 different real driving cycles, obtaining highly accurate results. Hong et al. [21] designed the state of health (SOH) estimation method for the battery system of EVs in the real world based on the actual data during EV driving within a year, and better performance is achieved. Li et al. [23] built a data set of EV operation and extracted accurate SOH estimation of EVs in the real world. Fang et al. [24] collected real-world driving data from twenty all-electric buses over many years and proposed a fault diagnosis method based on density-based spatial clustering of applications with noise algorithms, which has shown better effectiveness and accuracy. In addition, the simulation data also has a certain application value. In Ref. [25], the author combines vehicle simulation and LiBs multi-physical electrochemical and thermal models and uses Matlab/Simulink platform to simulate and generate data. The proposed multi-physical modeling framework for generating simulation data can be extended to many aspects, such as the thermal runaway trigger or the internal chemistry of the battery pack.

However, the test data of batteries in real EV scenarios now belongs to EV owners, this is private data so it is difficult to access. Developing a large real EV test platform will consume huge resources and costs. In addition, safely obtaining battery operation data during various faults for battery safety and fault early warning research is another issue to be addressed. Considering the need of BMS for actual operation data, an intelligent connected vehicle prototype test platform is built to obtain high-quality battery experimental data at a low cost. The overall framework of the platform is shown in Figure 1. The platform mainly includes equivalent EV, the energy and data interaction system, and an environment cabin. The EV is equipped with a self-designed BMS, which can run autonomously and intelligently in the environment cabin. Different EV driving conditions can generate different working conditions for the battery. With the automatic wireless charging function, the vehicle can automatically go to the charging sites and turn on the automatic wireless charging system to charge the batteries. Before starting, it can turn on alternating current (AC) heating to raise the battery temperature [26]. In this way, the automatic alternating cycle of charging and discharging can operate continuously to accumulate long-term operation data, supporting the research on battery management algorithms. It also collects battery parameter information in real time and uploads it through the data interaction system. The upper computer interface can display this information. The main contributions of this paper are as follows:

(1) The intelligent connected vehicle prototype test platform is built. The experiment is carried out under different artificially set road conditions and temperatures. Compared with the way of obtaining data from real vehicles, it greatly reduces the experimental cost and enriches the experimental scenarios;
(2) The platform is equipped with automatic wireless charging and AC heating systems, which ensures extensive energy interaction. It obtains rich data for wireless charging and discharging of the batteries;

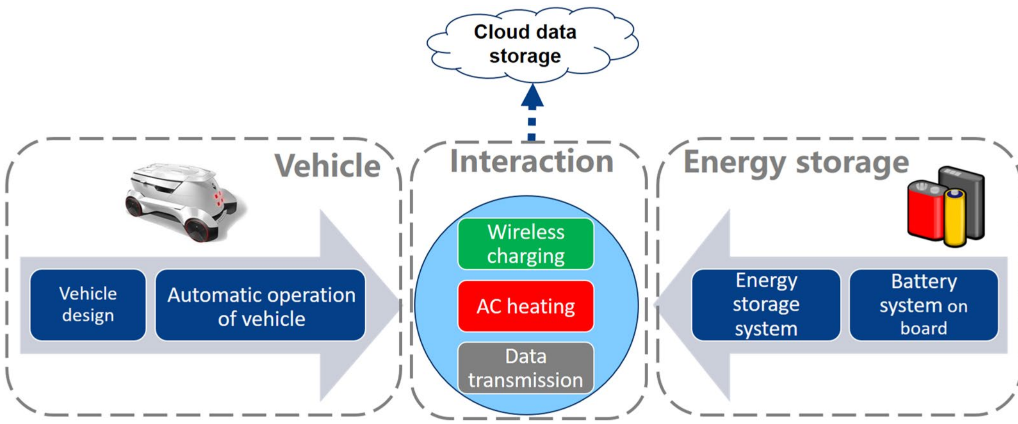


Figure 1 Overall structure of the platform

(3) The experimental data are obtained by a specially designed data interaction system, and battery SOC estimation is carried out based on the data-driven method using experimental data, which shows a good result.

The remainder of this paper is organized as follows: Section 2 introduces the overall composition of the platform; Section 3 introduces the control principle of the platform; Section 4 describes the data interaction system; Section 5 shows and verifies the experimental results of the platform; Section 6 gives the conclusions.

2 Platform Composition

2.1 Design and Implementation of Equivalent EV

The equivalent EV is a core part of the overall experimental platform. To implement a prototype experiment, there are some specific requirements for the EV in terms of its speed and turning radius. In addition, we adopt a coaxial design for the two rear wheels of the vehicle, whose drive system is designed with a single-motor rear-drive scheme. The battery system uses twelve 18650 cylindrical batteries connected in series to meet the voltage and power requirement of the drive system and its rated capacity is 2.4 A·h. The model and appearance of the vehicle are shown in Figure 2. The vehicle is composed of three modules: rear drive system, vehicle body, and steering system. This modular design makes the assembly and tuning process easy.

2.2 Orbit Road and Environmental Cabin

To allow the vehicle to run for a long time in the given condition, it is necessary to set up an orbit road and an environmental cabin. The orbit road gives the maximum utilization of space, the richness of working conditions, and the set of wireless charging sites. It has various uphill and downhill sections with different slopes to simulate various EV driving conditions. The design of several branch roads also provides more paths for vehicle operation, and the wireless charging sites are set on the branch

(a) Structure of the vehicle model (b) Appearance of the physical vehicle

Figure 2 Model and photo of the developed Intelligent connected electric vehicles roads, which are shown by the green in Figure 3(a). This design ensures that the vehicle can operate in a reliable closed-loop on the road for a long time. To simulate various ambient temperatures, the whole system is placed in a large-scale environmental cabin. The cabin can set the indoor temperature in a wide range of − 40 °C to 60 °C. The actual scene of the platform is shown in Figure 3(b).

3 Design of System Control

In the experiment, the vehicle needs to operate automatically for a long time without continuous human guidance and intervention. To this end, it is necessary to carry out automatic control of the system which includes:

(1) The vehicle can automatically adjust the speed and steering angle to ensure that it runs autonomously in the correct state.
(2) The vehicle can judge the road position information, which is convenient for the implementation of the operation strategy.
(3) The vehicle can automatically realize wireless charging if the battery is at low SOC.
(4) The vehicle can obtain information and take measures to ensure safety when facing dangerous situations, and can also be shut down in time when a fault occurs.

3.1 Autonomous Navigation Based on Electromagnetic Signals

The vehicle needs to detect a target and perceive a road when it operates autonomously according to a certain trajectory. Road perception relies on lidar and deep learning, and pattern recognition. Target detection relies on a camera. They are two mainstream methods, which are reflected in today's intelligent vehicles. However, considering the usage, development cost and actual needs, we use electromagnetic sensing to realize detection and perception in this experimental platform.

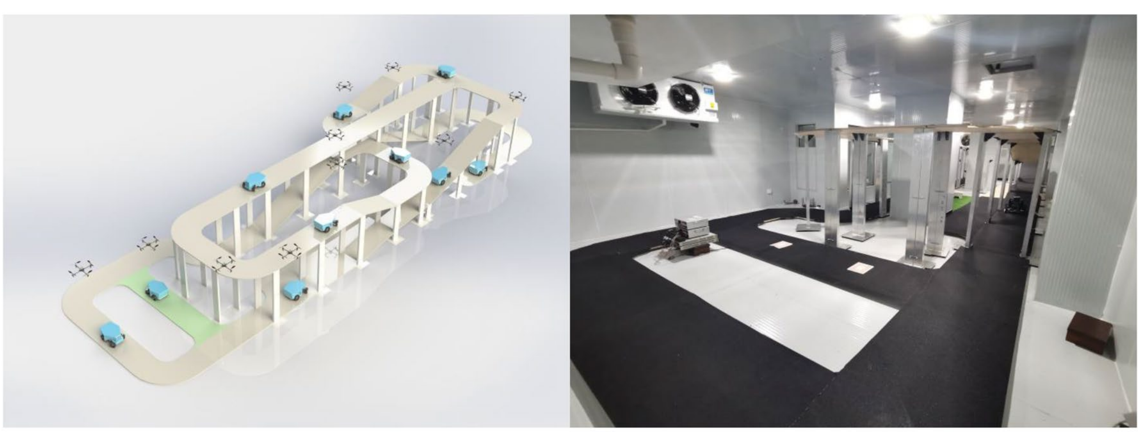
According to the Biot-Savart law, the magnetic induction intensity around an infinitely long conductor with direct current at a certain point is:

$$B = \frac{\mu_0 I}{4\pi r}, \tag{1}$$

where μ_0 represents the magnetic permeability in a vacuum, and r represents the distance from the point to the conductor. It can be seen that the magnetic induction intensity is inversely proportional to the distance from the point to the current flowing through the conductor.

Furthermore, the alternating current (AC) will generate an alternating magnetic field around the conductor. If a coil is placed at a certain point in the magnetic field, electromotive force can be induced in the coil, and an electromagnetic sensor can be developed based on this. Electromagnetic sensors can detect different electromotive forces at different positions, thus providing the relative position information between the point and the conductor. Based on this principle, we set AC current along the center line of the road, place electromagnetic sensors perpendicular to the driving direction of the vehicle in the front of it, and obtain the relative position and deviation between the vehicle and the center of the road. The layout of the electromagnetic detection system is shown in Figure 4.

Based on the signals detected from the four-channel sensors, the available signals are obtained after the necessary anti-pulse filter, moving average filter, and normalized process. The vehicle steering can be adjusted in combination with PD control [27]. Under the influence



(a) The orbit road designed (b) Actual scene

Figure 3 Environmental cabin

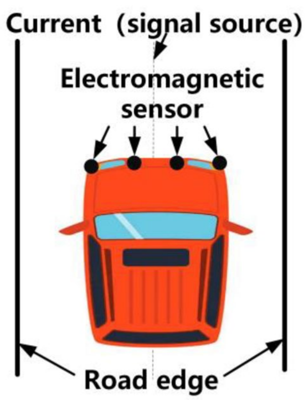


Figure 4 Layout of the electromagnetic detection system

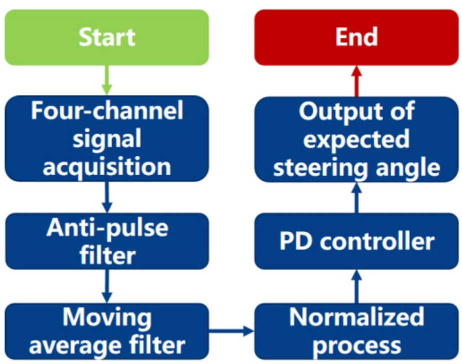


Figure 5 Flowchart of signal processing

of these processes, the stability and robustness of the control effect on the vehicle are significantly enhanced, which can form an effective and reliable navigation for vehicle operation. Such a control scheme can effectively reduce the influence of temperature and lighting conditions on the detection effect. The signal process flow is shown in Figure 5.

3.2 Extraction of Position Information Based on Radio Frequency Identification (RFID)

To allow the operating vehicle to perceive position information such as intersection, it is necessary to design a vehicle-road wireless sensing system. This platform uses RFID technology to achieve wireless communication [28] between the identification module and the sign module, where the sign module is preset at a specific position on the road and the identification module is installed in the vehicle. When the vehicle runs to the specific position, the expected communication can be realized and the position information can be obtained by reading the information in the sign module.

3.3 Automatic Wireless Charging System

Since the vehicle needs to run for a long time, the automatic charging system is also essential. In this platform, the wireless charging coils are set on the ground at the designated sites of the road, and a wireless charging coil is also set at the bottom of the vehicle. Wireless charging can be realized through matching the coil with the inverter, rectifier, and other modules. Once the battery system is at low SOC, the vehicle can run to a charging site to allow the battery system to be charged. The automatic charging system can be realized by encoding the vehicle state and performing actions in each state. The control flow is shown in Figure 6.

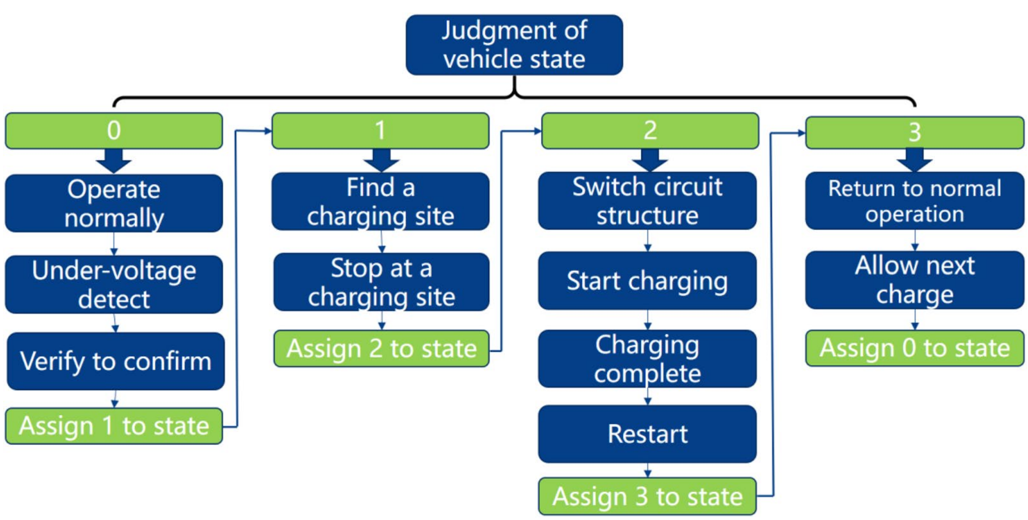


Figure 6 Flowchart of automatic charging system

3.4 Autonomous Safety Protection System

Considering that this experimental platform is a large-scale dynamic unmanned system, it is necessary to set up a safety protection system to deal with a certain danger in the event of abnormal failure. The safety protection system needs to shut down the vehicle when it encounters an obstacle, resume operation if the obstacle is removed, and stop in time when the control program is abnormal. To this end, this platform sets up multiple protections in time and space dimensions and active and passive safety dimensions.

During operation, the vehicle will automatically detect the distance to surrounding obstacles, update status information in time and space, and this information will be synchronized to both the main control board and the slave control board. Once an abnormal or dangerous situation occurs, multiple security protections allow the system to respond in time and take effective measures quickly. The practical application has verified its reliable effect. In fact, a single control chip can surely complete such detection and execution tasks. However, to avoid unexpected downtime as much as possible, a protection link is added here, i.e., redundant design. The protection function will be lost only when both the main control board and slave control board fail at the same time, which almost never exists in actual operation.

In addition, the main control chip receives different types of sensing signals to form and output signals through corresponding operations. At the same time, the main control chip is also interconnected with other modules, which can realize the communication function and various expansion functions. The overall control structure of the vehicle is shown in Figure 7.

To improve electrical and electromagnetic reliability, on the premise of meeting the working performance, the components are selected as low working frequency as possible and arranged reasonably to reduce the intensity of interference radiation. In practical application, the propagation of electromagnetic interference is suppressed by reasonably arranging the direction of high-speed signal lines, adding filters or decoupling capacitors, and special packaging. Furthermore, the modular design and redundant safety design for each functional part also provide **a** guarantee for the reliability of the whole system.

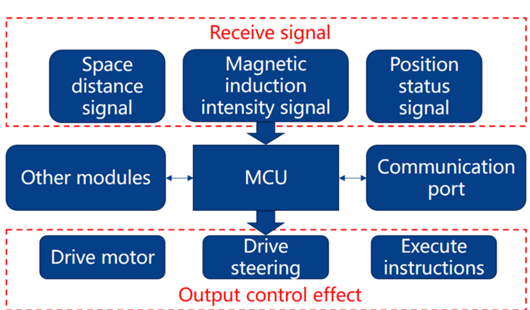


Figure 7 Overall control structure of the vehicle

4 Data Acquisition and Interaction

For the experimental platform, it is necessary to design the data acquisition and communication systems, which are also part of the BMS. Their tasks mainly include:

(1) Accurately collect various parameters of the battery system, including voltage, current, temperature, and other information.
(2) Realize reliable communication with the upper computer.

4.1 Battery Data Acquisition

LTC6811 is a chip specially designed by Linear Technology for EV battery voltage acquisition. Each LTC6811-1 chip can measure the voltages of 12 cells in series within 290 μs. The parallel use between chips is also very convenient. In specific use, the LT6811-1 is connected to the four pins of the control chip to realize the serial peripheral interface (SPI) communication between the chips [29]. In a specific process, once the initialization and open-circuit check are completed, the analog-to-digital converter (ADC) function will be turned on by sending the start command from the control chip to the LTC6811-1 chip. Then the control chip sends a read command to receive the voltage data when the ADC is completed, and a verification step is set to ensure the reliability of the data. Temperature and current acquisition use the thermistor and hall element, respectively, and its application in software is similar to voltage acquisition. Then, the voltage, temperature, and current acquisition modules are integrated into the same electrical network to collect data and send them to the upper computer for storage and display, thereby obtaining the experimental data. The precision of voltage and current data acquisition is 12 mV and 0.1 mA respectively.

4.2 System Communication Structure

In this platform, there are multiple modules that need to generate or receive data and communicate with each other. The stationary and nearby modules can use serial communication, controller area network (CAN), SPI, and other wired methods to communicate, while mobile modules need wireless communication [30]. For example, wireless communication is required between the control system of the vehicle and the upper computer so that the vehicle can be controlled and intervened by the real-time monitoring interface in the operating process, and the upper computer can also receive vehicle operation data and battery operation data. The WiFi communication method based on ESP8266 is used. It has a built-in communication protocol and can send or receive data wirelessly through the serial port. In practical application, both the vehicle-mounted communication module and the upper computer are connected to the same network, and wireless communication can be realized after configuring the IP address. The overall communication structure of the system is shown in Figure 8.

The real-time monitoring interface of the upper computer is shown in Figure 9. It includes the display of voltage, temperature, current, and other operating information, and has the function of data storage. The vehicle can also be controlled and intervened through the operation of some buttons on the interface.

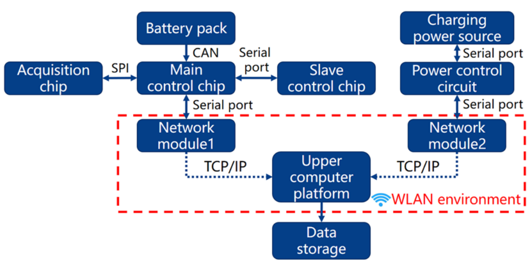


Figure 8 Overall communication structure of the system

5 Data Generation and Verification

5.1 Data under Different Conditions

When the vehicle runs under cyclic working conditions along the road, the battery operation data under the same cycle can be generated as shown in Figure 10(a). When the vehicle runs under the random working conditions along the road, the battery operation data can also be generated as shown in Figure 10(b).

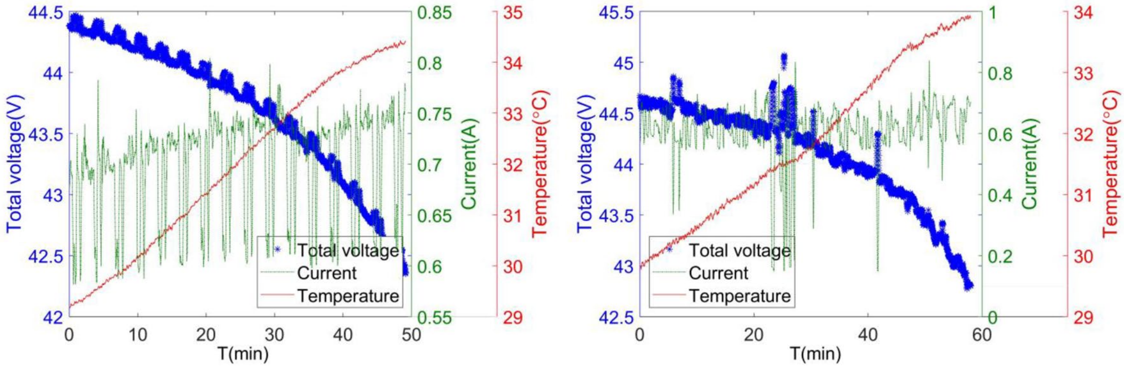
It can be seen that the discharge conditions in each cycle are different. Different from the test in the laboratory, this experimental platform can be adjusted to achieve different working conditions which can simulate more real-world EV driving on the road.

5.2 Analysis and Application

We operate the platform with cyclic and random working conditions and conduct the standard DST, respectively. The data generated are shown in Figure 11. It can be seen that the experimental data generated by this platform are closer to the real world, and have higher practicability and universality.

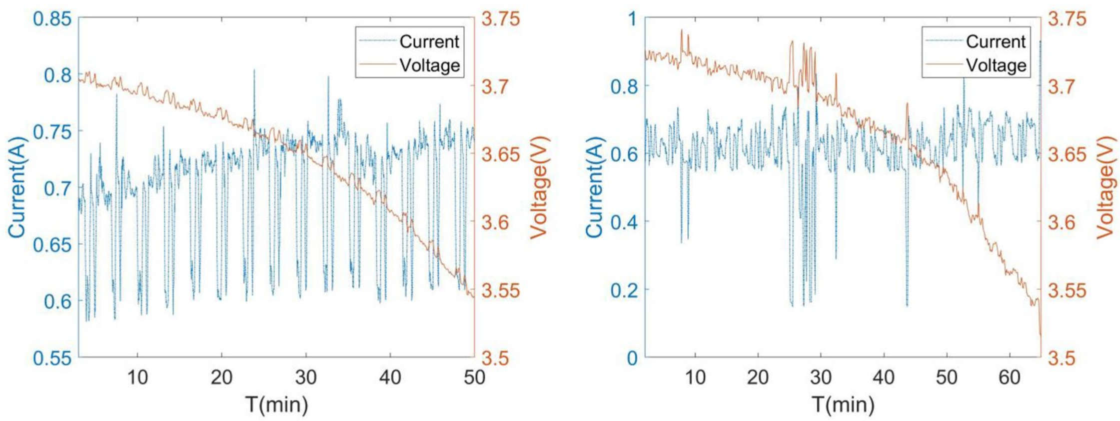
In order to show the data application of the experimental platform, the verification work is carried out based on the data-driven method. In this work, the NARX is used to predict the SOC of the battery system. NARX is a kind of neural network model for describing the nonlinear discrete system. It adds input delay and output feedback mechanisms to enhance the memory ability of historical data and is suitable for time series prediction. In this work, seven hours of data (about 25000 sample points)

Figure 9 Real-time monitoring interface of upper computer

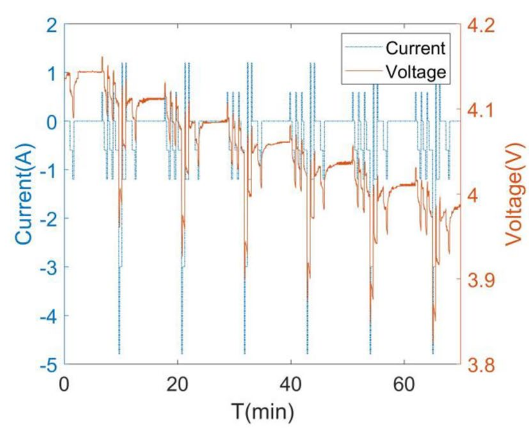


(a) Under cyclic working conditions (b) Under random working conditions

Figure 10 Experimental data under different working conditions



(a) The cyclic working conditions in exp. platform (b) The random working conditions in exp. platform



(c) The standard DST working condition in the laboratory

Figure 11 Data obtained from the experimental platform and the standard laboratory generated under cyclic working conditions are used as the training set, and 1.5 h of data (about 5000 sample points) generated under random working conditions are used as the test set. The way to obtain the true value of SOC is to calibrate the initial SOC, and then use the ampere-hour integration method to generate a complete sequence of SOC values.

The input delay, feedback delay, and the size of the hidden layer are set at 1:100, 1:10, and 16, respectively. The closed-loop mode is used to verify after 40 epochs of training. The training set and test set are shown in Figure 12. The test result is shown in Figure 13. It can be seen that the trained model achieves high accuracy, and the root mean square error (RMSE) of SOC estimation is about 0.15%.

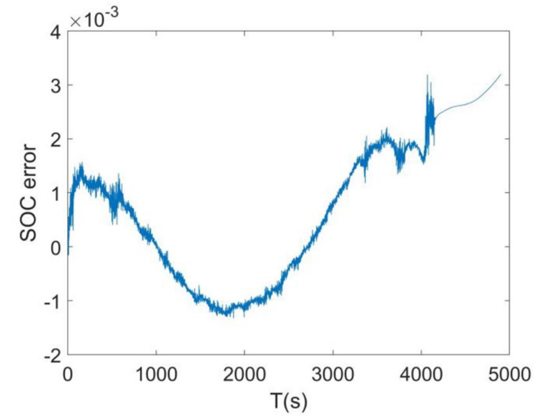
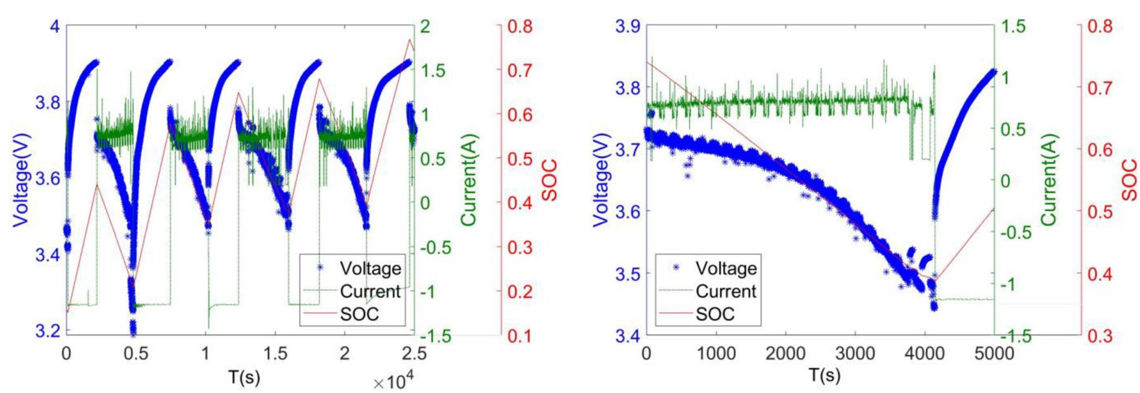


Figure 13 SOC estimation error

6 Conclusions

(1) This study develops an intelligent connected vehicle prototype test platform. The vehicle is independently designed and applied to meet the requirements of the experiment. The vehicle can run autonomously in the environmental cabin and collect data from the battery system. Several modules have been developed inside the vehicle to ensure its stable and safe operation.
(2) The platform can obtain the battery operation data in real-world EV scenarios by setting the working conditions of the vehicle, and a series of communication methods are set to realize data interaction. A large amount of battery operation data will be obtained from the continuous operation of the vehicle, and the battery operation data generated under different working conditions show the effectiveness of the platform.
(3) The platform realizes energy interaction between vehicles and battery systems through automatic wireless charging and AC heating system, which endows the platform with rich functions and higher application value.
(4) The experimental data generated under different working conditions can reduce the cost of data acquisition in real-world EV scenarios, and is conducive to excavating the key parameters of power batteries. The data can be applied in modeling and state estimation, fault diagnosis, and energy management, etc.



(a) Training set

(b) Test set

Figure 12 Experimental data for training and test

Authors' Contributions
RX conceptualization, supervision, writing—reviewing and editing the study; BZ, KZ, YD methodology, writing—original draft preparation; FS review & editing, Supervision. All authors read and approved the final manuscript.

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Availability of Data and Materials
Not applicable.

Declarations

Competing Interests
The authors declare no competing financial interests.

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