

A hybrid real-time safety monitoring framework for power battery packs using autoencoders and adaptive extended Kalman filter-based HARA

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Article Info	Abstract
Article History: Received 21 July 2026 Accepted 29 Sep 2026 Keywords: Power battery packs; Real-time monitoring; Hazard analysis and risk assessment; Fault diagnosis and isolation; Adaptive extended Kalman filter; Autoencoder	Power battery packs are a critical component of electric vehicles (EVs), and their safety and stability directly dictate the reliability and commercial viability of modern electrified transportation. Traditional battery monitoring systems often rely on static threshold-based models, which struggle to provide adaptive and accurate safety diagnostics under highly dynamic operating conditions. This paper integrates real-time sensor measurements with a systematic Hazard Analysis and Risk Assessment (HARA) framework to propose a real-time monitoring and analysis model for power battery packs. The system employs an Adaptive Extended Kalman Filter (AEKF) to adjust system parameters using sensor signals derived from battery performance and monitors various fault types based on HARA results. An autoencoder network enhances the performance of state estimation and monitoring. Experiments conducted on OBD, CALCE, and self-constructed datasets validate the model's performance in terms of fault detection consistency, isolation accuracy, and State of Charge prediction. The experimental results show that the fault detection consistency of the monitoring system based on sensor signals and HARA reaches $94.28\% \pm 0.76\%$, the insulation resistance estimation error is $1.492 \pm 0.067 \Omega/V$, and the SOC prediction accuracy is $98.46\% \pm 0.42\%$, which is better than the other three models.

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1. Background

With the accelerated growth of the electric vehicle industry, the application of artificial intelligence algorithms has become very common to ensure smooth system running [1]. Power battery packs are an indispensable part of electric vehicles, and the working efficiency of battery packs will have a direct effect on the running conditions and range of the vehicles [2]. When batteries undergo abusive conditions such as overcharging or internal short circuits, severe thermal runaway (or heat accumulation) may occur, potentially leading to catastrophic safety hazards such as fires or explosions [3]. Consequently, real-time monitoring of battery packs has emerged as a paramount and highly active research focus globally. Real-time monitoring systems are primarily based on direct detection by sensor signals and state estimation algorithms. These methods require high accuracy for battery models, and key parameters of the battery model, such as ohmic resistance, polarization parameters, and open circuit voltage, will fluctuate with temperature, aging, and changes in operating conditions, resulting in parameter uncertainty. There is a model mismatch between the simplified model and the real battery. Voltage, current, and temperature sensor noise and sampling errors can introduce disturbances. The non-linear characteristics of the battery itself also increase the difficulty of online identification. Therefore, the key values of the model are prone to insufficient accuracy, leading to state estimation errors and increased computational costs [4]. By contrast, the Hazard Analysis and Risk Assessment (HARA) approach provides a structured

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approach to systematically assess safety hazards. This reduces subjective bias in safety assessments and provides the opportunity, allowing the optimization of computational resource allocation based on the assessed risk levels. This will balance the related costs and safety more efficiently [5]. Thus, this study establishes an integrated real-time monitoring and analysis model for power battery packs by coupling sensor measurements with the HARA framework. This model is capable of overcoming the prediction limitations and processing delays of conventional monitoring schemes. Moreover, this model helps to improve battery reliability and risk prevention capabilities. The innovation and contributions of the work emerge at two ends. First, it introduces a novel hybrid safety monitoring framework that seamlessly integrates data-driven diagnostics with proactive risk evaluation. Secondly, it provides a technical solution for real-time monitoring of power battery packs under experimental conditions.

2. Related Studies

Since HARA can enhance the effectiveness and reliability throughout the lifecycle of detection targets, numerous scholars both domestically and internationally have joined the research. To better monitor the states during the power battery charging process, Kim et al. put forward a strategy based on an ensemble split learning algorithm. This strategy enhanced the accuracy of battery life prediction using the ensemble split algorithm, observed the temperature and current of batteries, and conserved power. Experimental results show that the strategy achieves an accuracy of 93.40% on the test set [6]. To solve the situation where the monitoring capability of batteries reduces each year, Saba et al. put forward a measurement strategy that utilized the digital twin and deep deterministic policy gradient method. This strategy monitored the life of batteries by recording digital twin values such as the charging state, and batteries' safety and reliability were improved by training the model based on the deep deterministic policy gradient method. The monitoring method considered battery safety and reliability [7]. For the battery monitoring issue, the researchers from Zhao and Bai put forward a model that utilized the whale optimization algorithm and long short-term memory algorithm. This model optimized the battery fault diagnosis by using the whale optimization algorithm, and the safety management capability of batteries was enhanced. Experiment results showed that the monitoring accuracy of this model was 95.3% [8]. Bai et al. put forward an electrochemical-magnetic-field-thermal coupling three-dimensional model for monitoring the operating state of batteries. This model fulfilled the battery state monitoring task by identifying the internal short-circuiting condition and crack defects, as well as the distribution of the magnetic field surrounding the battery [9]. The researchers from Wang et al. put forward a lithium battery type monitoring system with the aim of monitoring the power batteries. This system constructed monitoring programs through the laboratory virtual instrument engineering platform and conducted systematic testing to complete power battery pack monitoring. Results showed that the voltage measurement error of this monitoring system was constrained within 5% [10].

In summary, HARA related research provides a structured risk assessment process, but its analysis is mostly based on typical scenarios in the development stage, with relatively fixed risk parameters and insufficient coupling with real-time sensor signals and state estimation results. Research on battery monitoring has made progress in life prediction, digital twin, fault diagnosis, and condition monitoring. However, some methods rely on high-precision battery models, which are affected by parameter uncertainty, model mismatch, and sensor noise. Some methods have limited support for unknown anomaly detection and risk grading decisions, and there is also a trade-off between real-time performance and computational overhead. Therefore, this study combined sensor signals and the HARA method to propose a real-time monitoring model applied to power battery packs, achieving the goal of efficiently identifying hazard types and accurately monitoring battery operating states. It is expected that this model can effectively enhance real-time monitoring performance and provide reliable technical decisions for the stable operation of power battery packs.

3. A Battery Monitoring and Analysis System Combining Sensor Signals And HARA

3.1 Design of A Battery Safety Analysis Framework Integrating Sensor Signals and HARA

During the monitoring of power battery packs, issues such as inaccurate functional state estimation and inconsistent monitoring results easily occur. Traditional real-time monitoring methods obtain data with limited dimensions, which restricts the amount of available information and makes precise real-time monitoring difficult to achieve [11-12]. In contrast, HARA systematically analyzes potential issues in power battery systems and performs risk assessment. Based on risk exposure, severity, and controllability, it defines reasonable safety levels and provides reliable safety mechanisms [13]. In addition, battery signals collected by sensors show higher objectivity and directness. Therefore, this study applies HARA combined with sensor signals to perform real-time monitoring and analysis of power battery packs. The approach achieves high-precision and high-efficiency battery state monitoring. The application process of battery monitoring using HARA combined with sensor signals is shown in Figure 1.

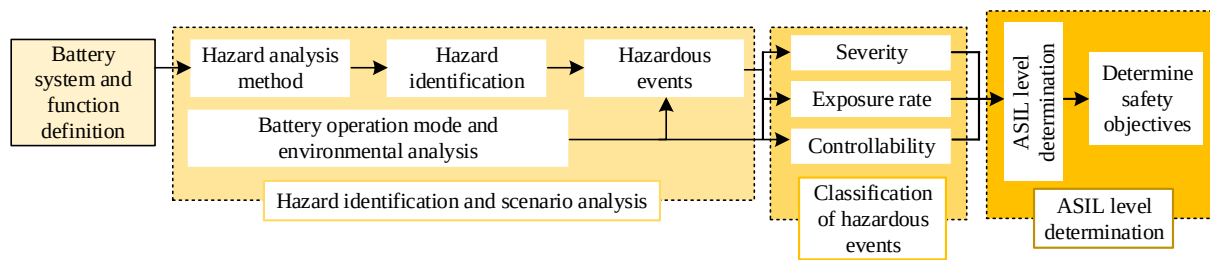


Fig. 1. Process of battery status monitoring based on the HARA method and sensor signals

As shown in Figure 1, the monitoring and analysis process of power battery packs based on HARA mainly includes hazard identification and scenario analysis, hazard event classification, and determination of the Automotive Safety Integrity Level (ASIL). During hazard identification and scenario analysis, HARA identifies potential hazards and adverse outcomes of power battery packs based on system definitions and hazard analysis methods. It then determines specific operating scenarios. HARA subsequently performs risk assessment and defines safety objectives for each hazard based on the assessment results. It also provides functional safety concepts to complete state monitoring. HARA hazard analysis and safety objectives are shown in Table 1.

In Table 1, severity, exposure/occurrence and controllability are classified according to S0-S3, E0-E4 and C0-C3 respectively. The detection conditions are composed of voltage, current, temperature, SOC, AE reconstruction error, AEKF innovation/residual and other signals. The trigger threshold is used to convert the risk level into executable monitoring logic. The threshold is set based on 12.8 v/60 ah lithium iron phosphate group and 10 hz/100 Hz sampling. The control action is performed by the battery management system (BMS). ASIL is determined according to ISO 26262 risk matrix. The standard HARA is oriented to vehicle functional safety. It usually conducts static analysis according to the system definition and typical scenarios in the development stage, and the risk parameters and ASIL levels are relatively fixed after being determined. The battery system has the characteristics of electrochemical nonlinearity, aging, multi-sensor coupling and rapid evolution of thermal runaway. In this paper, the hazard types are extended to battery specific faults such as overcharge, over discharge, internal short circuit, thermal runaway spread and insulation fault. The detection conditions introduce voltage, current, temperature, SOC, AE reconstruction error, AEKF innovation and residual. The exposure/occurrence probability and controllability are reevaluated with the real-time working conditions. The safety objectives and trigger thresholds directly correspond to the BMS control action. The hazard types, safety objectives and ASIL levels determined by HARA in the development phase are used as static baselines and are updated in rolling combination with sensor signals and state estimation results during operation. AEKF adjusts SOC, SOH and internal resistance estimates in real time according to voltage, current and temperature, re-evaluates the exposure/occurrence probability and controllability with the change of working conditions, and adjusts the trigger threshold and control action accordingly [14-15].

Table 1. HARA hazard analysis and safety objectives of power battery pack

Hazard Type	Operating Scenario	Detection Conditions	Severity S	Exposure E	Controllability C	ASIL	Safety Objective	Trigger Threshold	Control Action
Overcharge	Fast charging or slow charging, SOC close to full charge	Cell voltage, charging current, SOC, voltage consistency, temperature rise	S3	E3	C2	C	Prevent thermal runaway caused by cell overcharge	Cell voltage ≥ 3.65 V for 2 s, or the voltage difference between the highest and lowest cell ≥ 100 mV and temperature rise ≥ 1 °C/min	Reduce the charging current and cut off the charging relay, start cooling and alarming, and prohibit recharging
Over-discharge	Driving or static state, low SOC	Cell voltage, discharge current, SOC	S2	E3	C2	B	Prevent deep discharge and copper dissolution	Cell voltage ≤ 2.50 V for 5 s, or SOC $\leq 5\%$ and discharge current $> 0.1C$	Limit the discharge power, cut off the load when necessary, and prompt charging
Overtemperature	High-rate discharge, fast charging or high-temperature environment	Temperature, temperature rise rate, temperature difference, current	S3	E3	C2	C	Prevent thermal runaway	Temperature ≥ 60 °C, or temperature rise ≥ 1.5 °C/min, or maximum temperature difference ≥ 8 °C	Reduce power or cut off output, start cooling and trigger an alarm
Internal short circuit	Charging, driving or static state	Sudden voltage drops, temperature rise, abnormal SOC, AE reconstruction error, internal resistance estimation	S3	E3	C3	D	Identify and isolate internal short circuits at an early stage	Voltage drop ≥ 200 mV/s, or temperature rise ≥ 2 °C/min, or AE reconstruction error $> 3\sigma$	Cut off the high-voltage relay, prohibit charging, and start thermal management and alarming
Connection fault / Increased contact resistance	Vibration, aging and high-current working conditions	Connection point temperature, internal resistance estimation, voltage difference	S2	E3	C2	B	Prevent local overheating and electric arcs	The estimated internal resistance increases by $\geq 30\%$ compared with the baseline, or the connection point temperature ≥ 70 °C for 3 s, or the voltage difference ≥ 100 mV	Reduce power, cut off the faulty branch and give maintenance prompts
Voltage sensor offset / Stuck / Reduced accuracy	All working conditions	Voltage residual, adjacent cell consistency, AEKF innovation	S2	E3	C2	B	Avoid misjudgment caused by wrong voltage input	Voltage residual > 50 mV for 10 s, or variance < 1 mV when stuck, or accuracy deviation $> 2\%$	Switch to redundant or model-estimated voltage, degrade monitoring, limit fast charging

Current sensor noise / Rate deviation	Charge and discharge, dynamic working conditions	Current residual, SOC estimation deviation, power integration	S2	E2	C2	A	Ensure reliable SOC/SOP estimation	Standard deviation of current noise>0.05C, or rate deviation>5% for 10 s	and trigger an alarm
									Enable filtering or reconstructed current, reduce power and calibrate the sensor
Temperature sensor reading drift	All working conditions	Temperature residual, thermal model prediction deviation, temperature difference	S2	E2	C2	A	Avoid thermal management failure caused by temperature misjudgment	Temperature residual>5 °C for 30 s, or drift>2 °C	Adopt redundant or model temperature, reduce power and trigger an alarm
Thermal runaway spread	After collision, internal short circuit or overcharge	Temperature, temperature rise rate, smoke or air pressure, voltage	S3	E3	C3	D	Prevent occupant injury and thermal runaway spread within the pack	Temperature ≥80 °C, or temperature rise ≥5 °C/min, or sudden change in smoke or air pressure	Cut off high voltage, carry out emergency ventilation and fire extinguishing, unlock doors and trigger an alarm
Insulation fault	Water immersion, aging, collision	Insulation resistance, leakage current	S3	E2	C3	C	Prevent high-voltage electric shock	Insulation resistance <100 Ω/V, or leakage current>10 mA	Cut off high voltage, prohibit power-on and trigger an alarm

The HARA baseline monitoring strategy is used under normal conditions, and the sampling frequency is increased and the corresponding safety measures are triggered under dynamic or abnormal conditions. Therefore, this study combines AEKF with HARA to enhance real-time performance and adaptability. Therefore, this study combines AEKF with HARA to enhance real-time performance and adaptability. The battery model employs a second-order RC equivalent circuit. Let $x = [SOC, U_1, U_2, R_0]^T$ be the state vector, $u = [I, T]^T$ the input vector, and $Y = V_t$ the output vector. the expressions for the state and output equations are given by Equation (1).

$$\begin{cases} SOC_{k+1} = SOC_k - \frac{\eta \Delta t I_k}{Q_k} + W_{SOC,k} \\ U_{1,k+1} = e^{-\Delta t / (R_1 C_1)} U_{1,k} + R_1 (1 - e^{-\Delta t / (R_1 C_1)}) I_k + W_{1,k} \\ U_{2,k+1} = e^{-\Delta t / (R_2 C_2)} U_{2,k} + R_2 (1 - e^{-\Delta t / (R_2 C_2)}) I_k + W_{2,k} \\ R_{0,k+1} = R_{0,k} + W_{R,k} \\ Y_k = OCV(SOC_k) - I_k R_{0,k} - U_{1,k} - U_{2,k} + V_n \end{cases} \quad (1)$$

In Equation (1), SOC represents the state of charge. U_1 and U_2 represent the polarization voltages of the two RC branches, respectively. R_0 represents the ohmic internal resistance. I represents the discharge current. T represents the battery temperature. V_t represents the terminal voltage. η represents the coulombic efficiency. Δt represents the sampling time. R_1, C_1 and R_2, C_2 represent the polarization resistance and polarization capacitance of the two RC branches, respectively. $OCV(\cdot)$ represents the open-circuit voltage function. $W_{SOC,k}$, $W_{1,k}$, $W_{2,k}$, and $W_{R,k}$ represent process noise. and V_n represents measurement noise. The parameters are obtained through a combination of offline identification and online adjustment. During the offline phase, hybrid pulse power

characterization tests are conducted on the battery pack. pulse currents are applied at various states of charge (SOC) while terminal voltage responses are recorded, and the Recursive Least Squares (RLS) method is used to fit the initial values of ohmic resistance, polarization resistance, and polarization capacitance. The relationship between open-circuit voltage and SOC is determined via low-current charge/discharge and rest tests, utilizing polynomial fitting. In the online phase, the AEKF adaptively adjusts the process noise covariance and measurement noise covariance based on the innovation sequence, thereby maintaining parameter validity amidst aging and changing operating conditions. The battery pack has a rated capacity of 60 Ah and a nominal voltage of 12.8 V, utilizing a lithium iron phosphate chemistry. The parameters are set as follows: ohmic internal resistance $R_0 = 80 \text{ m}\Omega$. polarization resistance $R_1 = 0.5 \text{ m}\Omega$. polarization capacitance $C_1 = 2000 \text{ F}$. polarization resistance $R_2 = 0.3 \text{ m}\Omega$. polarization capacitance $C_2 = 5000 \text{ F}$. and coulombic efficiency $\eta = 0.98$. The AEKF linearizes nonlinear data by calculating the Jacobian matrix, which consists of the partial derivatives of the state and output equations with respect to the state variables. AEKF linearizes nonlinear data by calculating the Jacobian matrix. The state estimation process of AEKF is shown in Equation (1).

$$\hat{x}_{n|n-1} = \phi_{n|n-1} \hat{x}_{n-1|n-1} \quad (1)$$

In Equation (1), $\hat{x}_{n-1|n-1}$ represents the estimated value at the $n - 1$ -th step. $\phi_{n|n-1}$ represents the system transition matrix at the n -th step. $\hat{x}_{n|n-1}$ represents the prior estimate at the n -th step. The process of calculating the error covariance matrix in AEKF is shown in Equation (2).

$$P_{n|n-1} = \phi_{n|n-1} P_{n-1|n-1} \phi_{n|n-1}^T + Q \quad (2)$$

In Equation (2), $P_{n|n-1}$ represents the error covariance matrix of the prior estimate. Q represents the covariance matrix of system noise, $Q = \text{diag}(1 \times 10^{-8}, 1 \times 10^{-6}, 1 \times 10^{-6}, 1 \times 10^{-10})$. The calculation of the Kalman gain is shown in Equation (3).

$$K_{n|n-1} = P_{n|n-1} C^T (C P_{n|n-1} C^T + R)^{-1} \quad (3)$$

In Equation (3), $K_{n|n-1}$ represents the Kalman gain. R represents the covariance matrix of measurement error, with a value of $1 \times 10^{-6} \text{ V}^2$, corresponding to a standard deviation of 1 mV for the terminal voltage measurement. C represents the measurement matrix.

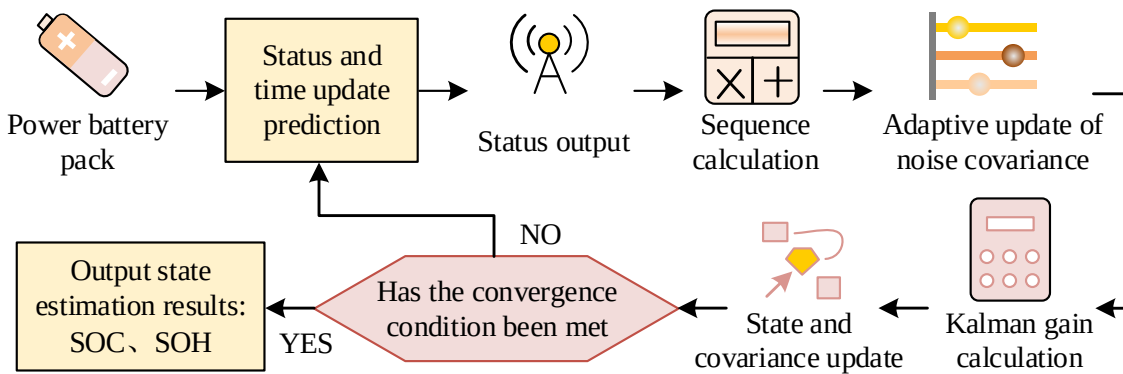


Fig. 2. Process of battery state estimation and monitoring based on the AEKF algorithm

The covariance matrix estimation for the next time step is shown in Equation (4).

$$\begin{cases} P_{n|n} = (I - K_{n|n-1}C)P_{n|n-1} \\ x_n = \phi_{n|n-1}x_{n-1|n-1} + W_{n-1} \\ Y_n = Cx_n + V_n \end{cases} \quad (4)$$

In Equation (4), $P_{n|n}$ represents the covariance estimation at the next time step. W_{n-1} represents system noise. V_n represents measurement noise. The battery state estimation and monitoring process based on this algorithm framework is shown in Figure 2.

As shown in Figure 2, AEKF updates the initial state estimate and covariance matrix of the battery pack to obtain the prior state estimate and prior error covariance. It then calculates the measured voltage difference using the innovation sequence. After updating and computing the covariance matrix, the algorithm determines the weight allocation between predicted values and measured values. The state and covariance measurements are then corrected to output the posterior state estimate. The algorithm performs a prediction and correction step at each sampling instant, with sampling intervals set to 10 Hz (0.1 s) or 100 Hz (0.01 s) depending on the experiment. The convergence criteria for the iteration are that the Euclidean distance between consecutive state estimates is less than 1×10^{-4} , or the rate of change of the innovation covariance is less than 1%. If the convergence criteria are met or the maximum of 50 iterations is reached, the real-time state estimate is output; otherwise, the process returns to the prediction stage to continue iterating. The monitoring process concludes when the total experiment duration reaches 5000 s or the battery pack ceases operation. This study combines HARA with AEKF to form the AEKF-HARA algorithm. The algorithm achieves high safety objective compliance and strong technical traceability. It also addresses the influence of redundant signals. The process of adjusting battery pack adaptability and observation noise is shown in Equation (5).

$$N_k = \hat{y}_k y_k^T - H_k P_{k|k-1} H_k^T \quad (5)$$

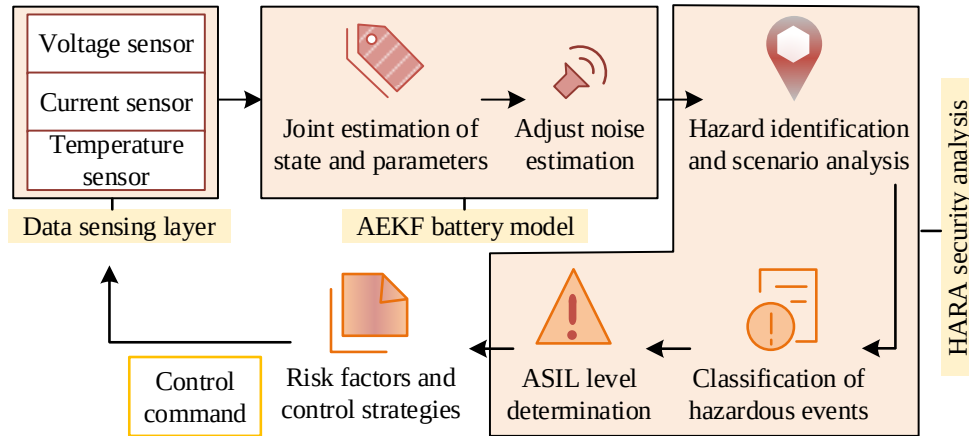


Fig. 3. Process of battery pack monitoring and analysis using the AEKF-HARA algorithm

In Equation (5), N_k represents the innovation covariance. H_k^T represents the observation matrix. The AEKF utilizes sliding statistics of the innovation to update the process and measurement noise covariance matrices online. The noise covariances are increased when innovation fluctuations rise, thereby enhancing dynamic adaptability, and are reduced when the innovation is stable to maintain estimation consistency. A forgetting factor is introduced to accelerate the update process when the rate of change of the innovation exceeds a specific threshold. The updated noise covariances are then employed for prediction and gain calculation in the subsequent time step, enabling adaptation to aging effects and changes in operating conditions. The monitoring and analysis process of power battery packs using AEKF-HARA combined with sensor signals is shown in Figure 3.

As shown in Figure 3, AEKF-HARA collects physical battery signals through sensors and inputs them into AEKF for parameter adjustment. AEKF predicts battery state estimation and error covariance based on sensor signals. It adjusts noise covariance in real time, maintains battery performance, and outputs the state of charge. The state of charge enters the HARA framework definition. HARA performs fault diagnosis of the battery pack through rule-based and residual analysis. It analyzes hazard types and events, evaluates hazard risks, and determines the ASIL level. Finally, AEKF-HARA triggers corresponding management decisions based on risk assessment results. It executes safety measures defined in HARA and outputs control commands that affect sensors. This process completes real-time monitoring and analysis of the power battery pack. The correction process of estimation values in AEKF-HARA is shown in Equation (6).

$$\hat{x}_{n|n} = \hat{x}_{n|n-1} + K_{n|n-1}(Y_n - C\hat{x}_{n|n-1}) \quad (6)$$

In Equation (6), $\hat{x}_{n|n}$ represents the posterior estimate. Y_n represents the measured value.

3.2 Establishment of A Real-Time Monitoring Model with the Introduction of the AE Algorithm

The HARA-AEKF algorithm predicts state estimation and trend evolution through AEKF, while HARA performs reliable and protective safety actions. The two components work together to complete real-time monitoring of power battery packs. However, this algorithm still shows limitations in data utilization and detection of unknown faults. Autoencoder (AE) extracts historical data and automatically learns operating patterns under normal conditions. It explores deeper and unknown faults as well as nonlinear relationships. This process improves the utilization of sensor signals and enhances real-time and automatic monitoring performance [16-17]. Therefore, this study introduces AE to optimize the AEKF-HARA algorithm and develops the AE-AEKF-HARA real-time monitoring model for power battery packs, referred to as the AAH model. The model aims to achieve accurate state tracking and provide real-time and reliable hazard mitigation solutions. The real-time monitoring process based on AE is shown in Figure 4.

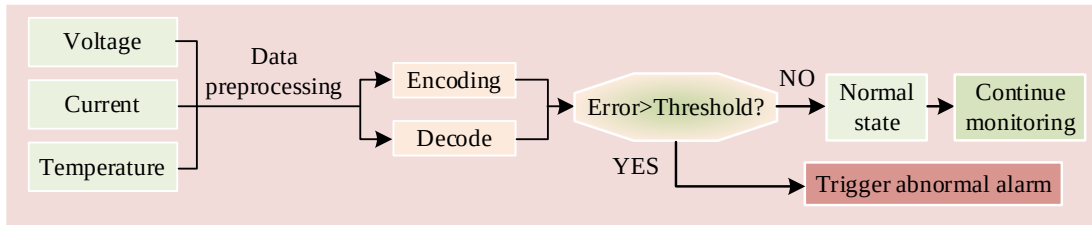


Fig. 4. Process of real-time battery pack monitoring based on the AE algorithm

In Figure 4, AE collects historical normal operation data of power battery pack, including voltage, current and temperature. The data were normalized by Z-score, and the missing values were supplemented by linear interpolation. The network input dimension is 3, the encoder and decoder are symmetrical, the number of neurons in the hidden layer is 16, 8, 4, 8 and 16, the activation function is relu, and the output layer is sigmoid. Adam optimizer was used for training, with a learning rate of 0.001, a batch size of 64, and 200 iterations. The training set and validation set were divided by 8:2. The abnormal threshold is determined based on the mean and standard deviation of the reconstruction error of the normal verification set. The threshold $\tau = \mu + 3\sigma$ is taken and verified on the fault verification set to ensure that the false positive rate and false negative rate meet the requirements. After determining the reconstruction error of each sample, the algorithm performs real-time anomaly detection. If the reconstruction error exceeds the threshold, the sample shows abnormal patterns and triggers an anomaly alarm. If the reconstruction error is less than or equal to the threshold, the battery sample remains in a normal state and the algorithm continues monitoring the next anomaly point. This process completes battery pack state monitoring. The encoder output of AE is shown in Equation (7).

$$h = g(x) = \sigma(Wx + b) \quad (7)$$

In Equation (7), g represents the encoder. h represents the hidden variable output of the encoder. σ represents the activation function of the encoder. b and W represent the bias vector and weight matrix of the encoder. The decoder output is shown in Equation (8).

$$\hat{x} = f(g(x)) = \sigma'(W'h + b') \quad (8)$$

In Equation (8), $\hat{x}$ represents the decoder output. f represents the decoder. h represents the hidden variable. σ' represents the activation function of the decoder. W' and b' represent the weight matrix and bias vector of the decoder. The loss function of reconstruction error in AE is shown in Equation (9).

$$L_{MSE}(\theta) = \frac{1}{n} \sum_{i=1}^n \|x_i - \hat{x}_i\|^2 \quad (9)$$

In Equation (9), θ represents the parameters used in the encoder and decoder. The training process minimizes reconstruction error through parameter θ . n represents the number of samples. x_i represents the original data. $\hat{x}_i$ represents the reconstructed data. The state monitoring and analysis process of power battery packs based on the AAH model with AE is shown in Figure 5.

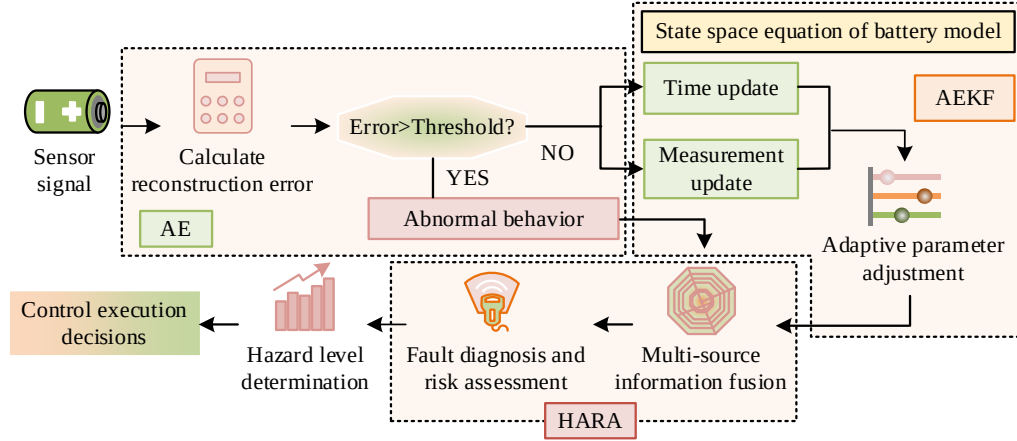


Fig. 5. Process of battery pack status monitoring and analysis based on the AAH model

As shown in Figure 5, the AAH model preprocesses physical signals collected from power battery packs by sensors and inputs them into the AE module. The encoder compresses sensor signals into low-dimensional features, and the decoder reconstructs the features into the original dimensions. AE performs primary anomaly detection. If the reconstruction error exceeds the threshold, the data pattern is abnormal and triggers a primary anomaly flag. If the error remains within the threshold, the AE output data enter the AEKF module. In AEKF, the algorithm updates time and measurement step and combines the battery state model to adjust parameters such as real-time noise. This process improves the accuracy of state of charge and state of health detection. Then, the model takes the self-encoder reconstruction error, anomaly flag, innovation and normalized residual of extended Kalman filter, state of charge, health state and internal resistance change as HARA inputs. The severity is determined in combination with hazard type, voltage difference, temperature rise and state of charge. The degree of occurrence or exposure shall be determined in combination with abnormal signs, residual overrun duration and occurrence frequency. Controllability is determined in combination with response time, redundant sensors and execution capability. ASIL level is determined according to ISO 26262 risk matrix, and corresponding safety objectives and trigger thresholds are selected from table 3-1. The control decision is implemented according to the level. Level D cuts off the high voltage and starts the emergency thermal management. Level C reduces the power and alarms. Level B limits the charge and discharge and encrypts the sampling. Level A record, prompts and calibrates. If the self-encoder anomaly flag triggers or the normalized residual continues to exceed the limit, the unknown anomaly or sensor inconsistency is input into HARA as an additional hazard, triggering degradation monitoring, redundancy switching or model estimation replacement. The domain reconstruction error calculation process of the AAH model is shown in Equation (10).

$$r(x) = \|x - \hat{x}\|^2 - \text{mean}_{z \in N_k(x)} (\|z - \hat{z}\|^2) \quad (10)$$

In Equation (10), $r(x)$ represents the neighborhood reconstruction error. z represents neighborhood samples. $N_k(x)$ represents the set of k -domain samples used to train observation values. The neighborhood size is set to 5, and the distance metric uses Euclidean distance. The domain sample set is composed of 80% randomly selected from normal training data, with a total of 10000 normal training samples. Therefore, the NN contains 8000 samples, and the remaining 2000 samples are used as the validation set. For each sample, first search for the 5 nearest neighboring samples from the domain sample set, calculate the mean reconstruction error of these neighboring samples, and then subtract the mean from the reconstruction error of the sample itself

to obtain the domain reconstruction error. This value is used to measure the degree of deviation of the sample reconstruction error from its neighborhood average level, with larger deviations being more likely to be abnormal. The process of detecting the variation rate of observation noise in the AAH model is shown in Equation (11).

$$\gamma = \left| \frac{\sum_{i=k-N}^k N_i - \sum_{i=k-2N}^{k-N} N_i}{\sum_{i=k-2N}^k N_i} \right| \quad (11)$$

In Equation (11), γ represents the estimated variation rate of observation noise and reflects the degree of observation noise variation. $2N$ represents the width of the time window. k represents the current time step. The process of adjusting the forgetting factor based on the variation rate of observation noise is shown in Equation (12).

$$b = b_{4\min_{\max_{\max}}} \quad (12)$$

In Equation (12), b represents the forgetting factor at the current time step. $b_{\max}$ represents the maximum value of the forgetting factor. $b_{\min}$ is the minimum value of the forgetting factor.

4. Performance of The Battery Monitoring Model Combining Sensor Signals And HARA

4.1 Verification of Monitoring and Analysis Performance Of AEKF-HARA

To verify the real-time detection and analysis performance of the AEKF-HARA algorithm, this study conducted comparative experiments with three real-time monitoring algorithms: Bidirectional Long Short-Term Memory Network (BiLSTM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and CNN-SVM, which combined Convolutional Neural Network (CNN) with Support Vector Machine (SVM). The bidirectional long short-term memory network can capture the temporal dependencies of battery signals. The adaptive neural fuzzy inference system combines the adaptive capabilities of fuzzy inference and neural networks. CNN-SVM uses convolutional layers to extract local features and is classified by support vector machines. These three types of methods represent typical applications of deep learning, fuzzy reasoning, and hybrid models in battery monitoring and fault diagnosis. To ensure fairness in comparison, all baseline methods were trained and tested under the same dataset partitioning, input features, and evaluation conditions. The experimental environment was set up as follows: the operating system was Windows 11, the CPU was Intel Core i9-14900K, the GPU was NVIDIA RTX 4090 24GB, the memory was 64 GB, the deep learning framework was PyTorch 2.0.1, and the programming language was Python 3.9. BiLSTM is set to two layers, with 64 and 32 hidden units respectively, dropout of 0.2, optimizer Adam, learning rate of 0.001, batch size of 64, maximum iteration of 200 rounds, using early stopping strategy, and patience value of 20. ANFIS adopts Gaussian membership functions, with 3 membership functions for each input variable. The training algorithm is mixed learning, with a maximum of 100 iterations. In CNN-SVM, CNN consists of two convolutional layers with kernel sizes of 3 and 3, and numbers of 16 and 32, respectively. The pooling layer uses max pooling, and the fully connected layer outputs 64 dimensional features. SVM uses radial basis kernel functions, and the penalty parameters C and gamma are determined on the validation set through grid search. All baseline methods use the same training, validation, and testing sets as AEKF-HARA, with consistent input features and evaluation metrics, and repeat the experiment 5 times to take the mean. The hyperparameters are determined on the validation set through grid search or early stopping strategy to ensure optimal performance for each baseline. The datasets used in the experiment are the Oxford Battery Degradation Dataset (OBD) and the University of Maryland CALCE Battery Research Group Dataset (CALCE). The OBD dataset uses Oxford Battery Degradation Dataset 1, which includes 8 Kokam SLPB 533459H4 batteries with a sampling interval of 1 second. The features include voltage, current, temperature, and SOC, and the operating conditions are constant current charging and discharging and dynamic driving cycles. The CALCE dataset uses CS2 and CX2 series, selects 12 batteries with a sampling interval of 1 second, and features voltage, current, temperature, and capacity. The operating conditions are constant current charge discharge and DST. Both datasets are divided in chronological order, with the top 70% used as the training set, 15% as the validation set, and 15%

as the testing set to avoid time series data leakage. The training set is used for model parameter fitting, the validation set is used for hyperparameter selection and anomaly threshold determination, and the test set is only used for final performance evaluation. All experiments were repeated 5 times, and the results were expressed as mean $\pm$ standard deviation. One way analysis of variance was used for inter group comparison, with a significance level of 0.05. This study conducted experiments with the AEKF-HARA algorithm and the three comparison algorithms (BiLSTM, ANFIS, and CNN-SVM) on the OBD dataset, using two metrics to measure performance: Root Mean Square Error (RMSE) of state of charge estimation accuracy and voltage boundary prediction accuracy. The root mean square error of the state of charge estimation accuracy is obtained by taking the square root of the difference between the predicted value and the true value, expressed as a percentage. The smaller the value, the smaller the estimation error. The accuracy of voltage boundary prediction is the proportion of samples whose predicted voltage falls within the allowable boundary of the true voltage. The allowable boundary is taken as 2% of the true voltage. This indicator is dimensionless, and the closer it is to 1, the more reliable the predicted voltage is. The results are shown in Figure 6.

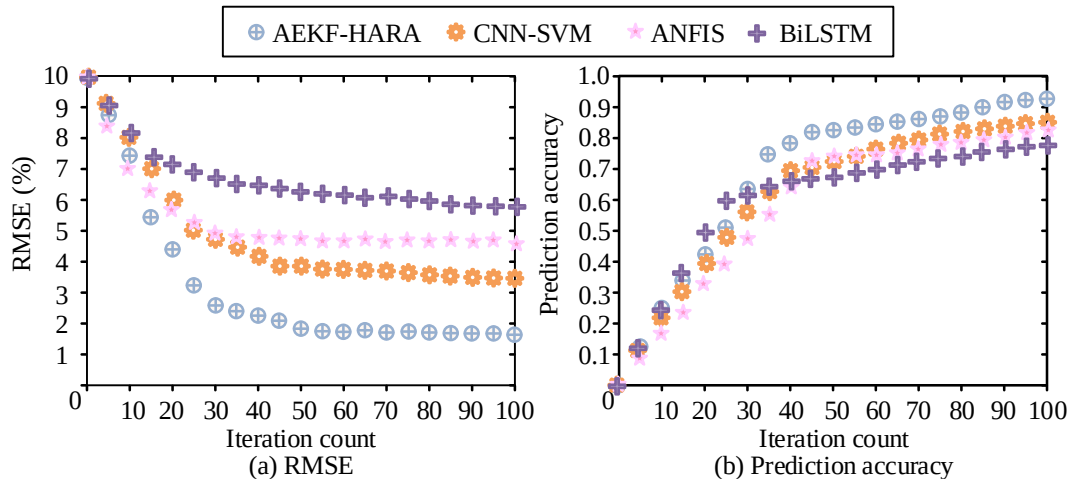


Fig. 6. Comparison of algorithm performance indicators on the OBD dataset

As shown in Figure 6(a), the root mean square error of the state of charge estimation accuracy of AEKF-HARA algorithm is $1.712\% \pm 0.085\%$, while that of BiLSTM algorithm is $5.804\% \pm 0.216\%$. The difference between the two is 4.092 percentage points, and the difference is statistically significant ($p < 0.05$). From the results in Figure 6(b), the accuracy of voltage boundary prediction using the AEKF-HARA algorithm reached a value of 0.934, which showed an improvement of 0.123 over the BiLSTM algorithm. The earlier results showed that the AEKF-HARA algorithm was capable of achieving higher accuracy in the estimation of the state of charge and voltage boundary prediction of the battery. By using the benefits provided by AEKF's adaptive adjustment of parameters, the analysis of the algorithm was improved. To further verify the superiority of the real-time monitoring performance of the AEKF-HARA algorithm, this study conducted experiments with it and the three comparison algorithms on the CALCE dataset, using two metrics for evaluation: fault identification delay time and identification accuracy. The fault recognition delay is the average delay of all fault types, including overcharge, over discharge, overtemperature, internal short circuit, connection fault, voltage sensor fault, current sensor fault, temperature sensor fault, thermal runaway spread, and insulation fault. The results are shown in Figure 7.

As shown in Figure 7 (a), the delay time for fault recognition using the AEKF-HARA algorithm is 29.87 ± 1.24 ms, and the recognition accuracy is $92.41\% \pm 1.05\%$. From Figures 7 (b), (c), and (d), it can be seen that the CNN-SVM algorithm achieved good results in various indicator tests. However, compared with the AEKF-HARA algorithm, its delay time increased by 10.72 ms and the recognition accuracy decreased by 5.22 percentage points, with statistical significance ($p < 0.05$). From the above results, it could be concluded that the proposed AEKF-HARA algorithm could react promptly to the identification of dangerous battery types and efficiently capture fault features. The timely and reliable data support offered by the proposed algorithm could play an important role in maintaining battery operation stability. This was due to the efficient combination of the AEKF

algorithm and HARA, enabling fast identification and feature extraction, increasing the efficiency of identification. To further analyze the real-time performance of each method, Table 2 compares the inference time, model size, and memory usage of each component of AEKF-HARA with the comparison model.

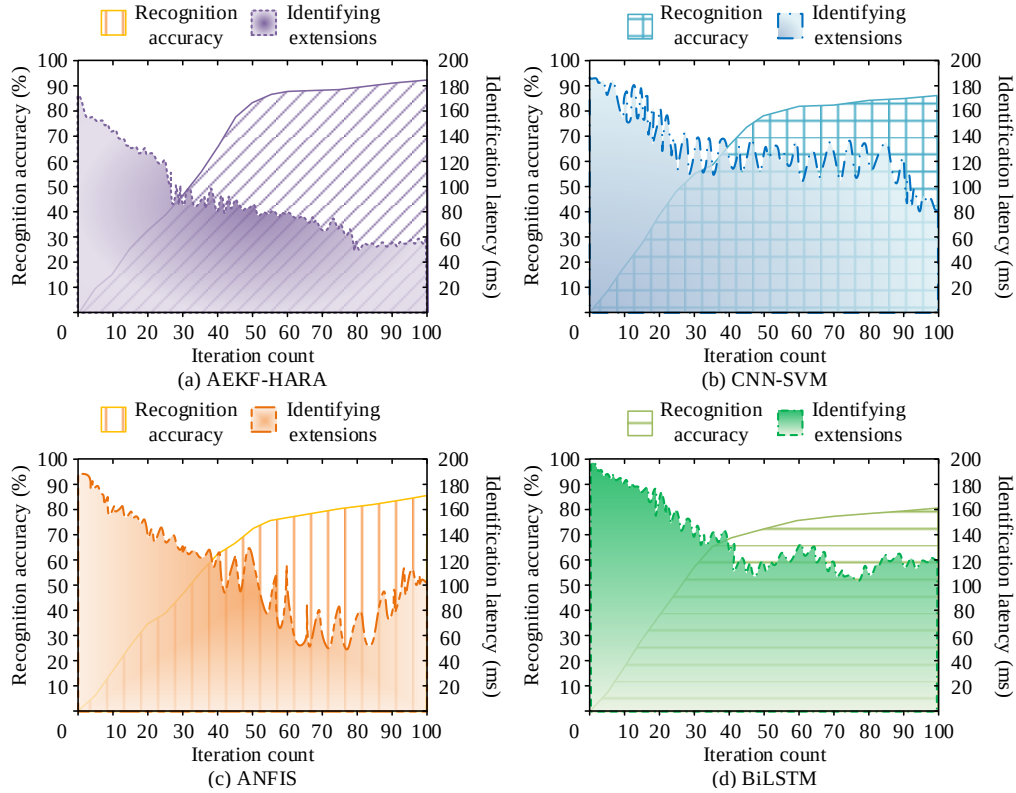


Fig. 7. Comparison of real-time monitoring performance on the CALCE dataset

Table 2. Comparison of real-time performance of different models

Model	Inference Time (ms)	Model Size (MB)	Memory Usage (MB)
AEKF-HARA	29.87±1.24	0.65	120
CNN-SVM	40.59±1.86	1.80	210
ANFIS	46.32±2.05	1.20	180
BiLSTM	52.14±2.31	2.50	260
Model based on Whale Optimization Algorithm and Long Short-Term Memory Algorithm	38.65±1.72	2.10	240

According to Table 2, the inference time of AEKF-HARA is 29.87±1.24 ms, which is lower than other models. The inference time of CNN-SVM and models based on whale optimization algorithm and long short-term memory algorithm are 40.59±1.86 ms and 38.65±1.72 ms, respectively. The inference time of ANFIS and BiLSTM both exceed 45 ms. In terms of model size and memory usage, AEKF-HARA is 0.65 MB and about 120 MB, respectively, which are lower than other models. The above results indicate that AEKF-HARA has lower inference latency and resource consumption while maintaining high recognition accuracy, making it suitable for embedded deployment. To verify that the proposed algorithm possessed more advantages in real-time monitoring performance, the experiments are carried out with the proposed algorithm and the other three algorithms on the OBD dataset and CALCE dataset. The experiments assessed the algorithms based

upon three metrics: monitoring precision, recall, and F1 score. At the same time, whale optimization algorithm and long short-term memory algorithm [8] were introduced. The experimental results are shown in Table 3.

Table 3. Comparison of algorithm performance indicators

Dataset	Algorithm	Precision (%)	Recall (%)	F1 Score (%)
OBD	AEKF-HARA	96.62%±0.58%	95.18%±0.62%	95.89%±0.55%
	CNN-SVM	91.35%±0.82%	90.47%±0.86%	90.90%±0.79%
	ANFIS	88.24%±0.91%	86.91%±0.95%	87.57%±0.88%
	BiLSTM	87.71%±0.96%	86.05%±1.02%	86.87%±0.94%
	The method proposed by Zhao and Bai	95.02%±0.67%	94.76%±0.70%	94.89%±0.65%
CALCE	AEKF-HARA	96.33%±0.61%	95.12%±0.64%	95.73%±0.58%
	CNN-SVM	90.58%±0.85%	89.96%±0.88%	90.27%±0.82%
	ANFIS	89.61%±0.89%	88.44%±0.93%	89.02%±0.91%
	BiLSTM	86.86%±0.98%	85.27%±1.05%	86.06%±0.96%
	The method proposed by Zhao and Bai	94.85%±0.69%	94.58%±0.72%	94.71%±0.67%

As shown in Table 3, the AEKF-HARA algorithm has higher accuracy, recall, and F1 score than other comparison methods on the OBD and CALCE datasets. On the OBD dataset, its F1 value is 95.86%±0.55%, which is 4.95, 8.29, 9.02, and 0.97 percentage points higher than CNN-SVM, ANFIS, BiLSTM, and models based on whale optimization algorithm and long short-term memory algorithm, respectively. On the CALCE dataset, its F1 value is 95.73%±0.58%, which is 5.58, 9.51, 8.70, and 1.02 percentage points higher than the four methods, respectively. The above differences are statistically significant ($p < 0.05$). The above data results indicated that the AEKF-HARA algorithm demonstrated excellent monitoring and analysis performance on both datasets, possessing accurate feature capture capability. This was because the HARA method in this algorithm provided accurate hazard type and risk assessment standards, and combined with the adaptive filtering capability of the AEKF algorithm, it adjusted and optimized battery system parameters in real time, monitoring battery states more effectively.

4.2 Performance Analysis of The AAH Battery Monitoring Model

After verifying the superiority of the real-time monitoring performance of the AEKF-HARA algorithm, this study conducted comparative experiments with the AAH model and three monitoring models: CNN-SVM, ANFIS, and BiLSTM. The experimental environment parameter settings were the same as those used in the experiments verifying the real-time monitoring performance of the AEKF-HARA algorithm. The experimental datasets used were the OBD dataset, CALCE dataset, and a self-made dataset. The content details of the self-made dataset are shown in Table 4.

As shown in Table 2, the self-built dataset is based on a second-order RC equivalent circuit model, with a rated capacity of 60 Ah and a nominal voltage of 12.8 V for the battery pack, using a lithium iron phosphate system. The circuit parameters are Ohmic internal resistance of 0.8 m Ω , polarization resistance R1 of 0.5 m Ω , R2 of 0.3 m Ω , polarization capacitance C1 of 2000 F, C2 of 5000 F, and Coulomb efficiency of 0.98. Fault injection includes voltage sensor offset of ± 50 mV, ± 100 mV, stuck holding constant, accuracy decrease noise standard deviation of 5 mV, current sensor noise standard deviation of 0.05C, rate deviation of $\pm 5\%$, temperature sensor reading drift of ± 2 $^{\circ}\text{C}$, and connection fault internal resistance increase of 30% and 50%. The duration of fault injection is randomly distributed between 10 s and 60 s, and each fault type is tested 10 times. The truth value is generated by the injection time and fault type label, and normal samples and fault samples are mixed in chronological order.

Table 4. Details of the self-made dataset

Type	Parameter	Specific settings
Battery data and model	Cell model	Second order RC equivalent circuit model
	Battery pack configuration	Rated capacity: 60 Ah Nominal voltage: 12.8 V (3.2V/cell)
	Experimental data source	Standard driving cycle (NEDC/WLTC) generates voltage, current, and temperature data
Fault injection setting	Fault Type	Generation of voltage, current, and temperature data based on standard driving cycles (NEDC/WLTC)
		Voltage sensor: offsets of ± 50 mV and ± 100 mV, signal sticking, and accuracy degradation (noise standard deviation of 5 mV)
		Current sensor: noise injection (standard deviation of 0.05C) and rate deviation of $\pm 5\%$ Temperature sensor: reading drift of $\pm 2^\circ\text{C}$ Connection faults: 30% and 50% increases in connection point internal resistance
	Injection timing	The time distribution was randomized throughout the experiment, lasting from 10 s to 60 s.
Experimental setup	Sampling frequency	10 Hz & 100 Hz
	Experimental time	5000s
	Ttest scenario	Environmental temperature: 25°C Charge discharge rate: 1C

The data is divided in chronological order, with the first 70% being the training set, 15% being the validation set, and 15% being the testing set. The experiment was repeated 5 times, and the results were expressed as mean standard deviation. One way analysis of variance was used to compare the differences between the models. The fault injection in the self-built dataset is divided into sensor level faults and physical battery faults. Sensor level faults include voltage sensor offset, jamming, and decreased accuracy, current sensor noise and rate deviation, and temperature sensor reading drift. Physical battery failures include increased internal resistance at connection points, which extends to internal short circuits and overcharging. The AAH model simultaneously detects these two types of objects, AEKF determines sensor signal consistency through information and residuals, AE identifies unknown anomalies through reconstruction errors, and HARA determines ASIL levels based on hazard type, severity, exposure/occurrence, and controllability. Sensor anomalies are mapped as voltage, current, or temperature sensor faults according to Table 2, triggering redundant switching or model estimation substitution. When voltage dip, temperature rise, and AE reconstruction error occur simultaneously, they are mapped as physical battery hazards such as internal short circuits, triggering the disconnection of high voltage and emergency thermal management. In this way, sensor level faults and physical battery hazards can be distinguished in monitoring and risk assessment, and corresponding safety decisions can be formed. This study conducted experiments with it and the three comparison models on the CALCE dataset, using two metrics to evaluate the monitoring performance of the models: Coefficient of Determination (R^2) and fault detection consistency. The coefficient of determination R^2 is calculated according to the standard formula, and the closer it is to 1, the better the fit. The consistency of fault detection is the proportion of samples whose fault types output by the model are consistent with the actual fault types, expressed as a percentage of the total sample size. The larger the proportion, the more reliable the monitoring results will be. The experimental results are shown in Figure 8.

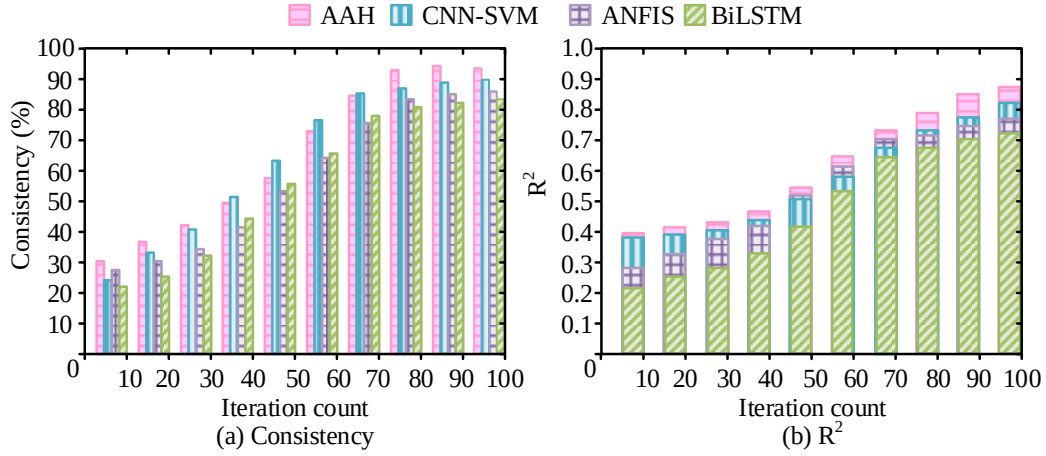


Fig. 8. Comparison of model performance indicators on the CALCE dataset

As shown in Figure 8(a), the AAH model achieved a result of $94.28\% \pm 0.76\%$ in the fault detection consistency test, outperforming the other three comparative models and showing an absolute improvement of 4.27 percentage points over the CNN-SVM model. The difference is statistically significant ($p < 0.05$). In Figure 8(b), the R^2 value of the AAH model reached 0.872 ± 0.015 , improving by 0.048 and 0.101 compared to the CNN-SVM model and ANFIS model, respectively, and the difference was statistically significant ($p < 0.05$). The above results indicated that the AAH model had high consistency, proving that this model could accurately identify battery fault features, effectively controlling the occurrence of missed or false alarms, and could deeply capture the intrinsic features of the battery system, thereby enhancing the real-time monitoring capability of the model.

In order to further evaluate the real-time monitoring performance of the AAH model, this study tested the AAH model and the three comparison models mentioned above on the OBD dataset, and evaluated them through insulation resistance estimation error (MAE). The estimation error of insulation resistance is obtained by dividing the absolute value of the difference between the estimated isolation resistance after fault isolation and the true isolation resistance by the nominal voltage, and then taking the average of all samples. The unit is Ω/V . The smaller the value, the higher the isolation accuracy. The test results are shown in Figure 9.

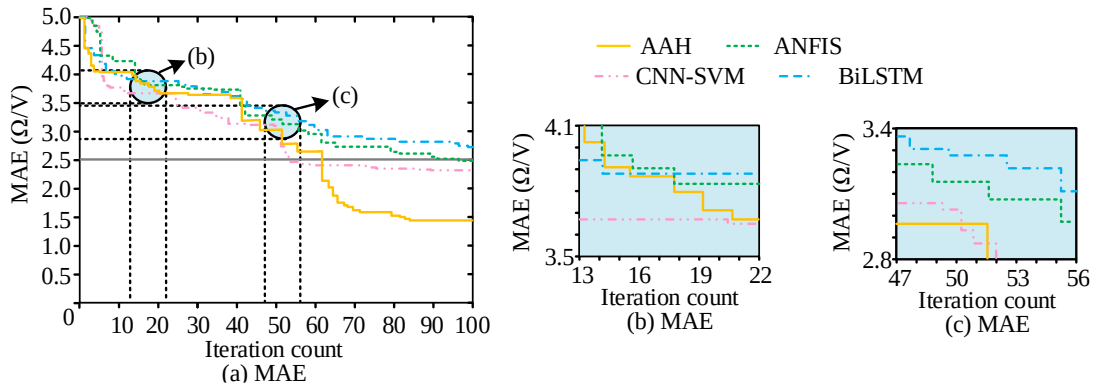


Fig. 9. Comparison results of insulation resistance estimation errors

As shown in Figure 9(a), After 100 iterations, the AAH model achieved the best performance with an estimated insulation resistance error (MAE) of $1.492 \Omega/V$. The weakest performer was the BiLSTM model, with an MAE value of $2.716 \pm 0.113 \Omega/V$, an increase of $1.224 \Omega/V$ compared to the AAH model, and the difference is statistically significant ($p < 0.05$). In Figures 9(b) and 9(c), the error reduction trend of the AAH model in the early stage was at a moderate level, but as the number of iterations increased, the error reduction speed of the AAH model accelerated and gradually stabilized at the lowest level. The above results demonstrated that the AAH model could perform effective error control and accurately locate fault positions, possessing excellent error convergence capability and the ability to capture nonlinear data features. This benefited from the AEKF structure, which enhanced the model's ability to process complex data and the adaptability of

battery performance, reducing the possibility of errors. To more comprehensively evaluate the real-time monitoring performance of the AAH model, this study tested it and the three comparison models on the self-made dataset, measuring through the comparison of the gap between predicted State of Charge (SOC) values and actual SOC values. The accuracy of state of charge prediction is the proportion of samples whose predicted SOC falls within the range of plus or minus 2% of the true SOC to the total number of samples, expressed as a percentage. The larger the percentage, the more accurate the prediction. The test results are shown in Figure 10.

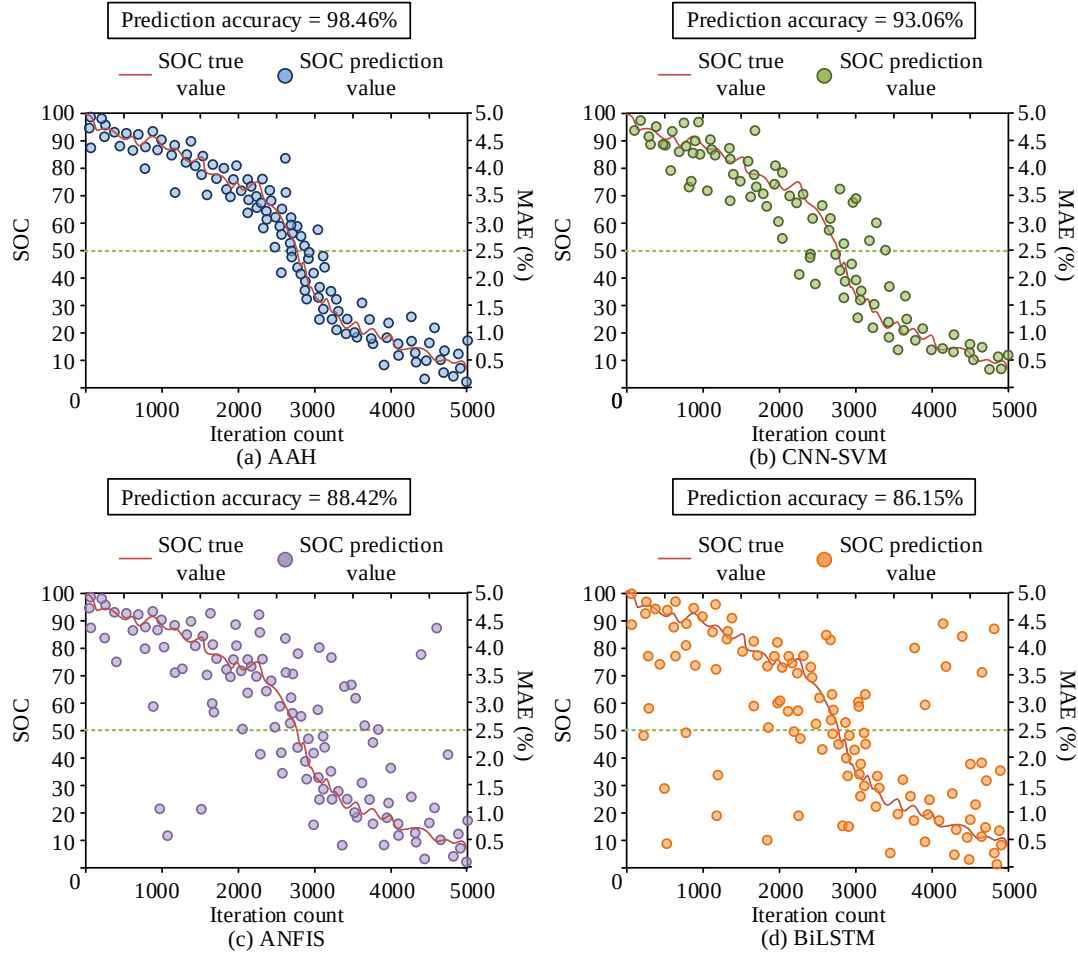


Fig. 10. Comparison of SOC prediction results

As shown in Figure 10(a), the average State of Charge (SOC) estimation accuracy of the AAH model reached $98.46\% \pm 0.42\%$ (representing a tracking error of less than 1.54%). In Figures (b), (c), and (d), the BiLSTM model had the lowest prediction result, reaching $86.15\% \pm 0.95\%$, and some prediction points were relatively scattered. Compared to the AAH model, the prediction ratio decreased by 12.31%, and the difference was statistically significant ($p < 0.05$). The above results indicated that the prediction points of the AAH model were closely distributed near the actual values, demonstrating that this model had highly accurate battery state estimation and measurement stability. This is because the HARA method in the AAH model can monitor the battery operating status in real time and reflect battery status information. While the AEKF structure and AE algorithm achieved detection and analysis of complex battery dynamics through adaptive and weight allocation mechanisms, dynamically adjusting parameters and improving the overall real-time monitoring performance of the model. To analyze the contribution of each module in the AAH model, this study conducted ablation experiments; the results are shown in Table 5.

As shown in Table 5, it can be seen that the fault detection consistency of AEKF when used alone is $85.34\% \pm 0.91\%$, the isolated MAE is $2.318 \pm 0.095 \Omega/V$, and the SOC prediction is $91.27\% \pm 0.74\%$, indicating its limited state estimation and noise adaptation capabilities. When used alone, the fault detection consistency of HARA is $82.16\% \pm 1.02\%$, and the isolated MAE is $2.506 \pm 0.108 \Omega/V$. The fault detection consistency of AEKF-HARA has increased to $90.57\% \pm 0.83\%$, the isolated MAE has

decreased to 1.896 ± 0.082 Ω/V , and the SOC prediction has reached $94.13\% \pm 0.61\%$, indicating that HARA's risk classification can improve monitoring decisions. The fault detection consistency of AE-AEKF is $88.92\% \pm 0.88\%$, the isolated MAE is 2.105 ± 0.089 Ω/V , and the SOC prediction is $93.58\% \pm 0.66\%$, indicating that AE enhances the ability of anomaly detection, but lacks the safety objectives and risk classification of HARA. The fault detection consistency of AAH reached $94.28\% \pm 0.76\%$, R^2 was 0.872 ± 0.015 , isolated MAE was 1.492 ± 0.067 Ω/V , and SOC prediction was $98.46\% \pm 0.42\%$, all of which were superior to other ablation models, and the differences were statistically significant ($p < 0.05$). The above results indicate that AEKF, HARA, and AE respectively undertake state estimation, risk decision-making, and anomaly detection functions. The combination of the three can effectively improve the accuracy and stability of real-time monitoring of battery packs. To evaluate the stability of the model under different operating conditions, voltage noise was taken as 1, 2, and 5 mV, current noise was taken as 0.01C, 0.05C, and 0.1C, temperatures were taken as -10, 25, and 45 °C, loads were taken as constant current, DST, and dynamic driving cycles, and aging states were taken as SOH of 100%, 90%, and 80%. The monitoring results under different noise levels, temperatures, load curves, and aging states are shown in Table 6.

Table 5. Results of ablation experiments on the AAH model

Model	Fault detection consistency (%)	R^2	Isolation MAE (Ω/V)	SOC prediction (%)
AEKF	$85.34\% \pm 0.91\%$	0.781 ± 0.018	2.318 ± 0.095	$91.27\% \pm 0.74\%$
HARA	$82.16\% \pm 1.02\%$	/	2.506 ± 0.108	/
AEKF-HARA	$90.57\% \pm 0.83\%$	0.834 ± 0.016	1.896 ± 0.082	$94.13\% \pm 0.61\%$
AE-AEKF	$88.92\% \pm 0.88\%$	0.812 ± 0.017	2.105 ± 0.089	$93.58\% \pm 0.66\%$
AAH	$94.28\% \pm 0.76\%$	0.872 ± 0.015	1.492 ± 0.067	$98.46\% \pm 0.42\%$

Table 6. Robustness results under different conditions

Condition	F1 score (%)	SOC RMSE (%)	Isolation MAE (Ω/V)
Benchmark, 25 °C, 1 mV, 0.01C, constant current, SOH 100%	$95.86\% \pm 0.55\%$	$1.712\% \pm 0.085\%$	1.492 ± 0.067
Voltage noise of 5 mV, current noise of 0.1C	$93.12\% \pm 0.85\%$	$2.45\% \pm 0.12\%$	1.82 ± 0.08
Temperature -10 °C	$92.35\% \pm 0.92\%$	$2.68\% \pm 0.14\%$	1.91 ± 0.09
Temperature 45 °C	$93.05\% \pm 0.88\%$	$2.31\% \pm 0.11\%$	1.78 ± 0.08
DST working condition	$94.20\% \pm 0.72\%$	$1.95\% \pm 0.10\%$	1.58 ± 0.07
Dynamic driving cycle	$93.88\% \pm 0.79\%$	$2.05\% \pm 0.10\%$	1.65 ± 0.07
SOH 90%	$93.56\% \pm 0.81\%$	$2.18\% \pm 0.11\%$	1.72 ± 0.08
SOH 80%	$92.74\% \pm 0.90\%$	$2.52\% \pm 0.13\%$	1.86 ± 0.09

From Table 6, it can be seen that under the conditions of voltage noise of 5 mV and current noise of 0.1C, the F1 score decreased to $93.12\% \pm 0.85\%$, a decrease of 2.74 percentage points compared to the baseline conditions, and the difference was statistically significant ($p < 0.05$). The SOC RMSE increased to $2.45\% \pm 0.12\%$, and the isolated MAE increased to 1.82 ± 0.08 Ω/V , with statistically significant differences compared to the baseline ($p < 0.05$). At -10 °C and 45 °C, the F1 scores were $92.35\% \pm 0.92\%$ and $93.05\% \pm 0.88\%$, respectively, with statistically significant differences compared to the baseline ($p < 0.05$).

The SOC RMSE were $2.68\% \pm 0.14\%$ and $2.31\% \pm 0.11\%$, respectively, and the isolated MAE were 1.91 ± 0.09 and 1.78 ± 0.08 Ω/V . Under DST and dynamic driving cycles, the F1 score remained above 93.88%, with statistical significance ($p < 0.05$) compared to the baseline, but the decrease

was relatively small. When SOH decreased from 100% to 80%, F1 score decreased from 95.86%±0.55% to 92.74%±0.90%, SOC RMSE increased from 1.712%±0.085% to 2.52%±0.13%, and isolated MAE increased from 1.492±0.067 to 1.86±0.09 Ω/V , with statistically significant differences ($p<0.05$). Overall, the model shows good robustness under extreme conditions, with F1 scores still above 92%, SOC RMSE below 2.7%, and isolated MAE below 2.0 Ω/V . To analyze the impact of hyperparameter selection on performance, F1 scores and SOC predictions were calculated for different network structures, anomaly thresholds, forgetting factors, and neighborhood sizes. The results are shown in Table 7.

Table 7. Sensitivity analysis of hyperparameters

Parameter	value	F1 score (%)	SOC prediction (%)
AE hidden layer neurons	8-4-2-4-8	92.15%±0.85%	96.12%±0.55%
	16-8-4-8-16	94.28%±0.76%	98.46%±0.42%
	32-16-8-16-32	94.35%±0.74%	98.51%±0.41%
Abnormal threshold	$\mu+2\sigma$	93.10%±0.82%	97.85%±0.48%
	$\mu+3\sigma$	94.28%±0.76%	98.46%±0.42%
	$\mu+4\sigma$	93.56%±0.80%	98.12%±0.45%
Lower limit of forgetting factor	0.90	93.42%±0.81%	97.95%±0.47%
	0.95	94.28%±0.76%	98.46%±0.42%
	0.98	94.05%±0.78%	98.30%±0.44%
Neighborhood size	3	93.65%±0.80%	98.05%±0.46%
	5	94.28%±0.76%	98.46%±0.42%
	7	94.12%±0.77%	98.35%±0.43%

5. Summary and Outlook

As the backbone of electric vehicles (EVs), the reliable and optimal function of power battery packs remains a significant task in optimizing automotive powertrain efficiency. However, conventional battery monitoring strategies often suffer from the deterioration of efficiency related to environmental factors and the lack of real-time capability. To address the aforementioned issue, the researchers suggested a new strategy of a sensor signal and HARA algorithm-combined battery monitoring and analysis model. This strategy not only employed sensor signal data with AEKF, aiming to improve the optimization of battery state identification and optimization, as well as the application of HARA to identify abnormal type classification. Subsequent to that, the strategy utilized the AE approach aiming to globally optimize the real-time capability of monitoring. Experimental findings confirmed that the RMSE of the state-of-charge estimation via the AEKF-HARA strategy was 1.712%±0.085%, the tracking accuracy was 0.934±0.012 (R^2), the monitoring precision exceeded 96%, the fault identification delay time was limited to 29.87±1.24 ms, and the identification accuracy reached 92.41%±1.05%, which is an absolute improvement of 5.22 percentage points compared to the CNN-SVM algorithm strategy. Meanwhile, the consistency of the AAH model strategy was measured to be 94.28%±0.76%, the insulation MAE is 1.492±0.067 Ω/V , and the predicted SOC accuracy was measured as 98.46%±0.42%, presenting a huge superiority over the other three models. This experiment successfully confirmed that the proposed AAH model strategy exhibited extremely high precision capability of monitoring and high-speed responses to the system monitoring. Although this experimental strategy has shown advantages over other methods in terms of monitoring efficiency and accuracy, its generalization ability in different battery chemistry systems and complex real-world operating conditions still needs to be improved. Therefore, future work will focus on integrating physics-informed machine learning (PINN) and transfer learning algorithms into the AAH framework to accurately predict long-term capacity degradation and state-of-health (SOH) trajectories under diverse operating histories and environmental temperatures.

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