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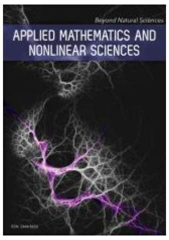

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A real-time early warning method for electric vehicle fast charging safety based on multiple time scales

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Abstract

This paper puts forward the support technology of fast charging supply and demand matching in charging stations and analyzes the common large-capacity electrochemical energy storage technical parameters in charging stations. For the safety of electric vehicle charging, the thermal reaction and thermal runaway processes of power batteries are introduced. Design the electric vehicle charging state monitoring and safety warning methods, and select the multi-timescale ARIMA algorithm to build the electric vehicle charging safety warning model. The sliding window method is used to process the residual mean and residual standard deviation of electric vehicle charging data to improve prediction data and decrease the chance of misjudging pre- and alarms. Combined with the evaluation standard of the safety early warning model, set reasonable pre- and alarm thresholds using the residual analysis method. The safety warning model designed in this paper is verified by different charging fault warnings. Different charging fault warning examples show that the ARIMA-based charging safety early warning model proposed in this paper can be good for the charging facility's output voltage, output current, and charging module temperature faults for early warning to ensure that the warning is carried out before the alarm of the actual fault information, to protect the charging safety of electric vehicles.

Keywords: ARIMA prediction model; Safety early warning; Residual analysis method; Sliding window method; Charging safety.
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1 Introduction

With the enhancement of environmental awareness and the transformation and upgrading of the automobile industry, electric vehicles, as a zero-emission and low-carbon transportation mode, have gradually gained people's attention and favor [1-2]. However, the charging safety of electric vehicles has been an important challenge for the development and popularization of electric vehicles [3-4]. With the popularization of electric vehicles and the increasing demand for charging, the safety hazards in the charging process become more and more prominent. During charging, the battery may generate safety risks due to various factors, such as overheating, overcharging, over-discharging, etc., and in serious cases, it may even cause vegetative fires, posing a serious threat to the safety of people and property [5-6]. Especially in the rapid charging scenario, due to the large charging current and short time, the heat and stress generated inside the battery will accumulate rapidly, making the safety and stability of the battery face greater challenges. In addition, the safety and reliability of the charging facility itself is also an important factor affecting the safety of the charging process [7]. Safety hazards may exist in all aspects of the design, manufacture, installation and maintenance of charging piles. For example, the mismatch between the power and current output of the charging pile may lead to overcharging or over-discharging of the battery, an imperfect cooling system of the charging pile may lead to overheating, and inadequate protective measures of the charging pile may lead to safety accidents, such as electric shock [8-9]. Therefore, in order to guarantee the safety of the rapid charging process of electric vehicles, it is necessary to establish an effective rapid charging safety early warning system, which should be equipped with the functions of real-time monitoring, data analysis, risk assessment, early warning prompts, etc., and be able to detect and respond to potential safety hazards in a timely manner [10-12]. At the same time, it is also necessary to strengthen the safety supervision and maintenance of fast charging facilities to ensure their safety and reliability. Only in this way can we promote the healthy development of the electric vehicle industry and bring more convenience and welfare to society [13-14].

Electric vehicles have become an important development direction for future automobiles due to their advantages of low noise, zero-emission, sufficient power and no fuel consumption, etc., and energy saving and safety are still the eternal themes for their development. Literature [15] proposed a comprehensive assessment methodology for electrical safety and a related proposed architecture from three aspects, namely, equipment degradation, communication network attack, and demand matching when coupling a large-scale electric vehicle hybrid system with renewable power generation, in order to facilitate the monitoring and management of electric vehicle safety. Literature [16] proposes a longitudinal outlier average method that can effectively detect the risk of thermal runaway of electric vehicle batteries, develops an alarm assessment mechanism associated with it, and proposes solutions related to false alarms and sporadic alarms after comprehensively evaluating the consistency of the battery packs utilizing an improved information entropy weighting method. Literature [17] utilizes an improved multiscale entropy algorithm for thermal runaway prediction of electric vehicles in order to facilitate the detection of fault signals before accidents occur, proposes a real-time multilevel prediction strategy based on determined anomaly coefficients, and empirically analyzes and verifies the validity of the proposed strategy, which improves the safety and durability of electric vehicles.

The electric vehicle is a strategic industry that the country focuses on developing, and the charging safety accidents of electric vehicles have been occurring continuously in recent years, which has a serious impact on consumer confidence and the development of the electric vehicle industry. Therefore, ensuring charging safety is crucial for the long-term development of electric vehicles. Literature [18], in order to solve the conflict between charging speed and battery aging in electric vehicles, reviewed more than 50 existing studies on fast charging strategies, which were synthesized, categorized, evaluated, and compared in order to develop a fast and health-focused fast charging strategy for battery management systems. Literature [19] improves the Gray Wolf Optimization (IGWO) algorithm to obtain the IGWO-BP algorithm, establishes an electric vehicle (EV) charging safety warning model on the basis of this improved algorithm, and verifies the validity and reliability of the warning model through an actual case study, which can timely and accurately identify the abnormal state of EV charging voltage and issue warnings. Literature [20] In order to maintain the stable and effective operation of the electric vehicle power system and ensure it is charging safety, a deep learning method for electric vehicle charging load prediction at multiple time scales is proposed based on the long and short-term memory model, and it is compared with the traditional artificial neural network, and the experiments verified that the prediction performance and accuracy of the proposed method are better than that of the traditional artificial neural network.

This paper compares the technical parameters of each large-capacity electrochemical energy storage device, analyzes the basic performance indicators of electric vehicle batteries, and simulates the thermal runaway process of lithium batteries. It also proposes a smart charging strategy for electric vehicle power batteries for short-term, medium-term, and long-term use. Create the electric vehicle charging status monitoring method and the electric vehicle charging safety warning architecture. Analyze the ARIMA algorithm, propose the process for building an ARIMA prediction model, build a charging safety prediction model based on the ARIMA algorithm, and conduct a model fitting test. Based on the evaluation indexes of the safety warning model, the ARIMA charging warning model is tested for safety failures in temperature, voltage, and current, respectively.

2 Electric vehicle charging technology development

2.1 Supporting technologies for matching supply and demand for fast charging at charging stations

1) Smart Grid Technology

   The intelligent technology of the entire grid, including the distribution grid, is called smart grid technology, and it is based on integrated, high-speed, two-way communication. It ensures efficient, safe, economical, and reliable operation of the power grid through modern sensing equipment, testing equipment, networked control modes, and an intelligent learning decision support system. The integrated, high-speed two-way communication system helps the grid to realize the intelligence of "power flow, information flow and control flow" as a whole and covers all aspects of power generation, transmission, substation and distribution, power consumption and scheduling of the grid with informatization, timeliness and interactivity to help the smart grid to realize intelligence, openness, interactivity and interconnectivity. The smart grid can become the cornerstone of the Internet of Things and Energy Internet due to this fundamental reason.

2) Electric Vehicle V2G Technology

   Electric vehicle V2G technology is the existence of two-way transmission of electric energy and information between electric vehicles and the power grid [21-22]. Electric vehicles under the control of the charging station participate in grid scheduling by charging and discharging, and they can also be used as energy storage equipment and standby power. When large-scale electric vehicles are used as distributed energy storage equipment to participate in grid operation and scheduling. According to the willingness of electric vehicles to participate, under the premise of meeting the user's travel requirements, they are discharged to the power grid when there is a power deficit in the grid, and at other moments, they are charged in an orderly manner for electric vehicles.

The battery management system of electric vehicles can achieve rapid conversion, convenient control, and rapid response to charging and discharging. Currently, the battery capacity of electric vehicles is generally between 30 and 200kWh. The battery management system of electric vehicles is the hardware foundation for the realization of V2G technology in electric vehicles. In order to allow more users to participate in V2G applications, EV V2G technology should be utilized in the interests of EV users on the premise of ensuring users' charging needs, taking care of users' travel habits, battery charge status, charging location, and real-time electricity prices.

3) Large-capacity energy storage technology

Large-capacity energy storage technology is essential to the development of smart grids, renewable power generation access systems, electric vehicles, and charging station support technology. Large-capacity energy storage technology is divided into three major forms according to the form of conversion and storage energy: electrochemical, mechanical, and electromagnetic.

Charging stations using electrochemical energy storage are common. These include lead-acid battery energy storage, lithium-ion battery energy storage, sodium-sulfur battery energy storage, and liquid current battery energy storage. These energy storage technologies are respectively in the specific energy, the number of cycles, energy storage power, charge and discharge duration of the existence of characteristic differences, common large-capacity electrochemical energy storage technology, the main technical parameters shown in Table 1. By comparing the parameters, it can be found that lithium-ion batteries and liquid current batteries are more suitable for charging stations to use large-capacity energy storage battery types. V2G technology that can realize the energy interaction between electric vehicles and the power grid in charging stations can also solve the problems of intermittency and volatility of renewable energy power generation, and the inverse of the characteristics of social electricity consumption.

Table 1. Main technical parameters

Battery type	Specific energy	Cycle number	Energy storage power	Charge duration
Lithium-ion battery	100~280	500~2000	1~20MW	1min~11h
Lead-acid battery	20~60	500~1000	1~15MW	1min~7h
Sodium sulfur cell	100~180	1000~4500	0.02~15MW	1min~2h
Fluid cell	10~30	5000~10000	1~12MW	1min~22h

2.2 Electric Vehicle Charging Safety Analysis

2.2.1 Power Battery Charging Safety Characterization

The basic performance indicators of electric vehicle batteries include battery capacity, internal resistance, battery voltage, charge/discharge multiplier, battery charge state, and service life.

1) Battery capacity

Battery capacity indicates the total amount of electricity discharged by the battery under the specified full charge state, usually expressed in Q, symbolized as $A\cdot h$.

2) Battery internal resistance

The internal resistance of the battery indicates that when the battery is working, the current flows through the internal resistance of the battery, including ohmic resistance and polarization resistance. Ohmic resistance is generated when the battery is charging and discharging, and polarization resistance is generated by the internal electrochemical reaction of the battery, and the unit is generally $\mu\Omega$, $m\Omega$.

3) Battery Voltage

Battery voltage represents the potential difference between the positive and negative terminals of the battery, which can be divided into nominal voltage, theoretical voltage, average voltage, open-circuit voltage, operating voltage and so on. Nominal voltage can be used to identify the type of battery expressed as the standard voltage value of the battery under the specified conditions.

4) Charge and discharge multiplier

Charge-discharge multiplier refers to the battery in a certain period of time to charge to the rated capacity (Q) or discharge is completed when the current value required, that is, a multiple of the rated capacity of the battery.

5) Battery State of Charge

The state of charge (SOC) of the battery is calculated according to the ratio of the remaining capacity of the battery to the rated capacity of the battery. The formula for calculating the state of charge of a battery is:

$$SOC = SOC_0 + \frac{\eta \int_0^t I_b dt}{Q} \tag{1}$$

In the formula, SOC_0 represents the initial state of charge, t represents the charging and discharging time, h, Q represents the rated capacity of the battery. $A\cdot h$, I_b indicates the charging and discharging current, which is positive for charging and negative for discharging. A, η indicates the charging and discharging efficiency.

6) Service life

The service life of the battery indicates that under ideal conditions, the battery undergoes charging and discharging with rated current and then its capacity decreases to 80% of the rated capacity by the number of cycles. In addition to the above major performance indicators, the charging efficiency and self-discharge rate of power batteries are also important parameters of battery performance.

2.2.2 Thermal Reaction and Thermal Runaway of Batteries

The heat generated by the lithium-ion battery when it works mainly comes from the following parts: heat of reaction Q_f, heat of polarization internal resistance Q_f, heat of ohmic internal resistance Q_o, and heat of side reaction Q_y, which generates heat as:

$$Q = Q_f + Q_f + Q_o + Q_y \tag{2}$$

Reaction heat indicates the electrochemical heat generated when lithium ions are de-embedded in the electrode reaction during the charging and discharging process of the battery, which is negative during charging and positive during discharging.

The heat of polarization resistance indicates that when the current flows through the lithium battery, the electrode potential is shifted to the equilibrium electrode potential, and at this time, the heat generated by the voltage drops between the open-circuit voltage and the terminal voltage of the battery.

The heat generated on the ohmic resistance when the current flows through the inside of the battery is called ohmic resistance heat.

The side reaction heat is mainly the reaction heat generated during the self-discharge of the battery, the overcharging and discharging process, and the heat generated by the decomposition reaction of the battery electrolyte.

The battery mainly exchanges heat with the environment through conduction, radiation, and convection. Thermal runaway occurs when the heat cannot be balanced in time during lithium-ion charging, which is mainly manifested as:

1) formed in the lithium battery first charging and discharging process covered in the electrode surface of the SEI membrane (SEI) due to the decomposition of the battery positive and negative electrode exothermic reaction, SEI membrane as a protective film between the electrodes, when the temperature rises, the reactivity of its reactive substances increased, SEI membrane decomposition of exothermic, which triggered the electrode material and electrolyte contact, and then the reaction of a large amount of heat emitted triggered thermal runaway.

2) When the charging voltage of a lithium-ion battery is greater than the decomposition voltage of the electrolyte, the electrolyte decomposes and releases heat and the anode starts to react with the binder, and at the same time, it triggers the inter-electrode reaction leading to thermal runaway. Different batteries have different mechanisms of thermal runaway due to the production process, material composition, and other differences. The lithium battery thermal runaway process is shown in Figure 1 to analyze different situations.

Due to short-circuit and other factors lead to a large accumulation of heat in the battery when the temperature reaches about 100, the SEI film begins to decompose at the same time to release heat, and the battery negative electrode begins to react with solvents, binders, etc. and release more heat. When the temperature reaches about 150 degrees, the electrolyte inside the battery begins to decompose, continuing to release a large amount of heat, exacerbating the rise in battery temperature. When the temperature rises to more than 200, the battery positive electrode begins to decompose, releasing a large amount of heat and organic gases, resulting in a continuous rise in battery temperature, ultimately leading to thermal runaway battery triggering safety issues.

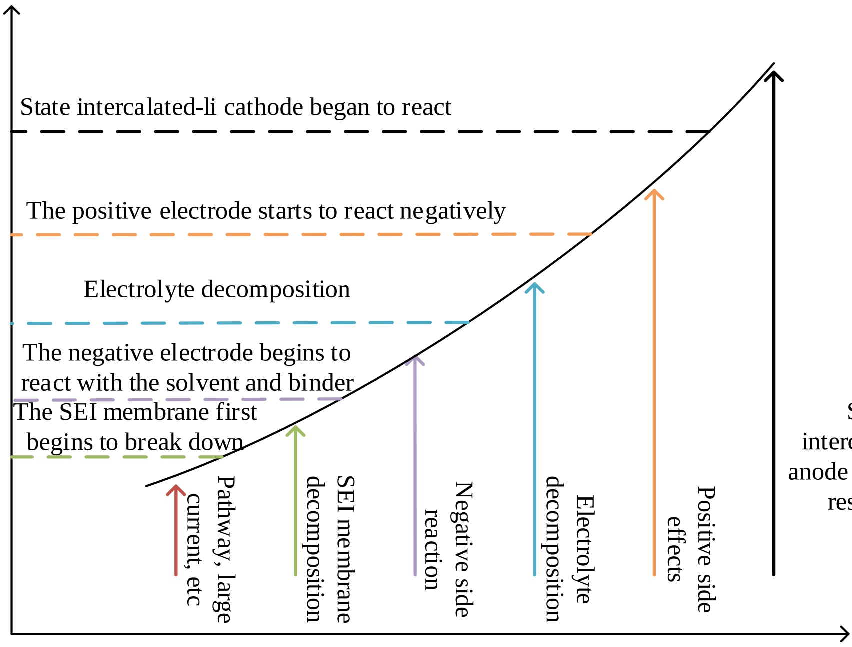


Figure 1. Lithium battery heat control process

2.3 Smart charging strategy for electric vehicle power battery with multiple time scales

2.3.1 Short-term safe and smart charging strategies

Common fault phenomena include battery pack capacity reduction, charging voltage being too high, the battery pack not being charged, low discharge voltage, battery self-discharge, local high temperature, single unit voltage consistency deterioration, battery arcing breakdown and so on.

Short-term charging safety intelligent protection strategy process, through real-time detection of lithium-ion battery charging and discharging current, single unit voltage, total battery pack voltage, environmental temperature and other data, and based on these data on the lithium power battery, possible faults to judge. Corresponding treatment measures are given to avoid serious failures and accidents in lithium batteries, and the data is uploaded to a cloud server for processing for long-term safety warnings. The battery data to be collected are:

1) Voltage of single cell
2) Ear temperature of a single battery
3) Total battery pack voltage
4) Total charge/discharge current

2.3.2 Medium to Long Term Safe Smart Charging Strategy

As the SOC of the battery increases, the acceptable charging current decreases. As the SOC of the battery increases, the ohmic internal resistance, polarization internal resistance, and entropy change coefficient change, resulting in different charging temperature rise rates in different SOC intervals. If the polarization characteristics limit the acceptable charging current, the charging current will be increased during the interval with a small temperature rise rate. The charging current is reduced in the interval with a large temperature rise rate so as to realize the balance between the whole charging time and charging temperature rise and to prolong the battery service life under the premise of ensuring the charging speed.

Therefore, this section proposes an optimized charging strategy (time-temperature rise strategy) with shortening charging time and limiting charging temperature rise as optimization objectives. The charging SOC interval is divided into N steps with ΔSOC as the interval. Under the constraint of the acceptable charging current curve for polarization limitation, the charging current for each step is selected reasonably and optimally to achieve the optimal value of the charging objective function. Because the temperature rise is related to battery life, the objective function integrates charging time and battery life, and will be composed of charging time and temperature rise during charging.

3 Analysis of electric vehicle charging status monitoring and safety warning methods

3.1 Analysis of Electric Vehicle Charging Status Monitoring Methods

The process of monitoring EV charging data at the present time is known as EV charging state monitoring. A large amount of historical normal charging data is recorded in the EV charging data set, and after considering the battery loss and SOC, the historical normal charging data can be utilized and predicted by the neural network model to get data that the EV is in normal charging state at the current moment, and the data obtained from the prediction and the data returned from the actual charging of the EV can be compared, and if the error is within a reasonable range, the EV charging state is normal. A normal electric vehicle charging state is achieved when the error is within a reasonable range; an abnormal electric vehicle charging state is achieved when the error exceeds a reasonable range.

It's crucial to detect abnormal charging status as soon as possible due to the rapid spontaneous combustion of electric vehicles and the irreversible damage to the onboard batteries caused by the burning accident. Therefore, early detection of abnormal charging states is necessary to ensure charging safety. The neural network model has the function of predicting the charging data of electric vehicles in the future, assuming that a charging state monitoring model of electric vehicles in the future can be reasonably designed through the neural network model, which theoretically can better guarantee the charging safety of electric vehicles and prevent the problem of spontaneous combustion of charging of electric vehicles.

Based on the above analysis, this paper designs a charging state monitoring method for electric vehicles and the electric vehicle charging state monitoring model is a hybrid model that synthesizes charging data, data processing, neural network model and evaluation criteria.

3.2 Analysis of Electric Vehicle Charging Safety Early Warning Methods

3.2.1 Design of security early warning model structure

After completing the model training and obtaining the model with high prediction accuracy, it is able to predict the abnormal charging state in future moments. In order to better take effective measures to avoid electric vehicle charging accidents, it is crucial to reasonably set up a complete set of electric vehicle charging safety warning methods. The electric vehicle charging safety warning method designed in this paper is shown in Figure 2.

The electric vehicle charging safety warning model is a hybrid model that integrates sliding windows, warning levels and state judgment [23-25]. The workflow is as follows: first, the training set data is inputted into the sliding window to obtain the corresponding residual values. The warning and alarm thresholds are set and calculated. Second, the real-time prediction data also passes through the sliding window and is compared with the calculated warning and alarm thresholds. Finally, the real-time prediction data is used to determine the charging state of the EV in the future according to the warning and alarm thresholds, and the charging state is categorized into three states: normal state, warning state, and alarm state.

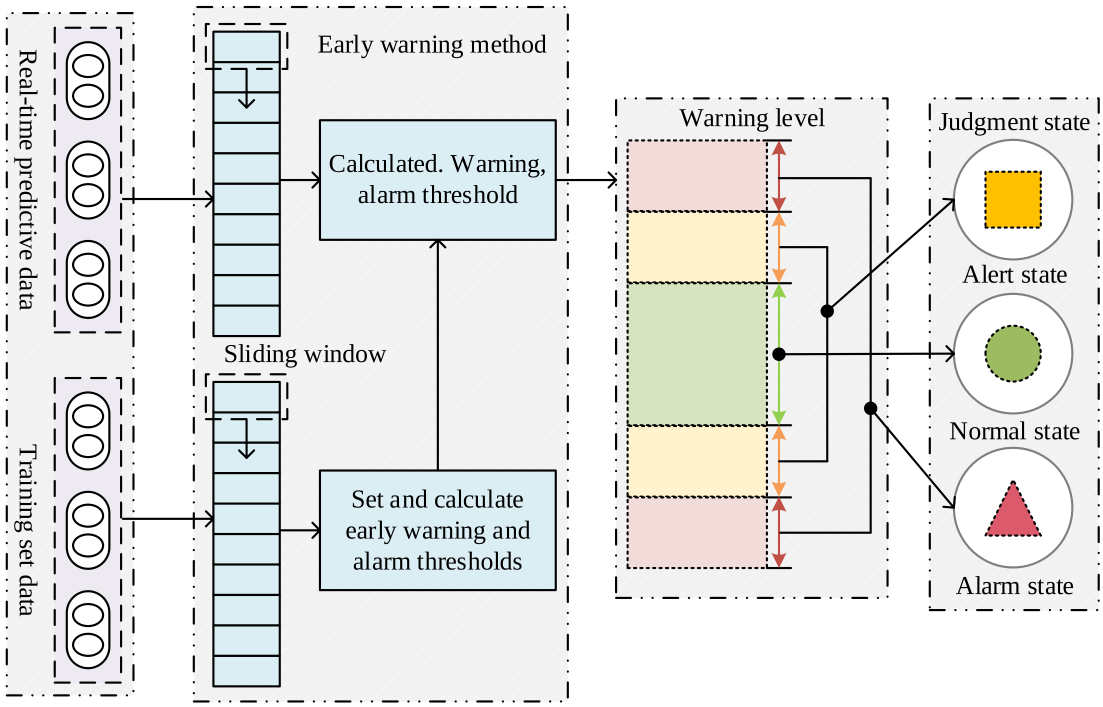


Figure 2. Design of electric car charging safety warning method

3.2.2 Criteria for evaluating security early warning models

Sliding window method: the electric vehicle charging data is divided into a sequence with a window size of N. After processing the charging data in the window with a length of N, the window is pushed forward by one step size, and the charging data continues to be processed in the window, and the process is looped until all the charging data are covered by the window, ending the above operation.

The sliding window method is used to process the residual mean and residual standard deviation of electric vehicle charging data, which effectively reduces the likelihood of erroneous prediction data misestimating the pre- and alarm. The calculation formula is:

$$\begin{cases} \overline{X} = \dfrac{1}{N}\sum_{i=1}^{N} e_i \\ S = \sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(e_i - \overline{X})} \end{cases} \tag{3}$$

Where $\overline{x}$ represents the residual mean of the EV charging data, s represents the residual standard deviation of the EV charging data, and e_i represents the residual of the i th sampling point in this sliding window.

It has been shown that high battery temperature is an important cause of spontaneous combustion accidents caused by EV charging. Therefore, this paper takes the charging temperature as the main observation quantity, analyzes and processes its residuals through the sliding window method, and sets the warning threshold by combining relevant experiences. Its calculation formula is:

$$\begin{cases} X_{E1} = k_1 \left|\overline{X}\right|_{\max} \\ X_{E2} = -k_1 \left|\overline{X}\right|_{\max} \\ S_E = k_2 S_{\max} \end{cases} \tag{4}$$

Where $\overline{X}$ represents the mean value of the residual of the charging temperature of the electric vehicle, X_{E1} represents its upper warning limit, X_{E2} represents its lower warning limit, $\left|\overline{X}\right|_{\max}$ represents the maximum value of its absolute value, and k_1 represents its warning coefficient. s represents the standard deviation of the residual of the electric vehicle charging temperature, S_E represents its upper warning limit, $s_{\max}$ represents its maximum value, and k_2 represents its warning coefficient.

The formula calculates the alarm threshold:

$$\begin{cases} X_{W1} = k_3 \left|\overline{X}\right|_{\max} \\ X_{W2} = -k_3 \left|\overline{X}\right|_{\max} \\ S_W = k_4 S_{\max} \end{cases} \tag{5}$$

Where $\overline{x}$ represents the mean value of the residual of the charging temperature of the electric vehicle, X_{w1} represents the upper limit of its alarm, x_{w2} represents the lower limit of its alarm, $\left|\overline{x}\right|_{\max}$ represents the maximum value of its absolute value, and k_3 represents its alarm coefficient. s indicates the standard deviation of the residual of the charging temperature of the electric vehicle, s_w indicates its upper alarm limit, $s_{\max}$ indicates its maximum value, and k_4 indicates its alarm coefficient.

3.3 ARIMA-based electric vehicle charging safety prediction

3.3.1 Basis for time series forecasting

In statistics, the following three main statistics are used to characterize the nature of a time series:

1) Mean value function. For time series $\{X_t\}$, the mean value function is:

$$\mu_t = EX_t = \int_{-\infty}^{+\infty} x f_t(x)dx \tag{6}$$

In the above equation, $f_t(x)$ is the probability density function of the time series.

2) Autocovariance function. The autocorrelation function describes the degree of correlation between the values taken by the random signal $\{X_t\}$ at any two different moments t_1, t_2. The correlation moments are calculated for any moment t_1, t_2 taken X_{t1} and X_{t2}:

$$\gamma_{t1,t2} = Cov(x_{t1}, x_{t2}) = E[(x_{t1} - Ex_{t1})(x_{t2} - Ex_{t2})] \tag{7}$$

3) Autocorrelation function. The autocovariance function is a second-order mixed central moment describing the correlation between the values of a random signal $\{X_t\}$ taken at any two different moments t_1, t_2, which is used to describe the degree of correlation between the ups and downs of the values taken at the two moments of $\{X_t\}$. It is also known as the centered autocorrelation function $\rho_{t1,t2}$.

$$\rho_{t1,t2} = \frac{\gamma_{t1,t2}}{\sqrt{\gamma_{t1,t1}\gamma_{t2,t2}}} \tag{8}$$

Introduction to the ARIMA modeling algorithm:

$AR(p)$ (p nd order autoregressive model) describes the relationship between the current value and the historical value, using the historical time data of the variable itself to make predictions about itself autoregressive model must satisfy the requirement of smoothness. The p rd order autoregressive model formula is:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots \phi_p X_{t-p} + \mu_t \tag{9}$$

The above equation is equivalent:

$$\left(1 - \varnothing_1 B^1 - \varnothing_2 B^2 - \cdots - \varnothing_p B^p\right) X_t = \mu_t \tag{10}$$

Or:

$$\phi(B) X_t = \mu_t \tag{11}$$

Where μ_t is the white noise series.

$MA(q)$ (q rd order moving average model), the moving average model is concerned with the accumulation of the error term in the autoregressive model, and the q th order moving average model equation is:

$$X_t = \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \cdots - \theta_q \mu_{t-q} \tag{12}$$

The above equation is equivalent:

$$X_t = \left(1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q\right) \mu_t \tag{13}$$

Or:

$$X_t = \theta(B) \mu_t \tag{14}$$

$ARMA(p,q)$ (autoregressive moving average model), and $ARMA$ is a combination of autoregressive and moving average models with the autoregressive moving average model formula:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \cdots - \theta_q \mu_{t-q} \tag{15}$$

Or:

$$\phi(B) X_t = \theta(B) \mu_t \tag{16}$$

Then:

$$X_t = \frac{\theta(B)}{\phi(B)} \mu_t = \frac{1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q}{1 - \phi_1 B^1 - \phi_2 B^2 - \cdots - \phi_p B^p} \tag{17}$$

ARIMA $\left(p,d,q\right)$ (Differential Autoregressive Moving Average Model), where I is the differential model and ARIMA is the ARIMA model after differencing to ensure data stability. The differential operation formula is:

$$\begin{cases} \Delta X_t = X_t - X_{t-1} = X_t - N X_t = (1-N) X_t \\ \Delta X_t = X_t - X_{t-1} = X_t - N X_t = (1-N) X_t \\ \Delta^{\mathrm{d}} X_t = (1-N)^{\mathrm{d}} X_t \end{cases} \tag{18}$$

The formula for the d nd order difference sequence is:

$$S_t = \Delta^d X_t = (1-N)^d X_t \tag{19}$$

Final Score:

$$\Delta^d X_t = \frac{\theta(B)}{\phi(B)} \mu_t = \frac{1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q}{1 - \phi_1 B^1 - \phi_2 B^2 - \cdots - \phi_p B^p} \mu_t \tag{20}$$

The main parameters of ARIMA are p, d, q. p, d, q The three parameters are denoted as $ARIMA(p,d,q)$. p, d, q are all integer values. The meanings of the three parameters are, p represents the autoregressive model, indicating the relationship between the predicted and single-shot values. d corresponds to the difference operation, indicating the difference order. q represents the moving average model, indicating the size of the moving window.

3.3.2 ARIMA-based charging safety prediction

1) Algorithm model

In the ARIMA (p,d,q) model: the AR is the autoregressive, p is the autoregressive term corresponding to the model. MA is the sliding average, q is the number of moving average terms corresponding to the model. d is the order of the differencing operation to obtain smooth data. The model is expressed as:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \Delta x_t = x_t - x_{t-1} \tag{21}$$

Equation (22) is the coefficient polynomial of the autoregressive model:

$$x_i = \alpha_1 x_{i-1} + \alpha_2 x_{i-2} + \ldots + \alpha_p x_{i-p} \tag{22}$$

Eq. (23) is the coefficient polynomial of the sliding average model, with Δx_t being the first order difference:

$$x_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{23}$$

Therefore ARIMA model is based on ARMA (autoregressive sliding average model), the difference of the data is smoothed.

A smooth time series is an important prerequisite for the accurate prediction results of the ARIMA model, to determine whether the time series is stable generally have the observation method, autocorrelation and bias organs method. In addition, the time series has white noise test, which is used to test whether there is any correlation between the values of the time series, and to detect whether the time series belongs to the stochastic distribution.

2) ARMIA modeling

ARIMA model modeling process needs to go through the process of data smoothing, model coefficient selection, model training and prediction, modeling specific steps are as follows:

STEP 1: Smooth the series. If the initial time series data is a smooth series, this step is skipped. Otherwise, according to the data situation for the difference calculation, it has been to get a smoother data series, while determining the parameter d.

STEP 2: Determine the range of parameter values. Determine the value or range of values of p and q of the model according to the autocorrelation and partial correlation of the smooth series after differencing.

STEP 3: Determine the model parameter values. Based on the determined candidate values of p and q, they are calculated separately through cross-validation, and finally, the parameter combination (p, d, q) values are obtained.

STEP4: Modeling and Prediction. The model is trained using the Python standard library, and then the data from the test set is evaluated for prediction.

From the data analysis in the previous section by observation method, it can be seen that the data is smoother after 1-hour data. After the feature processing data, its temporal smoothness is better, and its ADF test is performed on it. It has a good smoothness. After cross-validation tuning, the best ARIMA model was automatically obtained, and the best ARIMA model parameters were obtained as (1, 0, 1).

3.3.3 ARIMA model building design

1) Experimental design

The SML2010 dataset, which is a publicly available indoor temperature prediction dataset from the UCI Machine Learning Database, is used in this section and includes the indoor temperature, light intensity, and carbon dioxide concentration in 40 days. The experiment uses the outdoor temperature as the input sequence to construct the ARIMA model time series prediction experiment, and the experimental results will be used to argue that the time series prediction method proposed in this paper has an advantage in prediction accuracy, as well as the feasibility of the sequence prediction method in this chapter.

2) Experimental results

Using the unit root detection (ADF) method to detect the smoothness of the input sequence, the detection results are shown in Table 2. From the ADF detection results, the Test Statistic value is -4.569051, which is greater than the 1% confidence interval critical value of -5.622131, indicating that the unsteadiness of the sequences within the 1% confidence interval critical value is more significant.

Table 2. The result of ADF detection

Parameter	Value
Test Statistic	-4.569051
p-value	0.000589
Lags Used	50.468111
Number of Observations Used	5127.662810
Critical Value (1%)	-5.622131
Critical Value (10%)	-3.895212
Critical Value (20%)	-3.350127

Combined with the data analyzed in the previous section, so the sequence needs to be processed by the difference operation, and the ADF detection results of the sequence after the first-order difference operation are shown in Table 3.

From the ADF detection results after the first-order difference operation, the values of the Test Statistic are less than the critical value of 1%, 10%, and 20% confidence interval, indicating that the sequence after the first-order difference is transformed into a smooth sequence, which can be predicted using ARIMA model fitting.

Table 3. The result of ADF detection after first-order difference

Test item	Results
Test Statistic	-18.296515
p-value	0.000000
Lags Used	50.468111
Number of Observations Used	5127.662810
Critical Value (1%)	-5.622131
Critical Value (10%)	-3.895212
Critical Value (20%)	-3.350127

4 Analysis of charging safety warning algorithms

Setting both k1 and k2 to 1.2 and the threshold to 1.8 times the maximum value of the mean value of the residuals and the maximum value of the standard deviation of the residuals can avoid the charging facility false alarm situation.

The temperature maximum value fault warning threshold is: mean value ± 1.13428℃, standard deviation 0.53231℃.

The lowest temperature fault warning threshold is mean value ± 1.05703℃, standard deviation 0.51424℃.

The total voltage fault warning threshold is: mean value ± 5.28613V, standard deviation 3.74356V.

The total current fault warning threshold is: mean value ± 6.48061A, standard deviation 6.58301A.

Based on the determination of the safety warning thresholds, using the data set with charging facility anomaly data as input, the charging safety four types of fault warning effects are shown below.

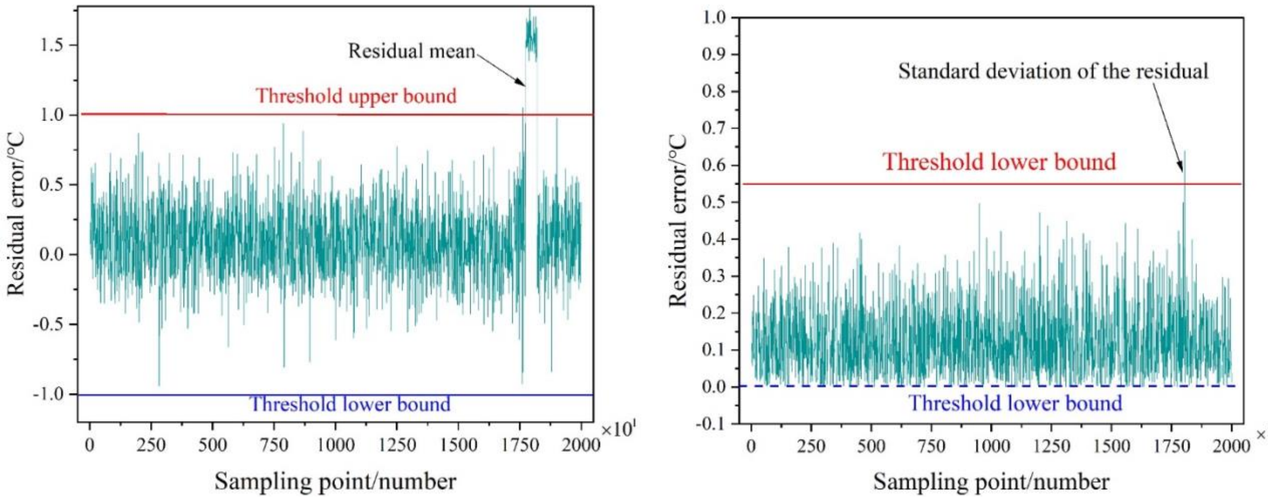
4.1 Temperature warning

4.1.1 Early warning of temperature maxima

The results of the temperature maximum warning are shown in Fig. 3. As can be seen from Fig. (a), at the beginning, the residual variations are in a stable interval variation, but at the 17740th data sampling point, its residual mean value exceeded the warning threshold. It then kept rising and eventually fluctuated around 1.55°C, and was maintained for 46 sampling points.

The standard deviation of the residuals of the temperature maximum prediction in Figure (b) shows that the residuals were below the warning threshold until the 17991st data sampling point, indicating that charging was in a normal state. The warning threshold has been exceeded at the 17990th data sampling point. The actual over-temperature fault alarm is issued at the 18050th data sampling point, and the standard deviation of the predicted residuals of the highest value of temperature reaches 0.639435 at the sampling point 18050. An early warning message is issued when the mean and standard deviation of the residuals exceed the early warning threshold, as per the analysis of this paper.

From this, it can be concluded that the warning information of this warning model is issued at the 17990th data sampling point, which can issue the warning information in advance to avoid the fault of over-temperature in the charging process.



(a) Residual mean variation (b) Variation of residual deviation

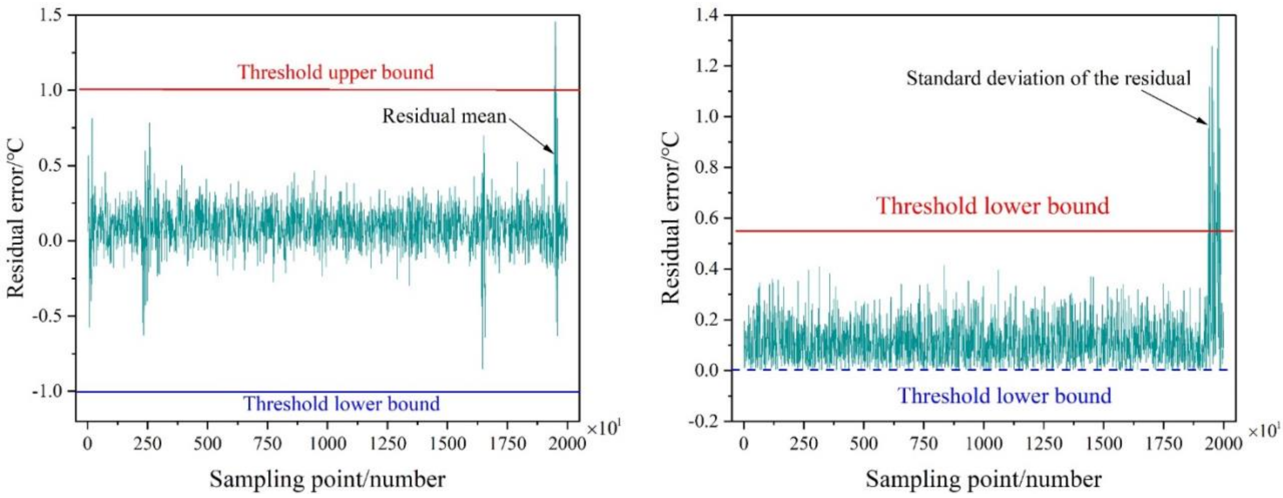
Figure 3. the highest temperature warning results

4.1.2 Temperature minimum warning

The temperature minimum warning results are shown in Fig. 4.

As can be seen in Fig. (a), the mean value of the residuals varied little before 20,000 sampling points, but at the 19,500th data sampling point, the mean value of the residuals exceeded the early warning threshold, then it kept on rising and finally fluctuated around 1.4°C.

The standard deviation of the residuals of the temperature maximum prediction in Fig. (b) shows that the residuals are below the warning threshold until the 19,020th data sampling point. At the 19020th data sampling point, the temperature is above 0.55°C, which is above the warning threshold. The actual over-temperature fault alarm is issued at the 19250th data sampling point, while the warning message of this warning model is issued at the 19250th data sampling point, which can issue the warning message in advance to avoid the fault of over-temperature in the charging process.



(a) Residual mean variation (b) Variation of residual deviation

Figure 4. The lowest temperature warning results

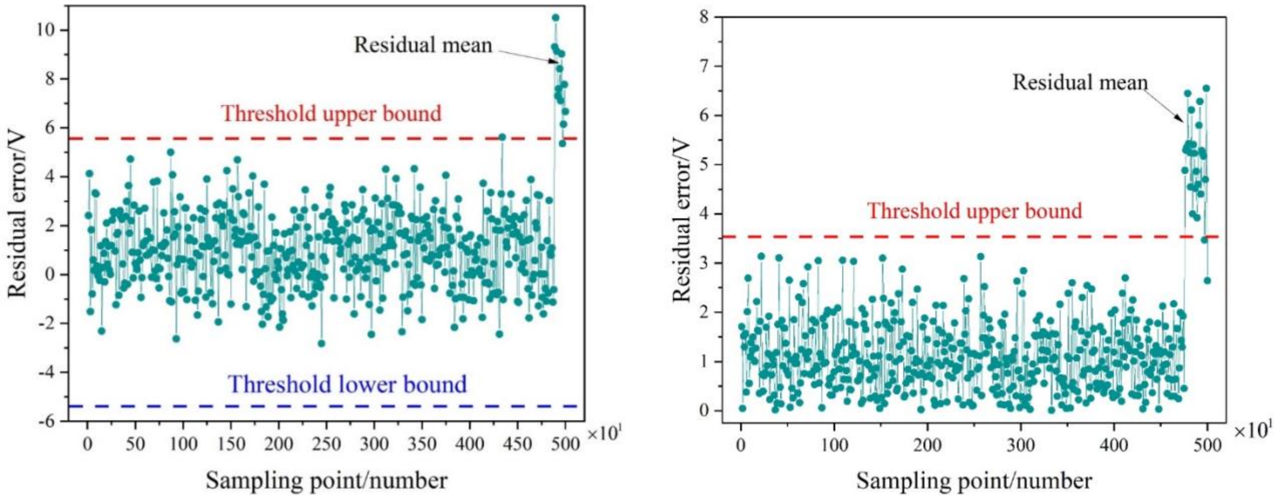
4.2 Voltage/current warning

4.2.1 Total voltage warning

The total voltage warning results are shown in Fig. 5.

As can be seen from the mean value of the predicted residuals of the total charging voltage in Fig. (a), the mean value stays at a very small value with a relatively smooth fluctuation trend until the 4330th data sampling point. However, starting at the 4340th data sampling point, the mean value exceeds the threshold for the first time, but then returns to the normal range. The residuals began to increase at the 4890th sampling point, and by the 4900th sampling point, they reached the threshold and remained transgressive.

The trend of the standard deviation of the residuals in Figure (b) is similar to that of the standard deviation, with the residuals starting to trend upward at the 4710th sampling point, exceeding the threshold at the 4760th sampling point, and remaining transgressive. As a result, the warning signal is issued at the 4772nd sampling point, while the actual alarm is issued at the 4865th sampling point, and this model is capable of detecting the fault.



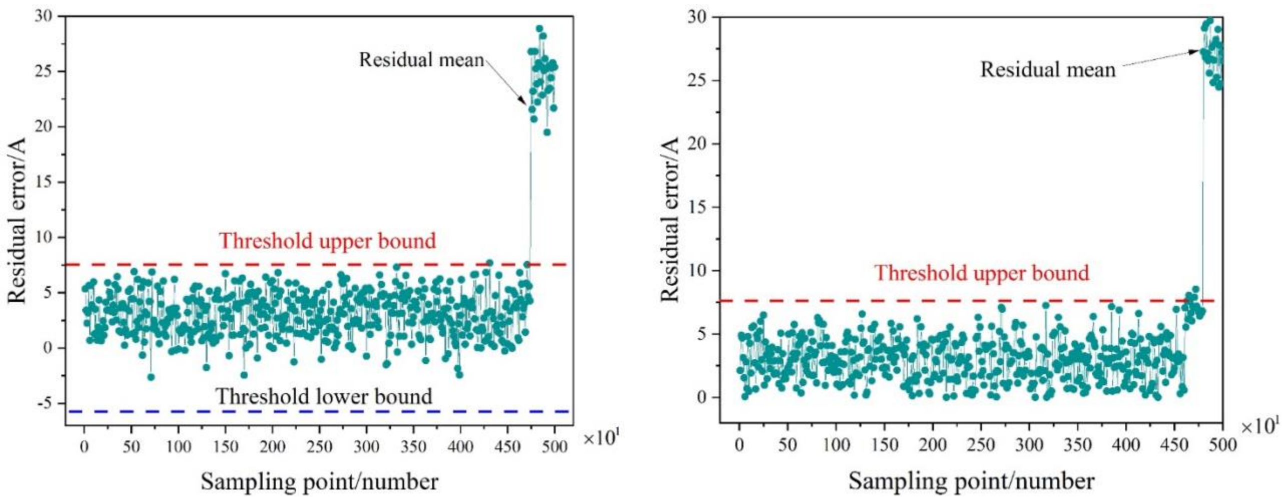
(a) Residual mean variation (b) Variation of residual deviation

Figure 5. Total voltage warning results

4.2.2 Total current warning

The total current warning results are shown in Fig. 6. As can be seen from the mean value of the residuals of the total charging current prediction in Fig. (a), the mean value stays in a controllable range with a relatively smooth fluctuation trend. However, the residual mean value starts to increase slowly from the 4710th data sampling point until the 4750th sampling point exceeds the threshold value, which keeps crossing the threshold and continuing to rise.

The standard deviation of the residuals in Fig. (b) follows the same trend, starting with an increasing trend at the 4610th sampling point, crossing the threshold at the 4630th sampling point, and rising rapidly. As a result, the warning signal is issued at the 4785th sampling point, while the actual alarm is issued at the 4891st sampling point, so the model is able to discriminate the overcurrent faults and provide early warning.



(a) Residual mean variation (b) Variation of residual deviation

Figure 6. Total current warning results

In summary, for the charging facilities of the output voltage, output current and charging module temperature faults, the model can be well in warning to ensure that the actual fault information alarm is before the warning, predict the charging process failures, to avoid charging process safety problems caused by the aggravation of the harm.

5 Conclusion

This paper analyzes the fast charging support technology of electric vehicle charging stations and designs the electric vehicle charging state monitoring and safety warning method based on the power battery charging safety characteristics and joint time series model. Analyze the feasibility of building the ARIMA model and conduct temperature, voltage, and voltage warning tests, respectively. The time series prediction model is tested for smoothness, and according to the results of differential operation processing, the values of the Test Statistic are all smaller than the critical value of confidence interval, which are smooth sequences and can be fitted with the ARIMA model for prediction. Using the evaluation criteria of the safety warning model, the maximum value of the residual mean and the maximum value of the residual standard deviation are set, respectively, and the constructed ARIMA charging safety prediction model is used to predict different faults. The synthesis of the four warning information shows that the ARIMA charging safety warning model is able to warn the actual fault information and predict the faults in charging, which can effectively improve the charging safety of electric vehicles. The high-temperature warning is a good example. Set the temperature maximum value fault warning threshold as mean ± 1.13428℃, standard deviation 0.53231℃. The charging temperature of the electric vehicle exceeds the warning threshold at the 17990th data sampling point. At the 18050th data sampling point, an alarm is triggered for an over-temperature fault. It can be considered that the scheme in this paper can issue early warning information on safety faults in advance to ensure safety in all aspects of time.

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