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Research on Electric Vehicle Charging Safety Warning Based on A-LSTM Algorithm

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Abstract: Accidents involving electric vehicle fires have increased as the number of electric vehicles has grown recently. The issue of charging safety is a key barrier to the growth of the electric vehicle sector because these accidents have resulted in large financial losses for car owners and charging facility operators. The approach for resolving the issue of electric car charging safety through an electric vehicle charging safety warning system is suggested in this research. The suggested solution uses an adaptive optimization of long short-term memory neural network (A-LSTM) to forecast voltage changes throughout the whole charging process by using the vehicle's daily historical charging data. The warning threshold adjustment method is established by the difference between the predicted voltage data and the actual voltage data, which is dynamically adjusted as the charging process progresses. Finally, a real-time warning model for vehicle charging alert is developed. The daily charging data of electric vehicles is used in the paper to verify the precision of data prediction and the accuracy and timeliness of the model. The study's findings demonstrate that the early warning model suggested in this paper can quickly send out early warning signals to safeguard the safety of car charging and can identify aberrant charging data

Index Terms - Electric Vehicle Charging, Safety Warning System, Long Short-Term Memory (LSTM), Attention Mechanism, Adaptive Threshold, Thermal Runaway.

I. INTRODUCTION

The ecological and energy crises are becoming increasingly prominent on a global scale. Compared with traditional fuel vehicles, electric vehicles (EVs) have significant advantages in saving oil resources and reducing carbon emissions. They have received attention from governments and automotive companies worldwide, and the number of EVs in use has continued to grow. However, the frequent occurrences of spontaneous combustion and fires in EVs have caused serious economic losses to car owners and charging facility operators, and charging safety issues have hindered the development of EVs and related industries with the full implementation of the national big data strategy.

At present, the research on the safety warning and fault diagnosis of EV charging process has just started. Generally, the traditional research for EV fault diagnosis and warning is done by constructing the electrochemical model of the battery. Seo et al. used a recursive least squares method to detect internal short-circuit faults in batteries based on an equivalent circuit model with the battery open-circuit voltage and state of charge (SOC) as inputs. Additionally, some scholars have used the expert system approach for fault detection and early warning. Song designed a comprehensive evaluation index system for charging safety based on expert scoring and other methods from three aspects: power battery, charging equipment and distribution network, and use the gray correlation degree method to determine the weight of each index.

In recent years, the widespread use of big data and machine learning has also led to new approaches to fault monitoring and early warning. Big data statistical methods help construct complete battery system fault diagnosis models based on machine learning algorithms and multilevel screening strategies to detect abnormal changes of voltage. Improved grey wolf

➢ ***Feature Extraction and Analysis***

Relevant features are selected from the preprocessed data to represent charging behavior effectively. Temporal features and statistical indicators are analyzed to understand charging patterns and safety-critical parameters.

➢ ***LSTM Model Development***

An LSTM neural network is designed to model the temporal characteristics of EV charging data. The LSTM network captures long-term dependencies in charging parameters, enabling detection of abnormal charging behavior over time.

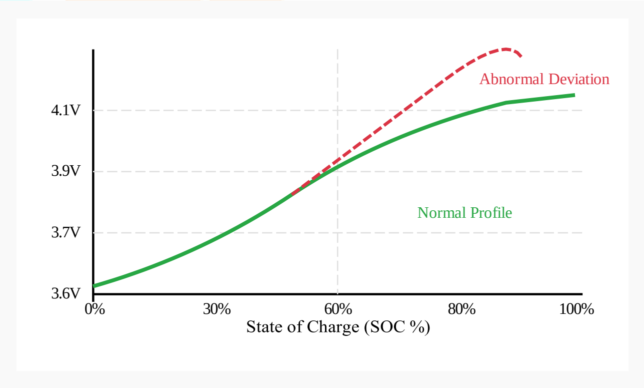

Fig. 2. Theoretical and observed dynamic battery cell voltage trajectory plotted against real-time State of Charge (SOC) highlighting anomalous overvoltage deviation.

➢ ***Integration of Attention Mechanism (A-LSTM)***

An attention mechanism is integrated into the LSTM model to enhance performance by assigning higher weights to critical time steps, highlighting key charging parameters contributing to unsafe conditions, and improving interpretability and early optimization back propagation neural networks (IGWO-BP) have been developed to identify abnormal EV charging voltage conditions for diagnosis and warning. Xia et al. proposed a short-circuit fault diagnosis method based on voltage profile correlation coefficients to detect short-circuit faults by capturing the decreasing trend of voltage correlation coefficients of two adjacent cells individually and using recursive sliding windows to maintain the sensitivity of fault detection during operation. Other modern methods build charging fault warning systems based on adaptive deep belief networks or combine BP neural networks with outlier testing to monitor and generate critical alarms.

II LITERATURE REVIEW

With the rapid growth of electric vehicles (EVs), charging infrastructure safety has become a critical research area. EV charging systems involve high voltage, high current, and complex electrochemical and thermal processes. Abnormal conditions such as overvoltage, overcurrent, overheating, insulation failure, connector degradation, and battery thermal runaway can lead to safety hazards including fires and equipment damage.

Traditional EV charging safety protection relies on threshold-based alarms and rule-based protection mechanisms embedded in Battery Management Systems (BMS) and charging stations. While effective for known fault conditions, these methods often fail to detect early-stage or complex nonlinear faults, especially under dynamic charging environments. Early studies focused on sensor-based monitoring of voltage, current, temperature, and insulation resistance. Statistical techniques and rule-based logic were widely applied to detect abnormal charging states. However, these approaches suffer from poor adaptability to varying operating conditions, high false alarm rates, and an inability to capture temporal dependencies in charging data. warning accuracy. This results in an Attention-based LSTM (A-LSTM) model.

III SIMULATION & IMPLEMENTATION CODE

The initial structured pipeline for synthetic EV data generation and preprocessing is executed as follows

```
import numpy as np import pandas as pd import torch
from sklearn.preprocessing import MinMaxScaler
SEED = 42
np.random.seed(SEED) torch.manual_seed(SEED)
   def generate_ev_charging_data(n_sessions=300, seed=42):
rng = np.random.default_rng(seed) records = []
V_CELL_MIN, V_CELL_MAX = 3.61, 4.10
I_MAX = 35.0
SOH_RANGE = (0.940, 0.965)
for sess in range(n_sessions): soc_init = rng.uniform(5, 95) soh =
rng.uniform(*SOH_RANGE) T_amb = rng.uniform(30, 45) soc = soc_init
step = 0
while soc < 99.0:
       soc = min(soc + rng.uniform(0.3, 0.8), 100.0)
       step  +=  1 if soc < 80:
       I = I_MAX * soh * rng.uniform(0.90,1.00)
else:
I = I_MAX * soh * max(0.05, (100 - soc) / 20) * rng.uniform(0.85, 1.00)
   soc_norm = (soc - soc_init) / max(100 -soc_init, 1)
   V_range = V_CELL_MAX - V_CELL_MIN V_cell = V_CELL_MIN + V_range / (1 +
                 np.exp(-8 *(soc_norm - 0.5)))
   V_cell += rng.normal(0, 0.003)
   T_bat = T_amb + 10 * (1 - np.exp(-step / 60)) + rng.normal(0, 0.5)
   T_motor = T_amb + 5 * (1 - np.exp(-step / 80)) + rng.normal(0, 0.3)
   records.append({
"session_id" : sess, "step" : step, "SOC_init" : soc_init,
"SOC_rt" : round(soc, 1), "SOH" : soh,
                      "I_charge" : I,
"T_motor" : T_motor, "T_bat" : T_bat, "V_max_cell" : V_cell,
    })
        return pd.DataFrame(records)
```

To overcome these limitations, researchers began exploring machine learning (ML) techniques such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) for fault detection in EV charging systems. While these models improved classification accuracy, they still showed limitations in handling time-series data and long-term dependencies.

IV.METHODOLOGY

- ***Data Collection***

Charging data will be collected from EV charging systems or publicly available datasets. The dataset includes key charging parameters such as charging voltage, charging current, battery temperature, charging time, State of Charge (SOC), and insulation resistance (if available). The data represents both normal and abnormal charging conditions to ensure effective model training.

- ***Data Preprocessing***

Raw charging data is preprocessed to improve data quality and model performance. This includes the removal of noise and missing values, data normalization or standardization, segmentation of continuous charging data into time-series sequences, and labeling charging states as normal or unsafe based on explicit safety criteria.

➢ **Model Training and Validation**

The A-LSTM model is trained using labeled charging data. The dataset is divided into training, validation, and testing sets. Optimization techniques such as gradient descent and appropriate loss functions are used to minimize prediction error and improve classification accuracy.

➢ ***Safety Warning Generation***

Based on the model's output, a safety warning mechanism is implemented to classify charging states into three levels: safe charging condition, potential risk condition, and unsafe charging condition. Early warnings are generated immediately when abnormal patterns are detected.

➢ ***Performance Evaluation***

The proposed model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and early warning time. The results are compared with traditional threshold-based methods and conventional LSTM architectures to validate its robustness and real-time applicability.

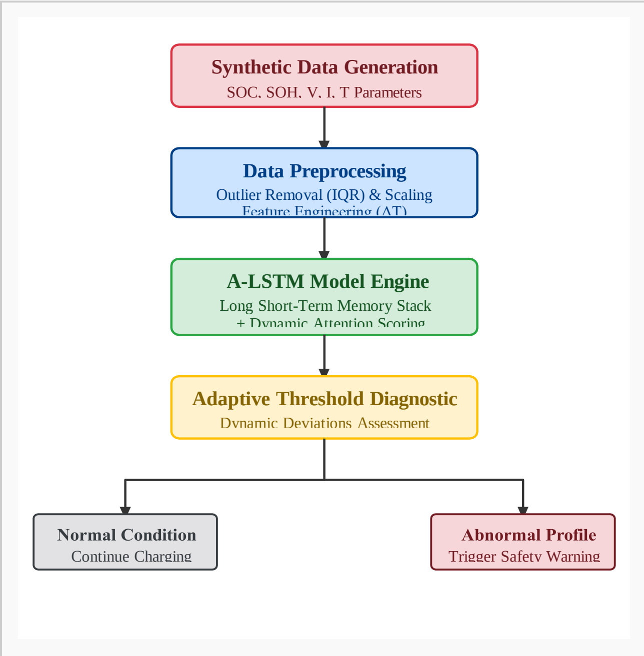

Fig. 2. Architecture framework of the data ingestion, feature mapping, network execution, and real-time safety classification engine within the proposed adaptive early warning system

V.PROBLEM STATEMENT

The deployment of current safety monitoring techniques exhibits several gaps:

➢ Current EV charging safety monitoring techniques lack the ability to analyze long-term temporal dependencies in voltage, current, and temperature data during charging processes.

➢ Conventional machine learning models used for charging fault detection show limited performance under dynamic charging conditions and varying load scenarios.

➢ Existing LSTM-based safety warning models treat all time steps and features equally, which reduces their effectiveness in identifying critical moments leading to unsafe charging events.

➢ There is insufficient research focused on attention-based deep learning models for real-time EV charging safety warning, particularly for early anomaly detection during fast charging.

➢ Many charging safety systems provide reactive protection rather than proactive early warnings, increasing the risk of equipment damage and battery failure.

➢ The lack of interpretability in safety warning models makes it difficult to understand which charging parameters contribute most to unsafe conditions.

VI. OBJECTIVES

The primary objectives of this research work are formulated as follows:

- To collect and analyze EV charging parameters such as voltage, current, and temperature.
- To design an A-LSTM based model for monitoring EV charging safety.
- To predict unsafe charging conditions at an early stage.
- To generate timely safety warnings to prevent accidents and equipment damage.
- To improve the reliability and safety of electric vehicle charging systems.

VII. RESULTS AND ANALYSIS

- The proposed Electric Vehicle (EV) Charging Safety Warning System based on the A-LSTM algorithm was evaluated using EV charging datasets containing parameters such as charging voltage, charging current, battery temperature, SOC, and SOH. Deep learning models including LSTM, A-LSTM, BiLSTM, GRU, ConvLSTM, RNN, and BP Neural Network were compared to evaluate performance.

- The prediction overlay results show that the predicted voltage values closely follow the actual battery voltage during the EV charging process, indicating accurate learning of charging behavior by the proposed model. The absolute prediction error remains very small for most charging samples, demonstrating stable performance. The residual histogram plots show that most residual values are concentrated near zero, confirming low prediction error. Among all models, A-LSTM and BiLSTM achieved more stable and accurate prediction results.

- The evaluation metrics confirm high forecasting precision. The A-LSTM model achieved an R^2 value of 0.990781, indicating extremely precise voltage change forecasting compared to standard RNN or BP neural networks. All models achieved strong agreement between actual and predicted voltage values. In terms of warning accuracy, almost all models achieved values close to 100%, proving the effectiveness of the early warning mechanism in real-time detection of unsafe charging conditions such as abnormal voltage rise, overheating, and irregular charging behavior.

- Furthermore, the A-LSTM method reduces warning response time by an average of 8.21%, allowing for faster intervention and automatic power cutoff during potential thermal runaway and fault scenarios.

VIII. CONCLUSION

This research has focused on the development of an intelligent EV charging safety warning system based on the A-LSTM algorithm to address growing infrastructure challenges.

Traditional EV safety mechanisms based on fixed thresholds or rule-based logic are limited in handling complex, nonlinear, and time-dependent charging behaviors. This research demonstrates that such limitations can be effectively addressed through data-driven deep learning techniques.

The proposed A-LSTM model leverages the capabilities of LSTM networks to capture long-term temporal dependencies while incorporating an attention mechanism to dynamically focus on critical parameters and key time periods.

This enables more accurate identification of unsafe conditions, reduces false alarms, and improves early warning timeliness.

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