

Predictive Maintenance of SiC Power Converters Using AI for Ultra-Fast Electric Vehicle Charging Systems

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Abstract

Widespread acceptance of EVs has led to greater development of the ultra-fast EV charging infrastructure, thereby raising demands on the power converter's reliability and efficiency. The SiC-based power converter has emerged as an ideal solution to the need of efficient and fast EV charging due to its superior switching characteristics and low power loss. However, continued operation under such high stress conditions can contribute to the acceleration of degradation processes that influence the performance and lifetime of the converter. The current periodic approach to maintenance of power converters fails to detect the early stages of degradation; additionally, the available techniques that rely on artificial intelligence (AI) cannot predict converter degradation in real time. This work presents an AI-based predictive maintenance approach for SiC-based converters used for ultra-fast EV charging. The presented methodology utilizes multi-sensor health data collected via voltage, current waveforms, junction temperature, switching frequency, and harmonic distortion measurements. The developed hybrid CNN-BiLSTM-attention model is designed to automatically detect degradation characteristics, learn aging patterns, perform fault diagnosis, and calculate remaining useful life (RUL). Evaluation experiments conducted based on varying conditions of the converter reveal that the presented approach outperforms the traditional methods for machine learning and deep learning. It provides fault classification accuracy of 97.3%, lowers detection latency down to 45 milliseconds, and delivers higher degradation prediction capacity via attention-based analysis of health features. These outcomes prove that the AI approach presented here allows for accurate fault detection, early degradation prediction, and maintenance planning for future ultra-fast EV charging systems.

Keywords: SiC Power Converter, Predictive Maintenance, Artificial Intelligence, Electric Vehicle Charging, Fault Diagnosis, Deep Learning.

Introduction

Background of Ultra-Fast EV Charging Systems

Due to the fast rate of electric vehicles (EVs) penetration, there is now an increased need for effective and reliable ultra-fast charging facilities, which would be able to provide large amounts of power in minimized charging periods (Okhueigbe & Bello, 2025; Rana et al., 2025; Franzese et al., 2026). Ultra-fast charging stations for EVs require efficient and highly reliable power conversion technologies that could handle high currents and voltages along with continuous operating modes (Suvvala et al., 2024; Sarath & Vijayakumar, 2025; Deb et al., 2021). Power converters play an essential role in EV charging systems since their efficiency has a direct impact on the performance, availability, and longevity of EV charging systems.

SiC-based power converters have become one of the most promising technologies to use in the future charging systems for EVs due to the better electrical and thermal properties of SiC power converters as compared to the traditional silicon-based power converters (Saha et al., 2022; Awais et al., 2026). High-frequency switching ability of the SiC power converters help in providing more effective power conversion along with reducing the number of passive elements required for power converters. Moreover, low switching and conduction losses increase the efficiency of the converters, while the ability to operate at higher temperatures increases their reliability.

Challenges in SiC Power Converter Reliability

Although there are some benefits of using SiC converters, their performance is subject to some degradation processes due to their prolonged use. The continuous thermal cycling that is caused by charging and loading variations can affect the semiconductor package because of mechanical stresses and material fatigue. Additionally, gate oxide degradation compromises switching reliability, while parameter drift accelerates semiconductor aging and degrades device performance. Besides that, capacitor degradation and switching stress increase power losses, distort the waveform, and cause the failure of the converter.

A time-based maintenance approach causes premature component replacement, which means that the expenses will be higher than necessary and operational efficiency will not be optimal. Threshold-based maintenance monitoring depends on preset limits and cannot recognize a gradual degradation process. The classic fault diagnosis approach is based on feature extraction and is unable to recognize nonlinear correlations between electrical, thermal, and operational parameters. Consequently, intelligent predictive maintenance methods are needed for early fault detection and health state estimation of SiC converters.

Role of AI in Predictive Maintenance

Predictive maintenance using artificial intelligence (AI) has become popular to enhance the reliability and availability of power electronic converters. Machine learning can be used to monitor the condition of the system based on the operational data collected from sensors. This includes identifying any abnormalities and predicting the failure to avoid any catastrophic situation. Fault prediction based on the data enables the learning of complicated relationships between the operation conditions of the converter and its degradation behavior, whereas RUL estimation gives essential information to the maintenance process.

Some of the popular AI approaches that are being used for power converter health monitoring include SVM, RF, CNN, LSTM, and Transformer. The traditional machine learning models give effective classification performance but suffer from requiring manual feature extraction and handling large-scale temporal data. Deep learning models like CNN and LSTM help in better feature learning capability by learning the degradation patterns automatically from the complicated signals. Transformer models provide better modeling of long-term dependency due to attention mechanisms. But their computational complexity is still challenging for real-time embedded applications.

Research Motivation and Contributions

In order to overcome the limitations of current maintenance solutions, this paper develops an AI-based predictive maintenance system for SiC power converters for ultra-fast charging of electric vehicles. The suggested maintenance system utilizes multidimensional health data, collected through electrical, thermal, and switching properties, in order to perform reliable state assessment and failure prediction.

The key contributions of this paper are listed below:

- The development of a predictive maintenance system based on AI that would help in predicting faults and ensuring reliability for SiC power converters in ultra-fast EV charging systems.
- The design of a multi-dimensional feature extraction approach by considering electrical parameters, thermal characteristics, and switching behavior to monitor the condition of converters.
- The development of an AI-based prediction model for the identification of faults and estimation of degradation to enable maintenance planning.

This approach can be used as an intelligent way to ensure the efficiency and reliability of ultra-fast EV charging systems based on SiC.

This paper is structured in the following way. Section I covers the background of research, problems, and contributions. Section II discusses the literature related to EV charging systems, SiC converter reliability, and AI-based predictive maintenance. Section III illustrates the AI-based predictive maintenance approach and the CNN-BiLSTM-Attention model. Section IV highlights the experiment methodology and evaluation criteria. Section V explains the results and their analysis. Section VI explains the discussion of results and implications. In conclusion, Section VII is given at the end of this paper.

Related Work

Advancements in Power Electronics for Ultra-Fast EV Charging Systems

As a result of the fast development of electric vehicle (EV) infrastructure, the need for high-efficiency, high-power, and reliable power electronic converters is becoming more pronounced (Valedsaravi et al., 2022; Florkowski, 2026; Dini et al., 2023). It was recently reported that the transition of power electronics from energy converters to energy management intelligent layers could lead to higher efficiency, flexibility, and reliability in today's energy systems (Hinov, 2025). High-frequency converters, solid-state transformers, and silicon carbide (SiC)-based converters are examples of new converter technologies that show remarkable advancements in terms of power density, switching characteristics, and efficiency of energy conversion. It was reported that fast charging systems should be designed with special consideration of proper converter design.

High-frequency converter topologies have been studied for EVs and renewable energy generation systems owing to their capability of reducing the size of the passive components and making the system more compact (Arévalo et al., 2024; Aman et al., 2025). High-frequency converters based on silicon carbide have attracted much attention owing to their higher switching frequencies and lower conduction loss, along with temperature resistance, than conventional silicon devices. Several studies on DAB converters and charging structures based on silicon carbide have shown enhanced efficiency and minimized charging times (Hinov, 2026). However, the problem with such converters and systems emerges related to thermal management, insulation, electromagnetism, and semiconductor degradation.

Predictive Maintenance and Intelligent Monitoring in EV Charging Infrastructure

The reliability of fast charging stations for electric vehicles largely depends on the state of power conversion components (Gupta et al., 2026; Mohammed et al., 2025). The past study was focused on improving the performance of monitoring systems at charging stations by means of innovative methods and approaches. Such intelligent systems include battery management, converter control, and monitoring systems.

There are some studies analyzing fault behavior, optimizing converter control algorithms, and improving the reliability of EV charging architecture (Van Mierlo et al., 2021; Hussein et al., 2024). Condition monitoring approaches based on electrical, functional, and environmental parameters were proposed in order to detect abnormal charging behavior and avoid unexpected failures. At the same time, the existing maintenance schemes for EV charging mostly analyze charging efficiency and interaction with the grid, but not the degradation of semiconductors.

The classical periodic inspection and maintenance approaches or maintenance schemes based on some specific operating limits are not effective enough for ultra-fast EV charging systems due to the gradual development of the degradation process. Thus, there is a need to use an intelligent prediction approach that analyzes multi-source information for estimating converter degradation and performing maintenance tasks.

Reliability Challenges and Degradation Mechanisms of SiC Power Converters

There are many benefits of using SiC semiconductor components in high-power charging systems; however, the reliability of such devices depends on many electrical and thermal stress factors. The effects of thermal management,

high-frequency switching, and packaging technologies on the SiC converter lifetime have already been examined. As far as thermal stress is concerned, it is caused by the thermal changes resulting from cycling operation and can lead to mechanical fatigue and overheating.

Switching degradation is one of the reliability problems associated with the high frequency of switching processes, voltage overshoot, current stresses, and increased electromagnetic interference. It has been suggested to use advanced thermal management solutions that would help reduce the thermal stress. Besides, high-voltage insulation, gate degradation, bond wire fatigue, and passive parts aging should be considered when discussing converter reliability.

Despite the fact that existing studies have contributed to a better understanding of the failure mechanism of SiC devices, most approaches examine particular types of stress factors independently of each other. Little attention has been paid to the study of the integration of electrical, thermal, and switching health indicators into a single intelligent system.

AI-Based Health Monitoring and Remaining Useful Life Prediction

AI technologies have recently gained popularity in solving problems related to fault diagnosis and predictive maintenance of complicated power electronic devices. Classification algorithms such as SVM, RF, and others are employed for fault recognition in converters based on the electric signal data analysis. Such approaches demonstrate high accuracy of classification tasks, but they usually require manual feature selection and cannot describe the complex non-linear degradation behavior of the device.

Among deep learning techniques, CNN, LSTM, and attention-based architectures demonstrate good feature extraction abilities and temporal pattern learning. CNN architectures allow discovering hidden patterns in the converter's signal, while LSTM is able to capture temporal degradation patterns of the converter related to its aging process. Among other recent developments in the sphere of intelligent converters, there is also an attempt to use hybrid AI algorithms to improve the energy efficiency, detect faults and optimize the operations of converters (Jabari et al., 2025). However, the existing approaches to using AI technologies in the mentioned tasks are mainly oriented at fault classification, but do not solve issues of fault detection and RUL estimation of the equipment.

Moreover, many existing AI-based models are designed for rather limited operational parameters and are not capable of taking into consideration the degrading impact caused by thermal cycles, switching stress and semiconductors aging. It significantly reduces the applicability of such models in ultra-fast EV charging due to reliability concerns.

Research Gap

Past studies indicate remarkable advances in various fields such as high frequency converters, SiC degradation modeling, EV charging, and intelligent sensing systems. However, the existing studies mainly focus on either improvement of efficiency in the converter system or optimization of charging system architecture, or they concentrate on fault analysis. Few studies have been conducted that aim at developing the integration of SiC degradation modeling, multi-sensor health metric extraction, fault classification using AI techniques, and remaining useful life prediction in one predictive maintenance framework. In order to address the above-mentioned shortcomings, this study develops a predictive maintenance system based on AI techniques and SiC power converters that are deployed in ultrafast EV chargers. The new predictive maintenance framework utilizes multi-sensor health metrics along with the hybrid model of CNN-BiLSTM-Attention for fault detection and remaining useful life prediction.

Proposed AI-Based Predictive Maintenance Framework

Overall System Architecture

Predictive maintenance of the SiC power converters used in the ultrafast EV charging stations could be done with artificial intelligence. The AI-based prediction process consists of five main stages, including data acquisition, pre-processing, health feature extraction, AI-based predictions, and maintenance decision making. First, multidimensional data are collected from the converter concerning the electrical, thermal, and switching conditions through sensors. Secondly, the collected signals are cleaned in order to remove noise and normalize the variability due to changes in operating conditions. Further, the health indicators are extracted that demonstrate the degradation process of the converter. An anomaly detection, fault classification, and prediction of RUL (remaining useful life) could be done using a hybrid CNN-BiLSTM attention model.

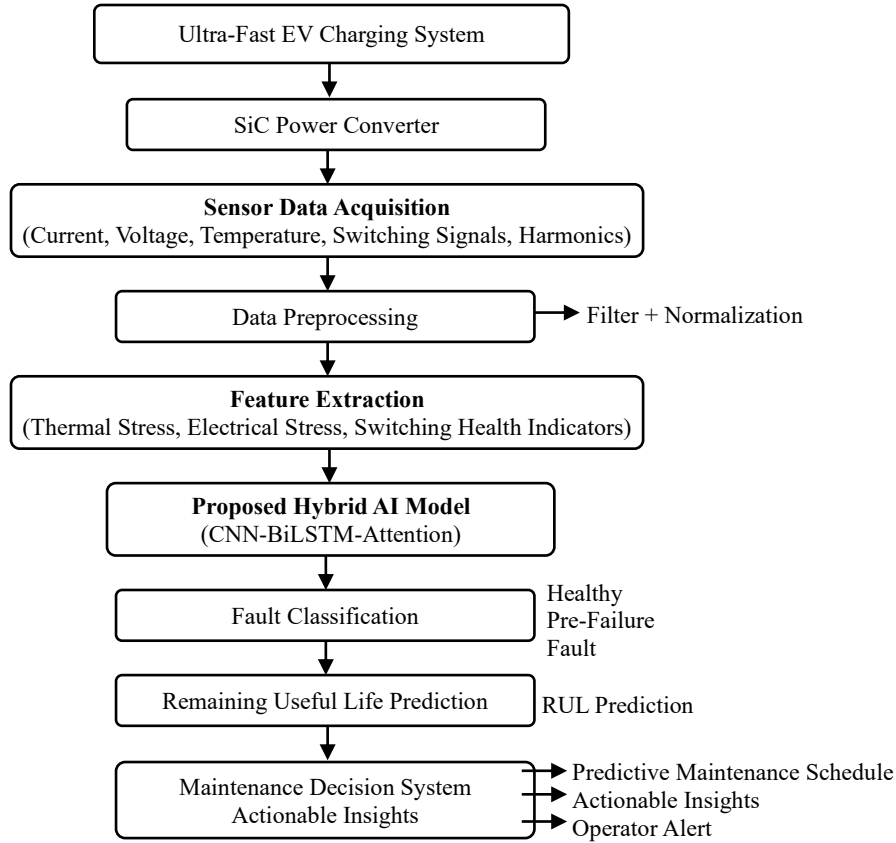


Fig. 1: Workflow Architecture of AI-Based Predictive Maintenance Framework for SiC Power Converters

In addition to that, the health features are obtained to represent the degradation process of the converter. The tasks of anomaly detection, fault classification, and prediction of the RUL (remaining useful life) are carried out in real time using the developed hybrid CNN-BiLSTM-Attention model. Fig. 1 shows the work process of the AI-based predictive maintenance system for ultrafast EV chargers. The system consists of SiC converter monitoring, data acquisition and preprocessing, health feature extraction, proposed CNN-BiLSTM-Attention processing network, fault classification, estimation of the remaining useful life, and maintenance decision-making.

Data Acquisition and Monitoring Model

For assessing the reliability of SiC power converters, it is necessary to constantly monitor many operational parameters indicating the electrical, thermal, and switching behavior. The suggested methodology gathers data on the health state of the converter through sensor-based monitoring approaches. Such parameters provide complete information on the malfunctioning, degradation, and failure states.

Table 1: Monitored Parameters for SiC Power Converter Health Assessment

Parameter	Purpose
Converter voltage	Identifies electrical abnormalities and voltage fluctuations
Current waveform	Represents load variations and abnormal current behavior
Junction temperature	Indicates thermal stress and degradation progression
Switching frequency	Represents switching stress and semiconductor operating conditions
Harmonic distortion	Provides information about converter health and power quality degradation

This set of factors allows the AI model to establish complicated relationships between operating conditions and patterns of converter deterioration, as shown in table 1.

Data Preprocessing

Raw data readings obtained from EV charging converters can have noise, inaccuracies, and fluctuations owing to dynamic operating conditions. As a result, certain preprocessing procedures are implemented in order to provide better data and increase the accuracy of prediction. Firstly, noise reduction is carried out to eliminate the noise signals that

appear due to sensor imperfections and switching processes. Missing values are interpolated in order to preserve continuous monitoring data. After that, normalization and scaling procedures take place in order to make different ranges of parameters equal to each other.

Min-Max normalization is used as per equation 1:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is the raw data from the sensor, X_{min} and X_{max} refer to the minimum and maximum values of the data set, respectively. The normalized output is denoted by X' . It improves the model convergence and equal contribution of all the inputs.

Health Feature Extraction

The health features extraction step uses the preprocessed sensor readings to extract health indicators to enable accurate assessment of the state of the SiC power converters. The features extracted can be grouped into electrical features, thermal features, and switching features that are used to capture the various failure modes. The electrical features like RMS current, voltage deviation, and power loss are used to denote abnormal working states and efficiency reduction. Thermal features like junction temperature variation and thermal resistance capture the effect of frequent heating and cooling of the semiconductor devices. The switching features, such as switching delay and duty cycle variation, capture stress levels experienced due to high frequencies. These multi-dimensional health indicators provide a comprehensive view of the operational states of the converter, which are input to the proposed artificial intelligence method to classify faults and estimate RUL.

ALGORITHM 1: CNN-BILSTM ATTENTION-BASED PREDICTIVE MAINTENANCE MODEL

Input: Extracted health features $F = \{Electrical, Thermal, Switching\}$

Output: Fault class and Remaining Useful Life (RUL)

Step 1: Initialize CNN-BiLSTM-Attention model parameters

Step 2: Load preprocessed health feature dataset

Step 3: Apply CNN layer

Extract spatial degradation patterns from input features

Step 4: Generate feature sequences from CNN output

Step 5: Apply the BiLSTM network to learn bidirectional temporal dependencies of converter aging behavior

Step 6: Compute attention weights

Identify significant degradation-related features

Step 7: Perform feature weighting using attention mechanism

Step 8: Pass weighted features to prediction layer

Step 9: Generate fault classification output

Step 10: Estimate remaining useful life (RUL)

Step 11: Calculate prediction error and update model weights
using optimization algorithm

Step 12: Repeat training until convergence

Step 13: Return predicted fault condition and RUL value

This algorithm facilitates constant monitoring of SiC converter status by combining feature extraction, temporal degradation learning, and attention-based predictions for predictive maintenance.

Experimental Methodology

Dataset Description

The performance of the proposed AI-based predictive maintenance approach is verified through a SiC power converter aging dataset that is constructed by combining the simulation and experiment of the converter. The dataset consists of realistic operational cases of ultra-fast EV charging systems by including the degradation of electrical, thermal, and switching behaviors. The gathered data consist of voltages, currents, changes in junction temperatures, switching features, and harmonic distortion values for different conditions of the converter status. The signal data from sensors are collected at a constant sampling frequency in order to analyze both the transient effects and degradation behaviors.

Table 2: Dataset Distribution Under Different SiC Converter Operating Conditions

Condition	Number of Samples
Normal operation	20,000
Thermal degradation	15,000
Switching fault	12,000
Device aging	18,000

The distribution of sample data in various health conditions for converter training and testing is presented in table 2 to train the AI-based predictive maintenance system. Data contains normal operation conditions and degradation cases like thermal stress, switching failure, and aging of the converter to classify faults and perform accurate degradation prediction.

The training and testing data sets will be developed to evaluate the learning and generalization capabilities of the model. Other operational conditions such as loading and thermal variations are also taken into account in order to provide accurate predictions in the real-life scenario of an EV charging station.

Experimental Setup

The evaluation of the experimental approach will be conducted using the power converter prototype designed on the basis of SiC MOSFET technology as an example of ultra-fast electric vehicle charging system. The system will include high-power SiC power converter module, EV charger interface, and sensor set up to monitor the parameters of operation. Voltage and current sensors will be applied for the measurement of the electrical parameters, while temperature sensors will measure the thermal degradation of the junction temperature.

The development and evaluation of the AI model will be done in a software environment with machine learning and deep learning tools implemented in Python. For CNN-BiLSTM attention model implementation, a platform like TensorFlow or PyTorch will be used. The platforms of MATLAB and Simulink will be applied for converter modeling and aging simulation.

Performance Metrics

The efficiency of the predictive maintenance system described above is analyzed using classification and predictive maintenance metrics.

Classification Metrics

Accuracy describes the general efficiency of the model in predicting the converter state and is defined by the following equation (2):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Where TP means true positives, TN means true negatives, FP means false positives, and FN Means false negatives. Precision characterizes the efficiency of positive fault prediction, whereas Recall characterizes the efficiency of the model to detect faults. F1-score shows a balance between precision and recall, which is estimated by equations (3) - (5).

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

Results and Discussion

Fault Classification Performance

Fault classification performance of the suggested CNN-BiLSTM-Attention model is assessed based on a comparison of this model with traditional machine learning models and deep learning models. SVM, RF, CNN, and LSTM models are used for comparison purposes. These traditional machine learning models have decent classification performance; however, their dependence on the manually extracted features makes it difficult for them to detect complex degradation behavior. This problem can be resolved using the CNN model that extracts spatial features from the health condition

indicators of the converter automatically, and the LSTM model that learns the time-dependent degradation behavior pattern.

Table 3: Comparative Fault Classification Performance of AI Models

Method	Accuracy (%)
SVM	88.6
Random Forest	91.2
CNN	93.5
LSTM	94.1
Proposed CNN-BiLSTM-Attention	97.3

Table 3 provides a comparison of the accuracy of fault classification using different machine learning and deep learning algorithms in monitoring the health condition of SiC power converters. It is clear from the above results that the designed CNN-BiLSTM-Attention model performs better than traditional methods in terms of capturing the spatial feature, temporal degradation, and health indicators.

It can be seen from the results above that the proposed technique increases the accuracy of fault detection when compared to traditional methods. The improvement in the performance of the model is due to the ability of the hybrid network to analyze the electrical, thermal, and switching degradation parameters.

Remaining Useful Life Prediction

The ability of the proposed framework to predict the RUL is examined by analyzing the association between actual and predicted health state deterioration of the SiC power converter. The AI framework successfully captures the progression of degradation under varying operating conditions and gives an accurate estimation of the health state of the converter. A satisfactory relationship exists between the expected path of degradation and the real-life variability in the health index, proving that the proposed model is able to successfully recognize degradation processes.

The use of the BiLSTM method allows obtaining effective aging tendencies at certain points in time, while the attention method is useful in recognizing key aging features. The prediction of the proposed framework shows lower errors than traditional methods and thus makes it possible to make early maintenance decisions before the critical deterioration of the converter.

Fig. 2 displays the actual and predicted aging behavior of the SiC power converter in terms of the health index variation.

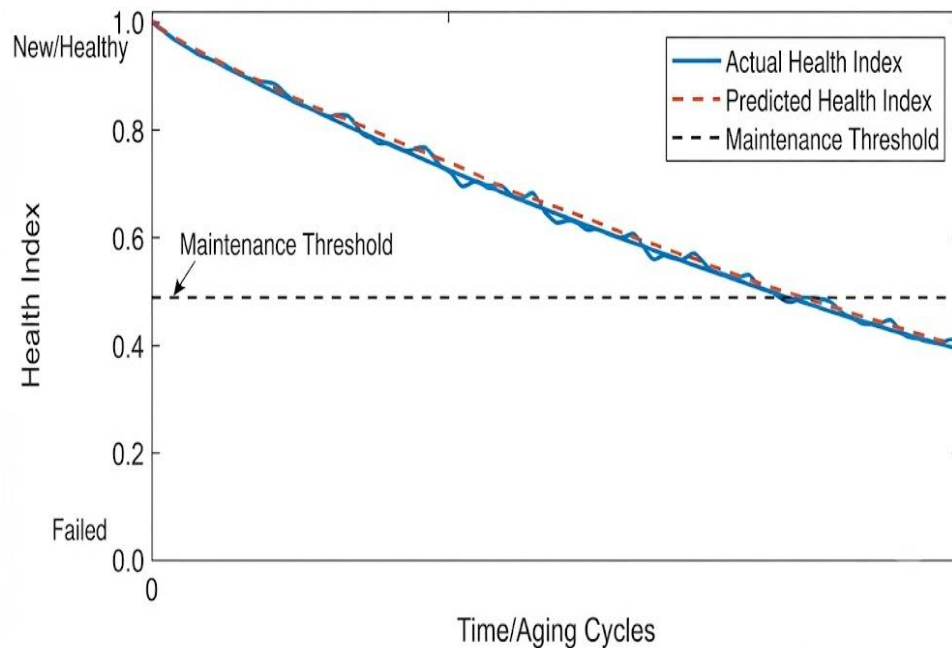


Fig. 2: Health Index Degradation Trajectory of SiC Power Converter Under Aging Conditions

Real-Time Performance Analysis

Real-time performance of the suggested framework for predicting maintenance can be evaluated using two parameters: latency in detection and accuracy of classification in comparison with conventional monitoring techniques and machine learning-based methods. The former ensures a quicker reaction but has restricted capacity for identifying problems because of the necessity to use predefined threshold values. Machine learning techniques offer more accurate predictions but take much longer to process computationally. The suggested AI-based framework is able to combine both parameters.

Table 4: Real-Time Performance Comparison of Predictive Maintenance Approaches

Method	Detection Time (ms)	Accuracy (%)
Traditional Monitoring	120	82.5
ML Model	75	91.4
Proposed AI Model	45	97.3

Comparison between different monitoring approaches according to detection time and accuracy of fault classification is shown in table 4. From the results, it can be seen that the proposed AI model detects faults at a higher speed with increased accuracy when compared to the other two approaches, thus enabling its usage in real-time health monitoring of SiC converters.

It can be observed from the results above that the proposed model is able to reduce the time taken for fault detection without decreasing its accuracy. This means that it is appropriate for real-time applications.

Ablation Study

The ablation study is performed in order to assess the impact of individual components within the proposed CNN-BiLSTM-Attention AI architecture. Different configurations of the model are assessed by eliminating some learning components and evaluating their classification performance.

Table 5: Ablation Study of CNN-BiLSTM-Attention Predictive Model

Model Variant	Accuracy (%)
CNN Only	92.8
BiLSTM Only	94.1
CNN-BiLSTM	95.3
CNN-BiLSTM-Attention	97.3

Table 5 illustrates the ablation analysis of individual components within the proposed AI model and their impact on fault classification performance. It can be seen that the combination of CNN, BiLSTM, and attention mechanisms increases classification accuracy due to better feature extraction, temporal degradation learning, and the selection of critical features.

The assessment results prove that all three components positively affect the increase in classification performance. The CNN layer increases the level of feature extraction from multi-dimensional converter signals, and the BiLSTM layer detects long-term dependencies of the signal degradations. Additionally, the use of an attention mechanism contributes to increased classification accuracy by emphasizing critical features of the degradations.

Discussion

As illustrated, the suggested AI-based maintenance approach for predictive maintenance contributes positively to the reliability evaluation and fault predictions of SiC power converters deployed within ultra-fast EV charging stations. Different from traditional approaches based on periodic monitoring and fixed threshold values, AI models allow continuous analysis of the multi-dimensional operational data with identification of more complicated patterns. The use of electrical, thermal, and switching characteristics allows the model to find early signs of the malfunctioning of a power converter, which are hard to detect using traditional tools.

Learning temporal degradation becomes a key aspect when estimating the health status of the SiC power converters. Degradation of converters represents a step-by-step process that is affected by such aspects as thermal cycling, switching stress, and operating conditions. BiLSTM of the suggested model helps to establish the relationship between historical states and current operational states of the power converter to provide a better understanding of the aging process. The attention mechanism makes it possible to find out the most critical degrading factors.

Practically speaking, the suggested framework could be implemented within the existing ultra-fast EV charging stations using sensors and edge computing devices. The real-time data collection about the converters' operating conditions makes it possible to estimate the condition of the equipment continuously without stopping the process of charging. Thus, the lightweight predictive ability of the suggested framework facilitates quick detection of faults and condition-based maintenance strategies.

The suggested approach will also increase the reliability of energy delivery because the performance of the converters will remain constant due to the prevention of their inefficiency caused by aging. Therefore, early detection of the thermal stresses, switching irregularities, and semiconductor problems will facilitate the maintenance of power conversion efficiency and, consequently, the reliability of charging. Hence, the AI-based predictive maintenance framework is an effective solution for sustainable ultra-fast EV charging systems based on SiC.

Conclusion

The research introduces a new AI-assisted approach for the predictive maintenance of SiC power converters employed in ultra-fast charging stations of electric vehicles. The suggested approach is designed to use multi-dimensional health-related data derived from electrical, thermal, and switching characteristics to perform the condition assessment of the converters. Due to the combination of feature extraction based on CNNs, temporal degradation learning with the help of BiLSTMs, and the attention mechanism, the model introduced in the study effectively performs the recognition of degradation patterns. The findings of the experiments conducted show that the proposed framework of CNN-BiLSTM-Attention significantly outperforms conventional machine learning and deep learning models in terms of fault recognition accuracy. The fault classification accuracy of the model was 97.3%, and the detection latency decreased to 45 ms, thus showing its effectiveness for the real-time monitoring of the condition of converters. Using multi-sensor feature analysis allows recognizing the faults by detecting electrical, thermal, and switching issues. Moreover, RUL estimation is possible with the help of the suggested approach to allow preventive maintenance activities. Further research will be dedicated to scaling the suggested framework to large-scale EV charging networks with the help of federated learning technologies. They can be used to train models on charging stations without compromising data security. Additionally, the use of digital twins can be considered to create virtual models of SiC converters for simulating their degradation and predicting its impact. Edge AI solutions will facilitate further deployment of the framework by decreasing the time of communication and allowing local health prediction of the converters at charging stations. Besides, future research will be directed toward development of self-adaptive maintenance scheduling mechanisms.

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