36th International Electric Vehicle Symposium and Exhibition (EVS36)
Sacramento, California, USA, June 11-14, 2023

Developing a Deep Learning Tool to Detect Electric Vehicle Supply Equipment Failures

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Executive Summary

Reliable and functional electric vehicle supply equipment (EVSE), which include electric vehicle (EV) chargers, are critical components in the global transition to EVs. Several studies have revealed that current EVSE reliability metrics, such as uptime, do not reflect the true reliability of EVSEs experienced by consumers. In this study, we have developed a novel tool that combines the powerful reconstruction capabilities of the Long Short Term Memory (LSTM) autoencoder with the long-term contextual awareness of an in-house naïve distribution method to learn the habitual usage patterns of EV chargers and effectively identify charging faults that may not be captured by traditional reliability measures.

Keywords: Charging Infrastructure, Electric Vehicles, Reliability

1 Introduction

The shift from conventional internal combustion engine vehicles to electric vehicles (EVs) hinges on both the quantity and quality of EV charging infrastructure. While much research has focused on the importance of and challenges to increasing the quantity of EV chargers worldwide, less has been devoted to assessing the quality of existing EV chargers. It is crucial to not only add more EV chargers to the map, but also ensure that the installed chargers are functional. According to the 2022 U.S. Electric Vehicle Experience Public Charging survey by J.D. Power, the growth of public EV charging infrastructure is making it easier for EV owners to locate public chargers, but one out of every five respondents were unable to charge their EVs at public charging stations [1]. Among those who couldn't charge, 72% cited charger malfunction or being out of service as the reason. In response to consumer dissatisfaction with public EV charger reliability, jurisdictions including California, Canada, Chile, the European Union, France, the Netherlands, New Zealand, the United Kingdom, and the United States are proactively advocating for stricter EV charger reliability requirements . In February 2023, the U.S. Department of Transportation and the Federal Highway Administration released national standards for federally funded electric vehicle chargers that include a minimum average annual uptime requirement of 97% and standardized reporting of additional data related to chargers such as location, pricing, and ports, which must be reported on a monthly basis for the previous twelve months, thus providing helpful information for jurisdictions designing a reliability standard [2]. Simultaneously, the California Energy Commission (CEC) is developing uptime recordkeeping and reporting standards for electric vehicle charging stations that received public funding [3]. California is considering requiring a 97% uptime requirement for public chargers for 5 years from the time of commissioning, with different requirements for Level 2 and DC fast chargers.

Within an electrical system, reliability is a measure of how effectively the system transfers electricity to the consumer in the amount desired. From the perspective of an EV driver, a reliable charger charges their vehicle at an expected rate for the expected duration and accepts the appropriate payment method. Whereas from the perspective of a charging service provider, a reliable charger is one that meets the minimum uptime requirement of its jurisdiction. Uptime is the measure of the time during which a machine is in operation and is the most commonly used charging reliability metric. This metric fails to consider all the technological and logistical challenges within the charging ecosystem that ultimately determine the true reliability of chargers, as perceived by consumers. Given the stark difference in the definition of reliability between charging consumers and providers, it is no surprise that there is a contradiction between the high average uptime reported by charging providers and the low user satisfaction scores reported by consumers. In 2022, .the California Air Resources Board (CARB) conducted a survey of 11 charging service providers, with four respondents claiming a national uptime of 95-98% [6]. This finding directly conflicts with a simultaneous survey of EV drivers in California, who reported mixed experiences with existing EV chargers, including broken plugs (9%), unexpected shut-off during charging (6%), charging station malfunctions (22%), payment issues (18%), and the need to contact customer service (53%) [7]. CARB's findings are consistent with a study by Rempel et al. that evaluated the functionality of all open, public Direct Current Fast Charging (DCFC) stations in the Greater Bay Area, revealing that around a quarter of surveyed plugs were unreliable or had design failures [7].

Rempel et al. revealed six types of charge failures that they encounter in their study: broken connectors, non-responsive screens, error message on screens, connection error, payment system failure, and charge initiation failure. **Table 1** abstracts these six failures to more comprehensively capture the most common obstacles consumer encounter while attempting to charge their EVs [8], [9].

Table 1 Common EV Charger Failures

	Failure	**Description**
Remotely Observable	Charger to Vehicle Communication Failure	Malfunction in the EV's charging port or the charging station's connector, issue with the communication protocol used by the EV and the charging station
	Connector/cable Issue	Charger cable improperly placed into vehicle charging port, poor conductivity due to corrosion
	Electrical Insulation / Safety Issue	Electrical system of charger may be overheating, insulation may need to be inspected
	Payment Errors	Technical issues with the payment system, compatibility issues with the payment method used, or user error during the payment process
	Vehicle Errors	Software or hardware malfunctions, charging port incompatibility, or battery issues.
	Charger Equipment Errors	Software or hardware malfunctions, power supply issues
	Power Outage	Power outage can cause EV charger to shup-down or interrupt an on-going charging process
Remotely Unobservable	Blocked Access to station	Access to chargers could be physically blocked by gas cars, other non-charging EVs, fences, snow, flood water, etc.
	Physically Damaged Equipment	External components of the EVSEs are prone to damage from various environmental factors.
	Logistical and interoperability Issues	Membership requirements, payment incompatibility, equipment incompatibility, complicated EVSE instructions/operations, difficulty locating EVSEs, lack of EVSE availability, and poor cell service/Wi-Fi availability make EV charging daunting to current and prospective EV drivers.
	Network Communication Failure	Configuration errors, line damage, power loss or traffic spikes, and hardware failure anywhere along the communication network

A Charge Point Operator (CPO) is typically the stakeholder that is responsible for ensuring optimal ongoing operations of EV charging infrastructure. This includes managing the backend technologies as well as the communications between the backend system and the chargers. The CPO needs to ensure that all chargers under their control are operational enough to at least meet the uptime requirement of their jurisdiction. As such, they need to have systems in place to notify them of any problems with the chargers. Ideally, the CPO should monitor its chargers' operational statuses in real-time to discover and fix issues before the customer is aware of them. If CPOs effectively monitor their chargers using Open Charge Point Protocol, they can effectively detect most of the electrical and software failures given an operational communication network. However, they may be in the dark when it comes to failures caused by mechanical, communication and logistical factors. For instance, they may be unable to detect a physically damaged charging cable if the EVSE is otherwise operational and detected as so via their communication network. Or communication lags may cause charging station operators to be unaware of inoperable charging ports for substantial periods of time, resulting in inaccurate uptime calculations. **Figure 1** illustrates the timeline of a charging attempt, accompanied by the possible charge failures that could occur at each stage of the attempt, separated by their level of visibility to CPOs.

A failure that is invisible to CPOs may persist until an unlucky EV driver encounters a charger with the failure and reports it to the CPO. As such, these invisible failures exacerbate the EV charger reliability issue. This study aims to develop a predictive tool to help CPOs quickly detect these invisible charge failures. EV drivers are likely to habitually charge their EVs in the same public charging locations along their daily travel routes. Therefore, any sudden gaps within the usage pattern of a given EVSE location could reveal a technical or logistical failure that standard reliability monitoring protocols fail to capture. In this study, we have developed a novel tool that combines the powerful reconstruction capabilities of the Long Short Term Memory (LSTM) autoencoder with the long-term contextual awareness of an in-house naïve distribution method to learn the habitual usage patterns of EV chargers and effectively identify charging faults that may not be captured by traditional reliability measures.

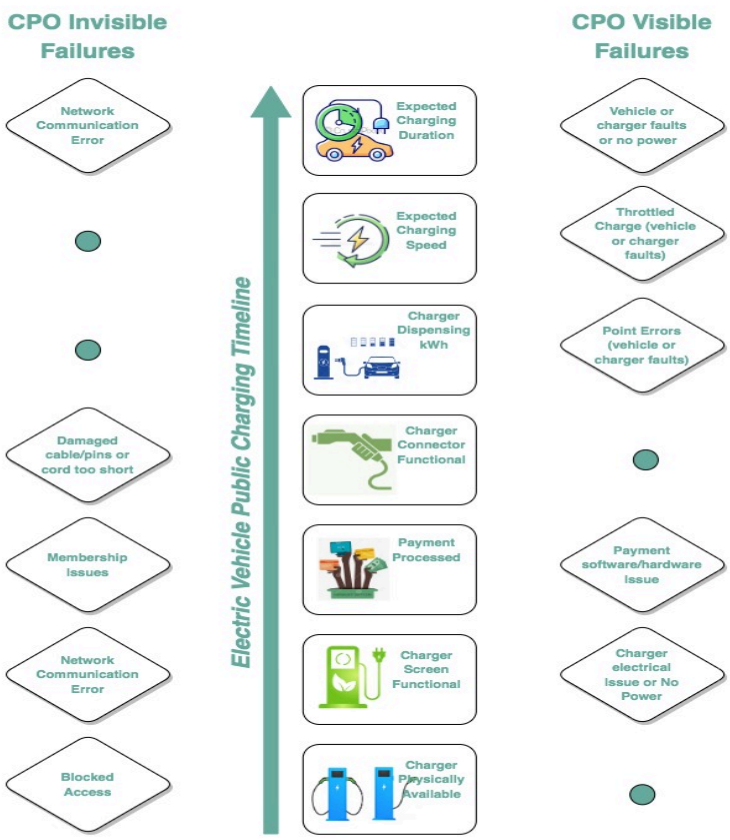

Figure 1 EV Charging Timeline and associated Failures

2 Literature Review

Time series anomaly detection is a process of identifying abnormal patterns within a sequence of data points collected over time. There are various techniques that can be employed for time series anomaly detection, including traditional statistics methods, machine learning algorithms, deep learning algorithms, data mining techniques, and signal analysis [10]. These techniques span across six categories of general approaches, including forecasting, reconstruction, encoding, distribution, distance and isolation tree approaches. We considered techniques from all these classes to isolate and develop the optimal technique to detect anomalous usage patterns and thereby CPO invisible charger faults within EV charging time series traces.

2.1.1 Forecasting Methods

Time series anomaly detection using forecasting methods involves using a learned model to predict future values based on a current window of data. The predicted values are then compared to the actual values to determine the extent of anomalous behaviour. Forecasting models are typically trained in a semi-supervised manner on normal data, and any deviations from the expected behaviour in the test dataset are identified as anomalous. The traditional statistical methods used for forecasting time series anomalies include Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), the median method, and Triple Exponential Smoothing (Triple ES) [11][12]–[14]. Forecasting methods that use deep learning include Long-Short Term Memory Autoencoders, Convolutional Neural Networks, Graph Attention Networks, and Echo State Networks [15]–[19]. These models are trained in a semi-supervised manner, where the training data without anomalies is used to learn the normal model of the data, which is then used to identify anomalies in the test dataset.

2.1.2 Reconstruction Methods

Reconstruction methods for time series anomaly detection techniques create a model of normal behaviour by encoding subsequences of a normal training dataset into a low-dimensional data space. This model is then used to reconstruct subsequences from a test dataset, and the difference between the original and the reconstructed time sequences is used to calculate an anomaly score. Traditional statistical approaches to reconstruction include Principle Component Isolation (PCI) [20]. Machine learning techniques include Principle Component Analysis (PCA) and Principle Component Classifier (PCC) [21], [22]. Deep learning approaches include autoencoders, variational autoencoders, LSTM-based variational autoencoders, Recurrent Neural Networks (RNN), Spectral Residual, and Generative Adversarial Networks (GAN) [23]–[31]. Most of these methods are semi-supervised, meaning they are trained on normal data and use this to identify anomalies in the test dataset.

2.1.3 Encoding Methods

Encoding methods for time series anomaly detection utilize techniques to encode subsequences into a low-dimensional latent space and compute anomaly scores directly from the representations of the encoded subsequences. These techniques employ a range of methods to encode subsequences and calculate anomaly scores, such as inferring hierarchical grammar rules, using bitmaps, constructing probabilistic models, and building directed cyclic graphs. Anomaly scores are attributed to the points corresponding to the encoded subsequences in the latent space, and subsequences that are difficult to compress or have low frequency are considered anomalous. Stochastic learning techniques are used in encoding methods such as Hidden Markov Models (HMMs) and Dynamic Bayesian Networks (DBNs) [32], [33]. Meanwhile, data mining techniques employed in encoding methods include grammar-based compression, graph-based compression, suffix trees, and time series bitmaps.

2.1.4 Distribution Methods

Distribution methods for time series anomaly detection involve estimating the distribution of the data or fitting a distribution model to the data, and then using probabilities, likelihoods, or distances to calculate anomaly scores for points or subsequences with respect to the prior calculated distributions. In contrast to other methods, the anomalous points or subsequences are judged by their frequency rather than their distance. To estimate Gaussian distributions or generic probability distributions of subsequences, various techniques such as histograms, copulas, and wavelet transforms are utilized. The anomaly scores are calculated based on the distance or likelihood of the points or subsequences with respect to the estimated distributions. Some of these methods assume a normal training time series for semi-supervised anomaly detection, while others are unsupervised and can detect anomalies in the tails of the distributions. Traditional statistical methods for distribution-based anomaly detection include extreme value theory and copula-based outlier detection [34], [35]. In the field of signal analysis, discrete wavelength transforms and maximum likelihood estimation are often employed [36]. Machine learning techniques, on the other hand, use Histogram-based Outlier Scores (HBOS) to identify anomalies [37]. Deep learning techniques for distribution-based anomaly detection use Normalizing Flows (NF) to model the data distribution and identify anomalies based on the estimated density values [38].

2.1.5 Distance Methods

Distance-based methods for time series anomaly detection involve comparing points or subsequences of a time series using specialized distance metrics. These methods assume that anomalous subsequences will have larger distances to other subsequences than those with normal behaviour. For the distance calculations, these algorithms may use either all other subsequences, some nearest neighbours, or certain cluster centroids as distance reference points. Some methods also perform a mapping of the subsequences into a multidimensional space before computing the distances. Distance-based methods are usually unsupervised and do not require training data. Nearest neighbour methods are a common example, where anomaly scores are determined by computing the distance of points or subsequences to their nearest neighbours. Infrequent or uncommon subsequences have large distances to their neighbours and are, therefore, scored as anomalous. Distance-based methods using traditional statistics involve identifying density- or cluster-based local outliers [39]–[41]. Machine learning methods using distance methods include k-means, K-nearest neighbours (KNNs), and Support Vector Machines (SVMs) [42]–[44]. Deep learning methods using distance methods include hybrid KNNs [45].

2.1.6 Isolation Trees

Isolation tree methods for time series anomaly detection involve building a collection of random trees that partition test time series samples (points or subsequences). Anomalous samples are closer to the root of the tree and have shorter path lengths than normal samples, so their reciprocal values can be used as anomaly scores. Representative algorithms use traditional statistics and include Isolation Forest (iForest), Extended Isolation Forest (EIF), Hybrid Isolation Forest (HIF), Sub-IF, and Isolation Forest - Local Outlier Factor (IF-LOF) [46]–[49]. The iForest algorithm is the basis for all algorithms in this category, and supervised variants include EIF and HIF. IF-LOF combines iForest and LOF.

3 Data & Methodology

3.1 Data Overview

We use charging session data from EV chargers in two locations in California to demonstrate the tool developed in this study. The dataset consists of three public level 2 chargers from the San Francisco civic centre garage, and four DC Fast chargers from a highway corridor in Northern California. The session details for the chargers were obtained from their corresponding installation companies. However, to safeguard their identity and confidentiality, we have anonymized the name of the installation companies. **Table 2** summarizes the charging session information for the DCFC, and level 2 charger analysed in this study. There are a total of 6018 level 2 charging sessions logged over 731 days between April 2021 and

January 2023 and 2341 DC Fast charging sessions logged over 263 days between January 2021 and October 2021**. Figure 2** illustrates the utilization of each charger over the logging period.

Table 2 EV Charger Data Overview

Charging Level	Charger ID	Number of Charging Sessions	Total kWh Charged	Days Logged	Utilization Rate
Level 2	1	2841	18729	731	0.3031
	2	1098	12672	731	0.1466
	3	2079	29703	731	0.4205
DC Fast	1	736	9959	263	0.0446
	2	396	6790	263	0.0295
	3	627	12684	263	0.0521
	4	582	6407	263	0.1639

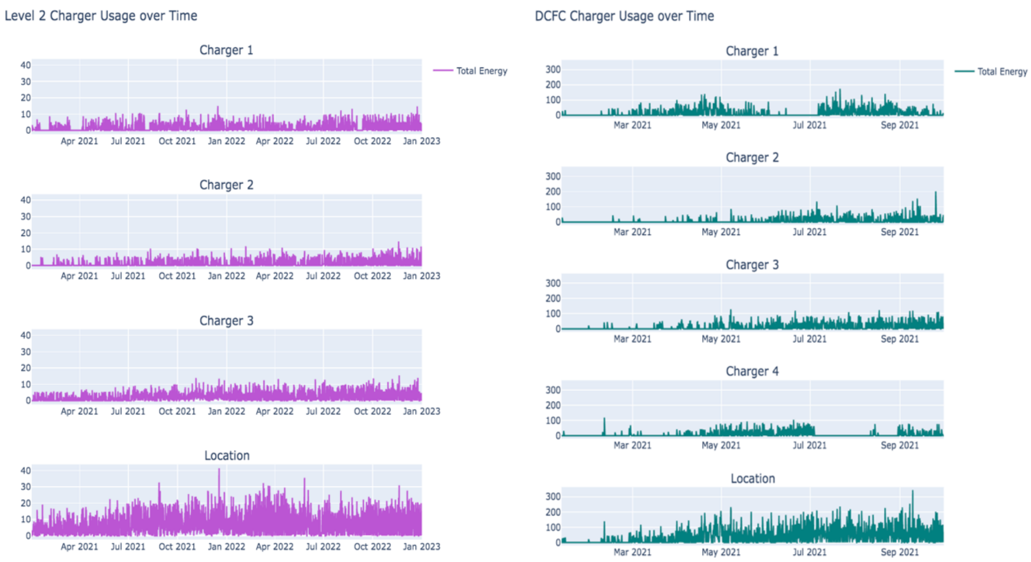

Figure 2 EV Charger Usage Time Traces

3.2 Methodology

Building on our knowledge of the aforementioned techniques for time series anomaly detection, we have developed a novel approach that combines the powerful reconstruction capabilities of the LSTM autoencoder with the long-term contextual awareness of an in-house naïve distribution method to effectively identify anomalous usage patterns in EV charging time series data.

3.2.1 Pre-processing

To pre-process the charging session data in our dataset and convert it into time series traces, we iterated through the entire logging period of each charger on an hourly basis. Then, we assigned the corresponding energy and number of charging sessions that occurred during each specific hour to that hour in the time series trace. This enabled us to capture the trends and patterns of EV charging over time and create a useful dataset for further analysis.

3.2.2 Naïve Distribution Method Specifications

In the naive method, we performed the following steps to detect anomalies in the charging behaviour of electric vehicle (EV) chargers. First, we calculated the daily charging probability distribution for each charger by taking into account the time of the day, the type of day (weekday or weekend), and whether it was a holiday. This allowed us to model the expected charging behaviour for each day and time slot. Next, we iterated through the time traces of the chargers with a window size of four hours. For each window, we checked if there were any logged charging sessions. If there were no logged sessions in the window and the joint probability of no charging sessions in that window was less than 0.5, we marked that window as an anomaly. The joint probability of no charging sessions in a window was calculated using the daily probability distribution of charging behaviour for the relevant time slot. If the probability of no charging sessions was low, it suggested that there might be an issue with the charger.

3.2.3 LSTM Specifications

LSTM Autoencoder is a deep learning-based approach that can be used to detect and classify anomalous events within time series data. The method is based on the Long Short-Term Memory (LSTM) network, which is a type of recurrent neural network (RNN) that is well-suited for modelling sequential data. We designed an LSTM autoencoder architecture in Keras. The autoencoder consists of two LSTM layers, one for encoding and one for decoding. The encoding LSTM layer takes the input sequence and reduces its dimensionality by encoding it into a smaller representation. The decoding LSTM layer then takes this encoded sequence and decodes it back to the original input sequence. The output of the decoding layer is compared to the original input sequence using mean squared error (MSE) loss function.

In Keras, we implemented the LSTM autoencoder using the Sequential model class. The encoder part of the network was defined using the LSTM layer, while the decoder can be defined using the RepeatVector and LSTM layers. **Figure 3** illustrates our model architecture for one of the Level 2 chargers in our study.

```
Training shape: (4151, 42, 1)
Testing shape: (145, 42, 1)
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_6 (LSTM)                (None, 128)               66560
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0
_________________________________________________________________
repeat_vector_3 (RepeatVecto (None, 42, 128)           0
_________________________________________________________________
lstm_7 (LSTM)                (None, 42, 128)           131584
_________________________________________________________________
dropout_7 (Dropout)          (None, 42, 128)           0
_________________________________________________________________
time_distributed_3 (TimeDist (None, 42, 1)             129
=================================================================
Total params: 198,273
Trainable params: 198,273
Non-trainable params: 0
```

Figure 3 LSTM Architecture

Our model training dataset consisted of all data points excluding the last month of the data logging period for each charger. While our testing dataset consisted of all the data points in the last month of the logging period for each charger. We trained the LSTM autoencoder on the training set for each charger separately using backpropagation algorithm with the ADAM optimizer. We trained the model for 100 epochs and a batch size of 32 for each charger. We used early stopping to prevent overfitting. Once the LSTM autoencoder was trained, we used it to detect anomalous usage patterns in the testing set. We fed the testing set to the LSTM autoencoder and calculated the reconstruction error (MSE) between the original sequence and the reconstructed sequence. We then defined a threshold based on the reconstruction error, above which a sequence is considered anomalous. The anomaly threshold for each charger was set to the 90th percentile value of the MSE of that charger's training data. We evaluated the performance of our LSTM autoencoder model using various metrics such as precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

4 Results

Figure 4 illustrates the detected anomalies using the naïve technique and the LSTM autoencoder for each level 2 and DC Fast charger in their study. The figures also include detected anomalies considering all charging activity in the two locations observed in the study. **Table 3** reports the total number of anomaly hours detected by the naïve and LSTM approaches, including uptime reduction resulting from the detected anomalous hours. The uptime reduction resulting from the detected anomalous hours ranges from 4% to 20%, depending on the charger. The range of the uptime reduction is greater for the DC Fast chargers than the Level 2 chargers; this is most likely because the usage patterns of DC Fast chargers are less predictable than the usage patterns of Level 2 charger.

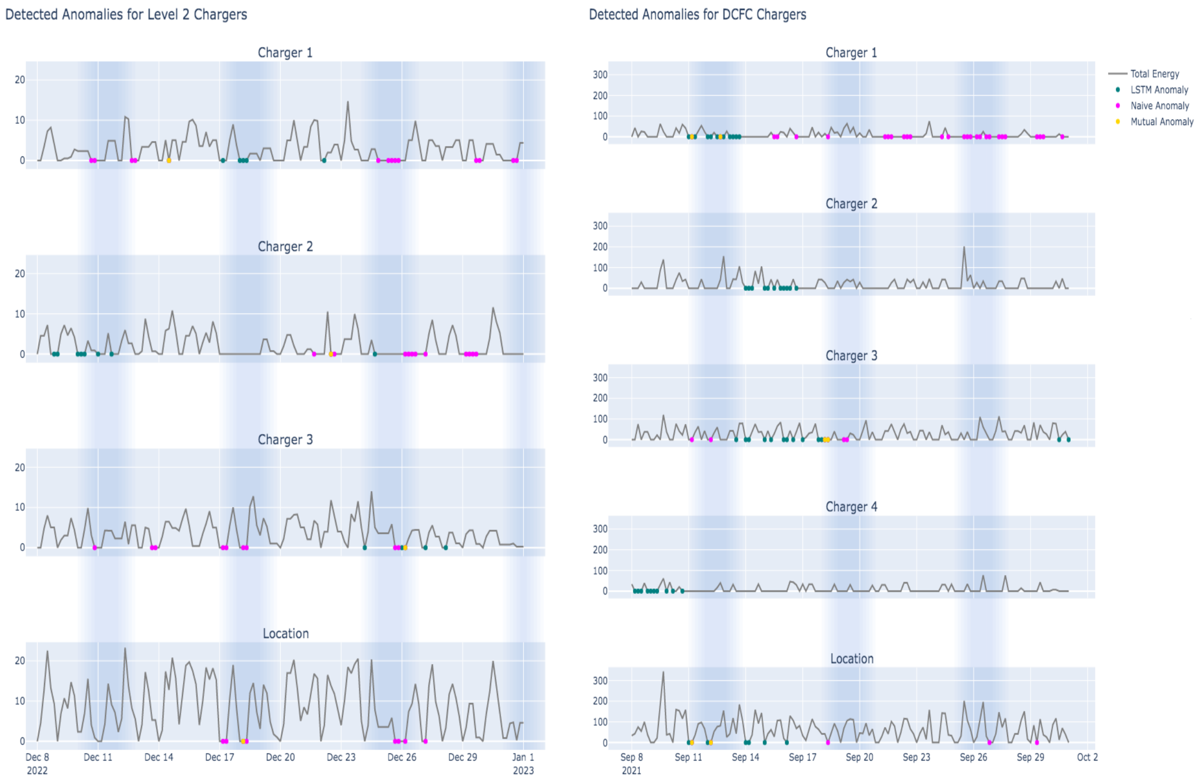

Figure 4 Detected Anomalies for Level 2 and DC Fast Chargers

Table 3 Detected Anomalies for Level 2 and DC Fast Chargers

Charging Level	Charger ID	Naïve Anomaly Hours	LSTM Anomaly Hours	Mutual Anomaly Hours	Total Reduction in Uptime (%)
Level 2	1	52	20	4	10.00

	2	44	32	4	10.56
	3	36	16	4	7.22
	Location	28	4	4	4.44
DC Fast	1	104	40	8	20.00
	2	0	44	0	6.11
	3	16	52	8	9.44
	4	40	0	0	5.56
	Location	12	24	8	5.00

5 Discussion

The goal of this study was to develop a tool that leverages the habitual usage patterns of EV chargers to effectively identify charging faults that may not be captured by traditional reliability measures. As such, we have developed a novel tool that combines the powerful reconstruction capabilities of the LSTM autoencoder with the long-term contextual awareness of an in-house naïve distribution to detect anomalous charging patterns that could indicate potential charger faults. Based on the developed tool, the uptime reduction resulting from the detected anomalous hours ranges from 4% to 20%, depending on the charger.

The California Energy Commission (CEC) is developing uptime recordkeeping and reporting standards for electric vehicle charging stations that received public funding [3]. The standards will address charger interoperability and payment system failures prior to installation, while charger and network failures and internal payment system failures will be addressed through performance standards and monitoring [3]. Remote and physical monitoring options are being considered, such as implementing an operative status of charge, conducting random field inspections, and requiring preventive maintenance. The tool developed in this study could aid CPOs to effectively meet these impending reliability standards.

CPOs can use the tool to monitor their charging infrastructure in real-time and detect any charge failures that may not have been captured via their internal fault detection protocols. Charge failures that are technically invisible to CPOs include network communication failures, blocked access, physically broken cable/equipment, and other unknown failures that cannot be captured via remote monitoring systems. By using this tool, CPOs can quickly detect these invisible charge failures and take the necessary actions to fix them before an EV driver encounters the same issue and reports it. The CPO can set up alerts and notifications to be sent out when an anomaly is detected, allowing them to take immediate action. Additionally, the tool can provide insights into the usage patterns of the charging infrastructure, allowing the CPO to make informed decisions about where to add more charging stations or when to perform maintenance on existing ones.

It's important to note that fault detection isn't enough to the thwart all charging infrastructure reliability concerns. Lack of stakeholder profit incentives, unclear division of responsibilities, lack of accountability, and lack of performance monitoring can significantly delay or impede fault resolution [50]. As such, measures should be taken to better define business models, operational structures, and incentives that can enable the reliable operation of EV charging infrastructure. Governments should encourage CPOs to provide access to data for hosts and third-party service providers to facilitate fault diagnostic and performance monitoring platforms. CPOs should make the charging process frictionless by eliminating the need for initiating a charge or logging in using apps or RFID cards [51]. All charge points should be mandated to have roaming SIM network providers and standardized communication restoration and synchronization processes to reduce the frequency and duration of lost communication [51]. The business models of charger ownership and operation should be carefully considered, particularly around public EV charging tariffs to provide sufficient revenue for maintenance and servicing [51]. Stakeholders should Increase training and recruitment of accredited EV charging repair workforce to avoid increased times to repair charge points. Lastly, a single trusted source of aggregated EV status information should be made available, rather than users having to access multiple apps, such as an improved National Charge Point Registry with real-time status for all public charge points.

6 Conclusion

Reliable and functional electric vehicle chargers are crucial for the widespread adoption of EVs. By proactively advocating for stricter EV charger reliability requirements, jurisdictions can ensure that the installed chargers are functional and meet the expectations of EV drivers, ultimately facilitating the global transition to EVs. While uptime is the most commonly used metric to measure the reliability of EV chargers, it fails to capture all the technological and logistical challenges within the charging ecosystem that ultimately determine the true reliability of chargers as perceived by consumers. This study has developed a novel tool that combines the powerful reconstruction capabilities of the LSTM autoencoder with the long-term contextual awareness of an in-house naïve distribution method to learn the habitual usage patterns of EV chargers and effectively identify charging faults that may not be captured by traditional reliability measures such as uptime. This tool can help CPOs quickly detect invisible charge failures that standard reliability monitoring protocols fail to capture, enabling them to effectively meet impending EV charger reliability standards and requirements. Based on the developed tool, the uptime reduction resulting from the detected potential charger faults ranges from 4% to 20%, depending on the charger.

There are various ways to enhance the predictive capability of our tool. One possible method is to include supplementary data sources beyond habitual charging patterns, such as weather forecasts, traffic patterns, and power outage maps. This proactive approach may help identify potential charger failures caused by external factors before they occur rather than retrospectively. Additionally, a closer integration of the tool with the charging infrastructure may be beneficial. If charging stations were equipped with sensors capable of detecting cable damage or port malfunction, this information could be fed directly into the predictive tool, resulting in quicker identification of potential failures. Furthermore, if the tool were able to communicate directly with the charging infrastructure, it could trigger automated maintenance or repair processes to resolve issues more efficiently. Despite the significant progress made by our tool in identifying EV charger reliability issues, further improvement could be achieved by incorporating more data sources and seamlessly integrating with the charging infrastructure. While our tool has made significant progress in identifying EV charger reliability issues., we can further improve its capabilities by incorporating additional data sources and integrating it seamlessly with the charging infrastructure.

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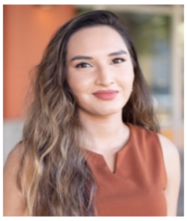
Presenter Biography



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